Analysing white maize hedging strategies in South Africa

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PREFACE

This thesis is dedicated to my father, Dr GHP (Hennie) Dreyer, who always encouraged us to further our education with the words: "On this earth, your education and experience are the only things nobody can take away from you…unless you lose your mind of course, but then it does not matter in any way."

He always told a very suitable inspirational story.

There was once a cardiac surgeon who performed a heart transplant. However, the transplanted heart did not respond to the standard procedure after the transplant, and the surgeon kept on palpating the heart until the heart reacted and started to pump blood on its own. When asked why he had continued palpating the heart for so long after the acceptable period for resuscitation of a heart had passed, he responded as follows: "It's always too soon to quit!"

I think every student who has completed a PhD will grasp the meaning of this story, and every aspiring PhD student should hold on to the phrase: "It's always too soon to quit!"

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ABSTRACT

The number of derivative-based hedging strategies available to maize producers or advocated by role-players in the maize market are endless. Hedging strategies are often based on a short-term market view or a very optimistic one-sided perspective of certain influential factors. These factors may include current and projected local and/or international stock levels, exchange rate expectations, as well as the maize producers' own financial situation. One of the most important determinants of an optimal hedging strategy is to ensure that maize producers understand the risk involved, as well as the purpose of imposing a hedging strategy. The main purpose of a hedging strategy is to protect the value of the physical commodity, and to lock in favourable, preferably profitable, price levels. This emphasises the importance for a maize producer to implement an optimised hedging strategy based on an informed decision.

The reality in South Africa is that maize producers are reluctant to adopt derivative instruments, which are the only means available to them to manage their price risk on SAFEX. The reason for this phenomenon is that maize producers do not always understand derivative instruments, what the outcome of these hedging strategies entail, and the risks associated with utilising derivative instruments. This aggravates their distrust of the market structure. This distrust is further exacerbated when the same strategies perform differently in different production seasons, as futures price formation may differ based on the influence of price determinant factors. The result is that maize producers struggle to see the advantages of hedging versus not hedging, causing them to distrust the use of derivative instruments which leads to avoidance of any form of marketing plan or hedging strategy. Inevitably, the absence of a structured hedging strategy leads to a scenario where producers sell most of their produce closer to market lows due to fear of further price declines.

In order to address these challenges, literature suggests that maize producers' general attitude could be changed if their perceptions about price risk management could be improved by the provision of reliable price formation predictions and the identification of more optimal hedging strategies. This study accomplished this feat by establishing a structured approach in the form of a filter model to enable producers to derive an informed price risk management decision. Firstly, the structured approach required the identification of seasonal similarities based on influential price determinant factors in order to identify a more probable price formation expectation. The identification of seasonal similarities by means of the filter model was enabled through the synergy provided by percentile rank grouping analyses and cluster analyses of the influential price determinant factors. The second step in the structured approach was to identify the more optimal course of price risk management action. The initial approach ranked hedging strategy returns by means of a performance measure analysis in order to determine whether specific hedging strategies would be more optimal to deploy in a specific type of production season. The performance measure results remained nonsensical despite an attempt to establish more logical rankings by changing the way in which hedging strategy returns were calculated. However, a comparison of hedging strategy realised prices to the average of the relevant July white maize futures contract price established the means to distinguish between more optimal hedging strategies to deploy, given the seasonal price formation expectation (upwards, downwards or sideways).

The established decision-making tool in the form of a filter model was able to combine all of these inputs in a meaningful manner. An example of the successful application of the model to link seasons based on factor similarities was provided in an ex-ante analysis of the 2018/2019 production year. The ability of the filter model to enable a thorough analysis of all the influential market factors in order to make an informed hedging strategy decision based on the expected price progression of the following production year, proved meaningful.

Key words: *cluster analysis, hedging strategy, influential price determinant factors, percentile ranking, performance measurement, price risk management, SAFEX, South Africa, white maize*

OPSOMMING

Die aantal afgeleide-instrument-verskansingstrategieë wat rolspelers in die mieliemark aan produsente bemark, en wat vir gebruik deur mielieprodusente beskikbaar is, is legio. Verskansingstrategieë word dikwels op 'n korttermyn-markbeskouing gegrond en vervat meestal 'n baie optimistiese en eensydige perspektief van sekere toonaangewende faktore. Hierdie faktore sluit onder andere onmiddellike en vooruitgeskatte plaaslike en/of internasionale voorraadvlakke, wisselkoersverwagtings, asook mielieprodusente se persoonlike finansiële situasie in. Een van die belangrikste bepalers van 'n optimale verskansingstrategie is, enersyds, die mielieprodusent se begrip van die inherente risiko van 'n spesifieke verskansingstrategie, maar ook van die doel waarmee die verskansingstrategie geïmplementeer word. Die hoofdoel van 'n verskansingstrategie is om die waarde van die fisiese kommoditeit te beskerm en om gunstige, verkieslik winsgewende prysvlakke vas te stel. Dit beklemtoon hoe belangrik dit is dat 'n mielieprodusent sover moontlik verseker dat die mees optimale verskansingstrategie wat op 'n ingeligte besluit berus, uitgevoer word.

Ongelukkig is Suid-Afrikaanse mielieprodusente steeds huiwerig om van beskikbare SAFEX afgeleide instrumente gebruik te maak, al is dit waarskynlik die enigste manier om hul prysrisiko effektief te bestuur. Die rede vir hierdie verskynsel is dat mielieprodusente nie altyd afgeleide instrumente verstaan nie. Hierdie gebrek aan kennis oor afgeleide instrumente sluit die implikasies en risiko's wat met die implementering van verskansingstrategieë gepaardgaan, in. Daarbenewens word produsente se wantroue in die implementering van 'n spesifieke strategie verhoog as gevolg van negatiewe uitkomste of slegte ervarings as 'n strategie nie in elke seisoen tot gunstige prysrisikobestuur-uitkomste gelei het nie. Dit veroorsaak dat mielieprodusente sukkel om die voordele van prysrisikobestuur in te sien en eerder alle bemarkingsplanne of verskansingstrategieë vermy, wat daartoe kan lei dat hulle later groot dele van hul produksie nader aan mark laagtepunte verkoop uit vrees vir verdere prysdalings.

Ten einde hierdie uitdagings die hoof te bied, stel die literatuur voor dat mielieprodusente se persepsies van prysrisikobestuur verander. Twee belangrike aspekte wat hierdie verandering kan teweegbring, is meer betroubare prysvormingvoorspellings en die identifisering van meer optimale verskansingstrategieë. Hierdie studie het dit ten doel gestel om hierdie twee kwessies op te los en het 'n gestruktureerde benadering gevolg ten einde 'n filtermodel saam te stel wat dit sou moontlik maak om 'n ingeligte prysrisikobestuursbesluit te neem. Die gestruktureerde benadering het eerstens gefokus op die uitkenning van ooreenkomste tussen verskillende produksieseisoene ten einde verwagtings vir prysvorming te bepaal. Hierdie bepaling van ooreenkomste is gegrond op ooreenkomste tussen spesifieke prysbepalende faktore

wat gewoonlik oorweeg word om menings oor verwagte prysvorming saam te stel. Die faktore is egter nie in roudatavorm beoordeel nie, maar verwerk na persentielwaardes en beoordeel deur middel van verkennende trosanalise ("cluster analysis"), ten einde ooreenkomste wat hierdie waardes of groepe op ’n spesifieke tydstip in verskillende seisoene vertoon het te gebruik om ooreenstemmende produksiejare te groepeer. Die uitslae van die verwerking se vergelykende interpretasie via die filtermodel het ook die sinergie tussen die twee metodes duidelik gemaak. Die tweede stap in die gestruktureerde benadering was om ’n optimale prysrisikobestuurbenadering te identifiseer. Die aanvanklike metode was om verskansingstrategieë se prestasie op grond van elke strategie se daaglikse strategie-opbrengs by wyse van prestasiemaatstafontleding te vergelyk. Die doel was om te bepaal of sekere strategieë moontlik in sekere tipes produksieseisoene beter presteer het as ander strategieë. Die uitslae van die prestasiemaatstafanalise het egter glad nie logies sin gemaak nie, selfs nadat die berekening van die daaglikse strategie-opbrengs aangepas is. Hierdie doelwit is egter wel bereik deur die strategieë se gerealiseerde prys per seisoen met die gemiddelde Julie-witmielietermynkontrakprys te vergelyk. Volgens hierdie maatstaf is daar bevind dat spesifieke strategieë meer optimaal was om te implementeer wanneer die seisoenale prysvorming hetsy opwaarts, afwaarts of sywaarts plaasgevind het.

Beide hierdie resultate is saamgevat in ’n besluitnemingsfiltermodel wat dit moontlik gemaak het om ’n ingeligte besluit te fasiliteer deur seisoene te koppel volgens die ooreenkomste in die prysbepalende faktore, en die meer optimale verskansingstrategie te implementeer na aanleiding van die verwagte seisoenale prysvormingsrigting. Die saamgestelde besluitnemingsfiltermodel se relevansie is verder geïllustreer deur ’n voorstel van ’n gepasde verskansingstrategie vir die 2018/2019 produksieseisoen, tydens die produksieseisoen se plantvenster te identifiseer. Die voorstel is gebaseer op die model se passing van die seisoen se ooreenkomste met vorige seisoene en die gevolglike seisoenale prysvormingsrigting-verwagting. Die filtermodel se doeltreffende fasilitering van ’n deeglike ontleding van die prysbepalende faktore en die gevolglike bepaling van ’n ingeligte verskansingsbesluit is duidelik bevestig.

Sleutelwoorde: *verkennende trosanalise, verskansingstrategie, invloedryke prysbepalende faktore, persentielgroepering, prestasiemaatstawwe, prysrisikobestuur, SAFEX, Suid-Afrika, witmielies*

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LIST OF ABBREVIATIONS

ADX	Average Directional Movement Index
AL	Average Linkage
AMD	Agricultural Markets Division
AMH	Adaptive Market Hypothesis
AMPEC	Agricultural Marketing Policy Evaluation Committee
ANC	African National Congress
ANOVA	Analysis of Variance
APD	Agricultural Products Division
BIRCH	Balanced Iterative Reducing and Clustering using Hierarchies
CAPM	Capital Asset Pricing Model
CBOT	Chicago Board of Trade
CBOT-C	Chicago Board of Trade Continuous Maize Contract Price
CEC	Crop Estimate Committee
CDF	Cumulative Distribution Function
CF	Clustering feature
CL	Complete linkage
CME	Chicago Mercantile Exchange
CVaR	Conditional Value at Risk
DMI	Directional Movement Index
EDF	Empirical Distribution Function
EMA	Exponentially Weighted Moving Average
EMH	Efficient Market Hypothesis
EM	Expectation Maximisation
ENSO	El Niño Southern Oscillation

EP	Export parity
EPR	Export parity ratio
IP	Import parity
IPR	Import parity ratio
JSE	Johannesburg Stock Exchange
LME	London Metals Exchange
LPM	Lower partial moment
MACD	Moving average convergence divergence
MTM	Mark-to-market
MVaR	Modified value at risk
NAMC	National Agricultural Marketing Council
NP	National Party
NOAA	National Oceanic and Atmospheric Administration
ONI	Oceanic Niño Index
RSI	Relative Strength Index
SAFCOM	SAFEX Clearing Company Pty Ltd
SAFEX	South African Futures Exchange
SAGIS	South African Grain Information Service
SASA	South African Sugar Association
SASDE	South African Supply and Demand Estimates
SERF	Stochastic efficiency with respect to a function
SL	Single linkage
SML	Security market line
SOI	Southern Oscillation index
SST	Sea Surface Temperatures
Stoch	Stochastic oscillator

TR	True range
US	United States
USDA	United States Department of Agriculture
USD/ZAR	United States dollar / South African rand exchange rate pair
VaR	Value at risk
WASDE	World Agricultural Supply and Demand
WM / WMAZ	White maize
WM-C	White maize continuous price
ZAR	South African rand

CHAPTER 1

Introduction

“Hindsight is always perfect, as the saying goes. However, the process that reaches that state of perfect vision is not instantaneous or in any way easy. The courage to question everything is the wheel against which the lenses of hindsight are ground. Accepting the unacceptable answers to questions you didn't know to ask is the quality which makes us human, and enables us to take the leaps of understanding, the leaps of faith, which grant wisdom.”

Justin E. Griffin (2012)

1.1 Introduction

A price risk management decision is one of the more difficult decisions maize producers are confronted with every season. At the end of a production year, it often seems easy to look back and evaluate what the right course of (price risk management) action should have been. Nevertheless, a white maize producer must be satisfied with the reality that he has to make a price risk management decision based on the information available today for the unknown of tomorrow. Although the futures market is probably the most effective way for a maize producer to mitigate price risk at any given time, it does not make it any easier to make price risk management decisions.

Price risk management decisions could have a significant effect on the profitability of crop production. This is not only due to producers failing to utilise available hedging tools, but to large cash flow losses as result of the hedging process itself. Maize producers are continuously instructed by specialists, consultants, commodity brokers and marketers – to name but a few – on how to hedge, how much to hedge, and when to hedge their produce. Also, the number of price risk management strategies that employ derivative instruments and are available to maize producers or advocated by traders or buyers of maize, are endless (Cass, 2009:6). However, even with all the available information, evidence shows that maize producers still hedge poorly (Dorfman & Karali, 2008:1). This sentiment has remained part of the stark reality of producer hedging since the outset. Producers postpone their hedging decisions for as long as possible, especially if the decision is only dependent on the individual instead of being a requirement set by production input financing institutions (Swanepoel, 2018).

There are various reasons for poor hedging by maize producers, and this study aimed to find and explain them. A related consideration was to identify the factors that influence market price formation and to test the efficacy of a number of popular basic hedging strategies during different market conditions. The various analyses done contributed to the identification of a more optimal hedging strategy, given the market price formation expectations arrived at after the analysis of a specific set of influential market price drivers. The identification of a more optimal hedging strategy could, in turn, help maize producers hedge more optimally in light of the seasonal price formation outlook based on the outcome of seasons when similar market conditions or circumstances were present.

In order to establish an understanding of the aspects that influence a producer's hedging decisions and the proposed requirements to improve the price risk management actions of producers, this chapter is structured to provide a background (Section 1.2) to the problem statement and research question (Section 1.3). This is followed by the motivation and research aim (Section 1.4) to establish the essential foundation for the relevant objectives the study addresses in Section 1.5. A description of each chapter in Section 1.6 provides a road map of how the individual objectives were undertaken. The chapter concludes with the envisaged contribution of the study (Section 1.7), which provides the context of the practical application of the results of this study in the industry. A short note to the reader was added as Section 1.8 to clarify certain aspects or terms in advance.

1.2 Background

Agriculture is an ever-changing environment. Given the many sources of risk inherent in the production of agricultural products, aspects of finance, and the marketing of the final product, maize producers are sometimes forced to make rushed decisions that contribute to income fluctuations (Boehlje & Eidman, 1994). In order to manage or mitigate these risks, it is important to apply specific methods that may cancel out or at least reduce the effects of the factors that give rise to risk in agriculture. These methods also depend on the individual maize producer's attitude to risk, as well as the financial situation of the farming operation, which may or may not render them able to afford the costs of each risk mitigation method (Akcaoz & Ozkan, 2005:662).

There are various risk management strategies that maize producers implement in order to reduce undesirable outcomes of risk events. One type of risk that a maize producer generally has no control over is adverse weather conditions that influence prospective planting decisions[1] along with the yield

[1] Planting decisions influenced by an expected weather pattern may include factors like planting date, row width and seed population per surface unit, as well as fertilisation application, herbicide and pesticide spraying programmes.

realised at the end of the season. Developments in crop insurance[2] are ongoing as specialists aim to better assist maize producers in mitigating the effects of hail, frost, fire, and yield variability due to drought or excess rain. Derivative instruments are another risk management tool available to maize producers to relieve the price risk associated with the sale of produced agricultural commodities. Arguably these specific risk management strategies differ in terms of their main aim. Crop insurance is based on the probability that a specific event may occur irrespective of the market price movement associated with the insured crop. The aim is predominantly to cover input cost when adverse events, affecting production, occur. Derivative based prise risk management however focus on the value management of the underlying crop with profitability as the main aim. Both alternatives nevertheless require that a producer determines the quantity produced and price ensured or hedged beforehand (Poitras, 1993:373). This reality influences a producer's willingness to adopt derivative based hedging (see Chapter 4, Section 4.2.1, Table 4.1) due to potential costly contract buy outs if delivery of the physical crop is not possible due to an applicable crop insurance related event. The focus of this study will be however be based on derivative instruments which are available to maize producers through an exchange traded free-market platform, colloquially known as SAFEX (South African Futures Exchange). It was later rebranded the Agricultural Products Division (APD) of the JSE Securities Exchange, but more recently as the SAFEX Commodity Derivatives Division (JSE, 2013:1).

SAFEX enables maize producers or commercial users of maize to hedge their price risk and thereby limit their exposure to adverse price movements, or lock in favourable prices. Yet these price hedging tools have been available for more than two decades and maize producers are still reluctant to use them. For example, a study conducted by Jordaan and Grové (2007:548) indicated that South African maize producers are reluctant to make use of SAFEX due to a "lack of capacity", "distrust of the market", and "bad experiences". Later on, Mofokeng and Vink (2013:10) confirmed that, after 15 years of deregulation, only 35 per cent of the South African producers in their sample made use of available price risk management instruments. These factors indicate that South African maize producers do not always trust the price formation effectiveness of the futures market, and may sometimes lack the necessary knowledge and experience to understand the implications of an executed hedging strategy.

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2 Multiple-peril crop insurance was first introduced in the USA in 1899 by private companies, but the US Government mainly took over the role of "all-risk" crop insurance provision after the implementation of the Federal Crop Insurance Act of 1938 and several failed attempts by private companies. Although the policies are referred to as "all-risk", it definitely refers to named and specific perils only (Kramer, 1983:181).

Results from Ueckermann, *et al*. (2008:222) also showed that maize producers' choices to use derivative instruments are influenced by their own prediction of daily market prices, trends, farm size, and geographical characteristics. Maize producers that do make use of derivative instruments tend to be younger, less experienced, more educated, and accepting of technology resources. They also operate larger farms which they are less likely to own since they prefer to hire land and processing equipment. However, in general, maize producers at the time perceived their marketing management skills to be relatively weak. The study by Mofokeng and Vink (2013:10) nevertheless showed that, as time passed, producers became more inclined to hedge, especially if they were older (more experienced) or better educated producers who managed larger operations. Other factors, such as off-farm income and insurance, however reduced producer's willingness to make use of derivative-based price risk management alternatives.

The possible reason for producers' unwillingness to apply derivative-based price risk management instruments may be ascribed to the fact that the use of modern-day derivative instruments is a relatively new development in South Africa (Mofokeng & Vink, 2013:2). Contrary to the Chicago Board of Trade (CBOT), the world's oldest futures and options exchange (in operation since 1848), the South African version was only formally established in 1995 in the form of the SAFEX Agricultural Markets Division (AMD). The first contracts on this exchange were for beef and potatoes (which were delisted due to inactivity in January 1999). Shortly after that, in 1996, the first white maize and yellow maize contracts were listed and gained momentum over the years. Today, in 2019, white maize remains the most liquid contract followed by yellow maize, soya beans and sunflower seeds. Figure 1.1 indicates the market volumes traded since 2010.

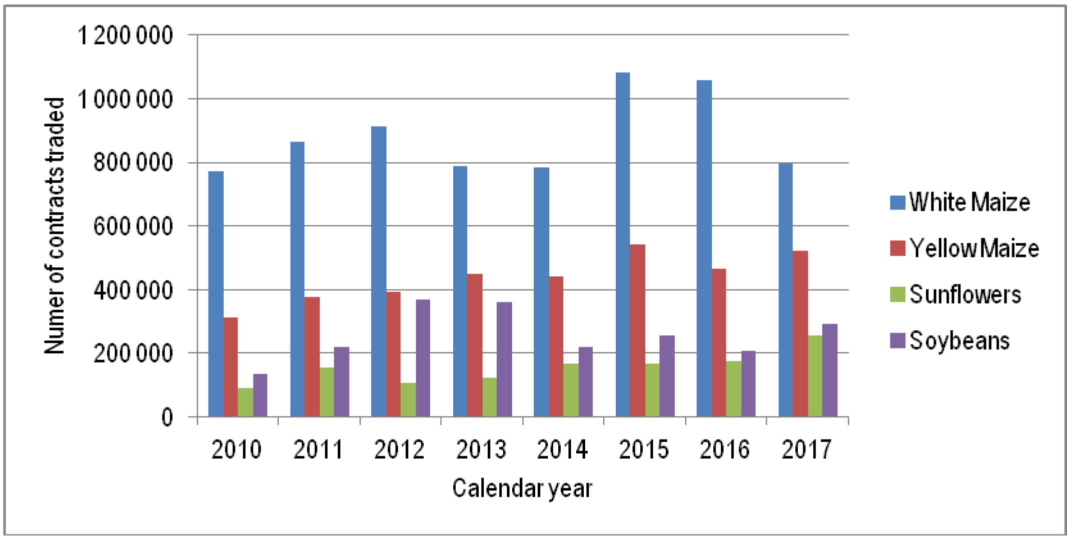

Figure 1.1: Annual market volume traded per commodity
Source: Compiled by author (data extracted from JSE (2018c))

The initial development of SAFEX was necessitated by the termination of a regulated system to pave the way for a free market system. The South African agricultural sector has had a long history of state intervention. The Marketing Act of 1937 could be considered the turning point in agricultural policy and marketing. Before 1937, all agricultural policies were aimed at improving and supporting the agricultural sector. After the implementation of the Marketing Act of 1937 – and in 1968, the consolidated version in the form of the Marketing Act, No 59 of 1968 – agricultural policy and marketing was seen as the same thing (Vink & Kirsten, 2000:9). During this period in time, fixed seasonal white maize contract prices were determined by the Maize Board (Bown *et al*., 1999:276). A single channel scheme for white maize was administered by the Maize Board and entailed that each maize producer in South Africa received the same pre-season determined price for their crop when delivering to their nearest agricultural cooperatives elevator. The cooperatives functioned as regional monopolies appointed by the Maize Board. The Maize Board, in effect, was the only buyer and seller of maize with the purchase price or farm gate price determined by a survey conducted by the Department of Agriculture. This price was then used to determine the average expected production cost. The Maize Board then set the purchase price at the average production cost, plus a profit margin. On the other hand, the Maize Board sold the maize to all millers and processors at the same fixed price all over South Africa. The selling price was set at the purchase price plus a margin to cover handling, storage and transport (Vink, 2012:558-559).

From a maize producer’s perspective it was an uncomplicated system, since it was clear what the price for the crop would be during harvest, even before planting. The miller would also know what the cost of his main input would be for the coming season. The consequences of this pan-territorial and pan-seasonal pricing[3] have been widely debated by De Swardt (1983) and Groenewald (2000). One of the implications of this method of pricing was that maize producers and millers further away from the main production areas were subsidised by maize producers closer to the market, resulting in an expansion of production in marginal areas and, in the end, a transfer of subsistence maize producers and consumers to producers (Van Zyl, 1988).

The period from 1937 to 1996 was also marked as the time when the majority of the South African maize market infrastructure development took place (Roberts, 2009:3). The single channel marketing system determined the layout of the infrastructure, where maize elevators were situated to minimise

[3] Pan-territorial and pan-seasonal pricing, as stated by Vink (2012:559): Pan-territorial pricing means that government establishes a system of nation-wide equal producer prices, sometimes to integrate remote areas and/or low potential areas, whereas pan seasonal pricing refers to a pricing regime where the price of food crops are kept unchanged throughout the season (Thomson & Metz, 1999:150).

regional overlap, the geographical placement of cooperatives, and the railway infrastructure was developed accordingly. However, in 1996, the new ruling African National Congress (ANC) government took over the responsibilities of the Department of Agriculture, and established the Marketing of Agricultural Products Act (Act 47 of 1996). Under this act, the National Agricultural Marketing Council (NAMC) initiated rapid deregulation of the different boards and schemes, as well as other policy changes that fundamentally changed the agricultural sector (Vink, 2012:564).

With the demise of the Maize Board, the existing infrastructure was taken into consideration, and although SAFEX determines the cash and future prices of maize, the regional prices available to maize producers were linked to their location relative to Randfontein. This location was chosen as a reference point since it contained a concentration of milling capacity, as well as relevant rail links to the rest of the existing South African rail infrastructure (Roberts, 2009:3). A transport differential system determined the cost of transport from specific maize elevators to Randfontein. Therefore, maize producers further away from Randfontein would receive a larger differential deduction from their cash or hedged SAFEX price. This would only be the case if the maize producer decided to deliver and sell to the nearest maize elevator, which was now no longer owned by a cooperative but by a profit maximising company. Maize producers would also have the option to deliver and sell directly to maize buyers, traders, and millers operating in their area at a SAFEX-derived price.

Consequently, after 60 years of fixed prices, the responsibility of the marketing of maize was placed in the hands of individual producers (Bown *et al*., 1999:276) (Chapter 2, Sections 2.2 & 2.3, expands on the history pertaining to market development and the challenges producers were faced with before and after the market mechanism transition period). This sudden new set of rules prompted maize producers to acquire knowledge and understanding of abstract derivative instruments. Maize producers also needed to learn how to evaluate the effect of factors such as local and international supply and demand, currency fluctuations, crude oil prices, and external factors like equity market volatility or financial crises on the South African commodities market.

Maize producers, as a result, had no choice but to adopt a sudden change in policy and market structure. This casts some light on the reluctance of maize producers to utilise derivative instruments to manage their price risk. Furthermore, this reluctance also gives rise to maize producers ironically becoming “risk averse” to derivative instruments and adopting high-risk strategies, like selling their crop in the cash market after harvest when supply is at its highest and prices tend to be lower (Strydom *et al*., 2010:2). Research has however shown that an important factor influencing a maize producer’s willingness to adopt the use of derivative instruments is their risk perception about daily market prices (Ueckermann *et al*., 2008:233-234) (Several other reasons which influence a producers willingness to implement derivative instruments as part of their price risk management strategy is discussed in Chapter 4, Section 4.2.1). This suggests that, if their understanding of derivative instruments and the reliability and efficiency of price formation expectations could be improved, maize producers may become more willing to participate in the derivatives market with the desired outcome of reducing their uncertainties and, ultimately, their price risk. Therefore, there is no denying that one of the critical determinants of an optimal strategy is the maize producer's understanding of the associated risk and the purpose of a hedging strategy.

Strydom, *et al*. (2010) and Venter, *et al*. (2012) investigated the evaluation of basic derivative-based hedging strategies for the South African agricultural commodities market in particular. Their studies applied a stochastic efficiency analysis of basic maize marketing strategies with the main objective of determining the benefit of implementing some form of basic hedging strategy, as opposed to selling the whole crop in the cash market. They deployed stochastic efficiency in the form of the Stochastic Efficiency with respect to a Function (SERF) and the Cumulative Distribution Function (CDF) in order to determine the possible benefit of deploying some form of hedging strategy versus adopting no strategy at all. Additionally, the profitability of routine marketing strategies was evaluated. The evaluation was done by assessing different production regions to determine their profitability per hectare in terms of a CDF of the strategies deployed. Both these studies concluded that it would be better to establish some form of hedging strategy, but they struggled to conclusively rank strategies. In both cases, the CDF as well as the basic statistical measures produced different results, indicating that a hedging decision would be influenced by the risk preferences of maize producers.

In a related study, Jordaan, *et al*. (2007:318) measured the price volatility of field crops in South Africa. They found that volatility changed throughout a production season and proposed different hedging strategies for the different periods of varying volatility in order to mitigate the different levels of risk. In terms of white maize they found highly leptokurtic behaviour in the volatility, which indicated that the conditional standard deviation of white maize price returns was not normally distributed. In light of this, it was deemed meaningful to deploy a ranking mechanism for hedging strategies by means of specific measures that are able to account for the presence of non-normality. This finding amplifies the relevance of this study, which aimed to contribute to identifying a suitable ranking mechanism to evaluate applicable hedging strategies in order to identify a more optimal hedging strategy, given the seasonal price formation expectation.

1.3 Problem statement and research question

Derivative instruments are currently the only applicable measures available for maize producers to manage their price risk; despite this, South African maize producers are reluctant to adopt derivative instruments due to their lack of understanding of the possible outcomes and risks included in derivative-based hedging strategies. This uncertainty aggravates their distrust of the market structure, since different strategies do not perform equally well in various production seasons. The reason why a hedging strategy may not always be optimal in every production season is probably due to the volatility of the agriculture market. This implies that the variables included in the futures price formation process may differ for each production year, as each year could be influenced by different price determinant factors. The result is that maize producers struggle to see the advantages of hedging over not hedging, which leads to general distrust towards derivative instruments. Hence, maize producers avoid any form of marketing plan or hedging strategy and sell most of their produce closer to market lows for fear of further price declines.

Given the issues outlined above, the **problem** is threefold: **Firstly, a South African maize producer without a marketing plan or hedging strategy has no means to remove or partly reduce price risk. Secondly, a South African maize producer without the necessary knowledge pertaining to white maize hedging strategy performance over time may remain reluctant to implement any form of hedging strategy with confidence. Thirdly, the optimal hedging strategy may differ from one production year to the next. By this premise, indiscriminate application of one type of marketing plan or hedging strategy – without due consideration of all the elements that affect price formation – may be less prudent.**

From this problem statement, the following broad **research questions** were formulated: **Would it be possible to identify a proposed optimal hedging strategy for different seasonal price formation expectations by linking different production years, based on specific influential price determinant factors? Additionally, would it be possible to rank, and more conclusively determine optimal white maize hedging strategies by developing a ranking measure or criteria?**

The problem statement and research questions were broken down into a set of objectives. However, these will make more sense once the motivation and research aim of the study have provided some context.

1.4 Motivation and research aim

The primary motivation for this study stems from the premise that if the reliability of expected futures market price formation can be improved, producers may become more inclined to make use of the available derivative instruments to deploy a more optimal hedging strategy. The aim of this study, therefore, was to address the general shortcoming in existing literature in terms of a current model or structured course of action that a producer could follow to establish a more optimal course of price risk management action. An optimal price risk management plan or hedging strategy should, as a result, be based on the applicability or ability of the hedging strategy to include or adapt to expected or anticipated seasonal futures contract price formation. In order to achieve this aim, the study attempted to establish a means of identifying seasonal similarities according to influential price determinant factors that characterise a specific production year. The main aim was broken down into four specific outcomes, and the background of each outcome formed the foundation of the respective objectives (Section 1.5).

The first outcome was to identify the influential price determinant factors (Chapter 2, Section 2.4.2). A review of the literature showed one relevant study by Auret and Schmitt (2008:105), who derived an explanatory model for white maize futures prices by means of a regression model. Several influential price determinant factors were identified and confirmed from this review and other sources that included Geyser and Cutts (2007), Moholwa and Liu (2011), Monk, Jordaan and Grové (2010), and Geyser (2013). However, this study deviated from past research by not using a regression model or similar approach in its evaluation of influential price determinant factors in order to group production years according to similarities in the factor values at a specific point in time. Auret and Schmitt (2008:129) identified the presence of autocorrelation between the factors included in their regression based explanatory model for white maize prices. In order to account for the presence of autocorrelation, several factors were omitted in their final model. An updated regression model or similar model would probably not have been able to replicate the regression model according to the findings by Stone, *et al*. (1996) or that of Meyer, *et al*. (2006). In general terms, these findings indicated that a model based on fundamental price influential factors should be able to account for the effect of individual factors on price formation, but also for the influence individual factors may have on each other, and changes in these influences over the course of a production season. Both studies confirmed that the impact of a specific factor may change over time and that changes in a specific factor value may emphasise the effect another factor may have on price formation.

This premise was already addressed by Meyer *et al*. (2006:370-374) in their suggestion to divide production years into three categories that characterise price formation closer to export parity, import parity, or a neutral state. As a result, these categories tend to focus on specific factors that may be more relevant in price formation, given the specific fundamental market conditions linked to the supply of white maize. For instance, a low supply scenario may be seen as the main reason why market prices were pushed to higher levels to account for the cost of substituting supply shortages by imports (import parity). The cost of imports, however, immediately incorporate other factors in the form of the international maize price or exchange rates, which play an essential part in the calculation of import parity (Auret & Schmitt, 2008:107-109).

The specific methods considered in this study consisted of cluster analysis and percentile rank grouping analysis (Chapter 5, Section 5.3). These methods analysed and compared the stance of specific influential price determinant factors at a specific point in time in order to provide a meaningful link between production seasons based on similarities in the influential price determinant factors. Cluster analysis may be seen as an exploratory analysis method that enables the recognition of data patterns that statistically link or group specific data (Jain, 2010:651). Percentile ranking and grouping of data, on the other hand, is merely a statistical process whereby data is assigned a statistical percentile value based on the ranking of a new data point relative to the historical values in the same data set. The ranking of each data point at a specific point in time may consequently provide a measure by which to evaluate whether the new data point is relatively high or relatively low compared to the factor data in the same data set. The ranking and grouping of data in this manner provides a practical approach to comparing factor values over time in order to link production years based on factor value similarities. Although these methods were implemented and individually evaluated, the synergy that evolved between the results formed a vital cornerstone in the confirmation of the comparative results obtained.

The second outcome rather served as justification for the study than an input to the methodological approach (Section 1.5). The justification involved the specific inclusion of a thorough analysis of the notion of market efficiency (Chapter 3), since the premise of market efficiency could also serve to detract from the applicability of the aim of this study. Market efficiency and its formalisation by means of the Efficient Market Hypothesis (EMH) coined by Fama (1965a,1965b,1970), has a long history of results favouring the assertion that market information arrives in the market in a random fashion. This means that market participants only react to new information as it arrives in the market space and becomes available to all role-players at the same time. According to the EMH this results in the inability of market participants to outperform the market return on a sustainable basis by using analyses of historical results in order to identify specific market trends or recurring patterns that may enable them to anticipate price formation developments. This notion has however been disproved by several studies, which encouraged further EMH-opposing research, such as establishing the existence of market anomalies (Chapter 3, Section 3.2.4.2) and, eventually, the development of the field of behavioural finance (Chapter 3, Section 3.2.4.3). The analysis of relevant literature, however, concluded that neither view of market efficiency could be entirely written off. On the contrary, a combination of the opposing views in the form of the Adaptive Market Hypothesis (AMH) (Lo, 2004, 2005) provided a suitable conclusion to meaningfully incorporate the notion of market efficiency as part of the aim of the study.

The AMH states that the market tends to go through different phases or levels of market efficiency, which helps justify the aim of this study to compare and link different production years. This justification stems from the AMH notion that different role-players will always seek to identify opportunities in the market that are based on potential market inefficiencies (Lo, 2004:24-25, Lo, 2005:31). Role-players will, as a result, act on these inefficiencies, which ultimately eliminates the opportunity presented by the potential inefficiency. In terms of this premise, all role-players will be evaluating the influential price determinant factors in order to derive an expected price formation development based on the market's previous reaction when the same set of circumstances were present. It therefore seems relevant and possible to predict the expected price formation action based on an evaluation of influential price determinant factors. This justifies the aim of linking similar developments in the influential price determinant factors in order to implement a more optimal course of price risk management action.

The essence of the AMH – that the market is always evolving and tends to go through different phases (or levels) of market efficiency – is captured in outcomes three and four. Outcome four entails the construction of a filter model as decision-making tool (Section 6.4) to enable an all-inclusive overview of the status of the influential price determinant factors at a specific point in time. This implies that the model would be able to identify and incorporate influential price determinant factors (market drivers), allowing a price risk manager to classify the evolving upcoming production season to determine a more suitable hedging strategy given the price development expectation of the particular production season. This evolving feature of the filter model is activated by the model's ability to provide a holistic, but also specific, overview of market price drivers in order to derive consensus regarding seasonal similarities between the different production years. The aim of the filter model is to evaluate the evolving statuses of selected influential price determinant factors to enable the identification of a more probable price formation development on the basis of past logical reactions of market participants to changes in and between these price determinant factors. The success of the filter model to compare different production seasons at a specific point in time in order to make an informed hedging decision may also be seen as one of the contributions of the study. Armed with this knowledge, a white maize producer may become less reluctant to participate in the derivative market with the desired outcome of overcoming their uncertainties and, ultimately, reducing price risk.

To achieve this, outcome three – which served as an input in the filter model – is briefly discussed. This entails identifying the most suitable hedging strategy for each type of production season. In order to accomplish this goal, this study intends to establish a more effective ranking method that will help to determine the most suitable hedging strategy. This requirement is due to the fact that previous suggested ranking methods were inconclusive (see for example Strydom *et al*., (2010) and Venter *et al*., (2012)). This study therefore endeavoured to apply several well-known and applicable financial performance measures to the daily strategy returns. The latter was generated by subtracting the direct cost of production (input cost per tonne) from the daily hedging strategy price valuation (Chapter 5, Section 5.4.2) for each strategy, and dividing it by the input cost. These returns may be positive if the realised daily strategy price were above the input cost level, or negative if the realised daily price were below the input cost level. The application of financial performance measures was based on the finding by Jordaan, *et al*. (2007:318) that the return volatility in the conditional standard deviation of white maize price returns was highly leptokurtic in nature. This finding triggered the idea that specific financial performance measures were developed to overcome the assumption that all return distributions are normally distributed. The reason why these developments in performance measure analysis were necessary, was for instance due to the fact that Brooks and Kat (2002:37) found that investment returns with a high kurtosis and negative skewness may lead to a biased result when applying a performance measure that uses the standard deviation as a measure of risk. However, financial performance measures were not the only method applied to derive consensus as to the more pertinent hedging strategy to deploy. The reason for the inclusion of an additional ranking criteria is explained in Section 1.6.4 below.

1.5 Objectives of the study

Based on the explanation provided in discussing the aim of this study, the objectives were the following:

- to identify the influential price determinant factors that should be included in the analysis to enable a comparison between production years based on similarities in the factors at a specific point in time;
- to link previous and upcoming production years by means of historical and recent factor data in order to establish an expectation of price formation for an upcoming production year;
- to identify applicable derivative-based hedging strategies from previous literature studies in order to implement 10 specific hedging strategies against the July white maize futures contract from 2003 to 2018 (16 production years);

- to determine the daily realised strategy price for each hedging strategy and production year from 2003 to 2018. The purpose was to calculate daily hedging strategy returns by subtracting the input cost per metric tonne from the daily strategy realised price for the main white maize production area of the central and western Free State. These specific regions are the main white maize producing areas (DAFF, 2018:10);
- to compare the return results of each of the 10 implemented strategies for each of the 16 production years by means of applicable ranking measures in order to determine an optimal strategy for each production year;
- and, finally, to compile a decision-making model (filter model) to enable the linkage of similar production years based on similarities in the influential price determinant factors at a specific point in time. The linkage of production years should function as a means to establishing a more probable price formation expectation for a developing season so that a more optimal or preferred hedging strategy could be deployed, given the seasonal outlook and expected circumstances.

1.6 Literature, methodology and results: chapter descriptions

All of these objectives are addressed in specific chapters and sections in this study. A description of each of the literature review chapters, and the empirical review included in the study are provided in the following subsections in order to provide an overview.

1.6.1 Chapter 2 - South African agricultural market structure development and influential market drivers

All market-related studies require at least fundamental knowledge of how the markets developed over time to understand why market participants react in specific ways. This chapter begins by providing a thorough historical background of the changes in market structure and agricultural policy in South Africa (Chapter 2, Section 2.2). The literature background explains why agricultural policy in the form of single-channel or regulated marketing of agricultural products was implemented in the first place. The review also addresses the shortcomings of the system and how the economic unsustainability of the system was the main reason for the deregulation of single-channel marketing and the formation of a free-market system.

Furthermore, several of the aspects discussed by means of relevant literature reviews in Chapter 2 formed a foundation for the rest of the study. The first may be seen as the background to market development in South Africa, explaining the changes producers were faced with and were forced to adapt to. These changes and their consequent impact on price risk management decisions may be seen as one possible reason as to why South African producers may be viewed as reluctant to make use of the new marketing mechanism and the price risk management tools available to them.

Chapter 2 also provides an important background that explains how derivative instruments in the form of futures and option contracts work. It provides the information required to understand the literature review on price risk management strategies in Chapter 4 (Section 4.2.2), as well as the implementation of the relevant hedging strategies in this study (Chapter 5, Section 5.4.2). The final aspect, which also addresses the first objective, is the identification of influential price determinant factors. These factors are also discussed as part of the literature review on white maize market efficiency in Chapter 3 (Section 3.3.1), and provides meaningful insight into price formation in the derivatives market, as well as the factors included in explanatory models of white maize price formation.

1.6.2 Chapter 3 – Market efficiency

The inclusion of market efficiency in the study stems from the premise discussed as part of the study aim. The fact that the study aimed to make use of historical influential price determinant factor data to find similarities between previous and current production seasons, and hence identify a more optimal course of price risk management action, may be seen as contradictory to the concept of market efficiency. That is why a thorough review of market efficiency was warranted and why the second objective of the study was set to justify the relevance of the study within the realm of market efficiency as a whole.

The chapter includes an overview of the historical development of market efficiency literature over time. This includes pioneering studies that were relevant to the development of the hypothesis, as well as the formalisation of a joint hypothesis that identified different forms or levels of market efficiency. This formalisation of market efficiency in the form of the Efficient Market Hypothesis (EMH) formed the foundation from where research findings pertaining to the confirmation as well as contradiction of the EMH developed.

Contradictions to the concept of market efficiency became known as market anomalies and the premise of behavioural finance provided an explanation of market price formation based on the psychological influence of decision making. The psychological effect of decision making could furthermore be linked to the factors influencing the hedging decisions of market role-players. The chapter furthermore includes an evaluation of relevant literature on technical analysis, which may be seen as a means to capturing some of the findings contradictory to the EMH that relate to the psychological factors affecting human decisions and, consequently, price formation. Technical analysis was also applied in the evaluation of a specific hedging strategy identified in Chapter 3 (Section 3.2.5) and included in the hedging strategy method description in Chapter 5 (Section 5.4.2.10).

The justification of the study in terms of market efficiency does not rely on the argument of possible market inefficiencies based on market anomalies or behavioural finance. The inclusion of the alternative market efficiency approach in the form of the Adaptive Market Hypothesis (AMH) provided the necessary justification for the implementation of this study. The AMH specifically postulates that market participants always aim to exploit potential inefficiencies, which inevitably improves the level of market efficiency. As a result, it is reasonable to expect that market participants evaluate the stance of influential price determinant factors and anticipate a more probable price formation development based on the logical reaction of market participants to changes in the influential price determinant factors.

1.6.3 Chapter 4 – Price risk management and performance measurement

This chapter builds on the premise of market efficiency and starts off by providing an overview of price discovery and sustainable price risk management, which entails a literature review of the factors (market drivers) that were found to influence hedging decisions. These factors also include the reasons why producers are reluctant to make use of the derivative instruments available to manage their respective price risk. The review reiterated the importance of a versatile, though purposeful hedging strategy that is able to incorporate meaningful price predictions. Such a strategy should also enable a producer to share in upward market price potential to ensure effective price risk management and limit potential costly contract buy-outs. As a result, the review of price risk management or hedging strategies were linked to the specific characteristics an applicable hedging strategy should include to increase the willingness of a producer to adopt derivative instruments as part of a more optimal price risk management decision.

Furthermore, in order to attempt to more conclusively rank hedging strategies and partly address the aim of the study as well as the fifth objective, a thorough literature review of performance measures was included. The main reason for the review was to ensure the identification of specific popular performance measures to implement in the evaluation of hedging strategy returns, but also to identify possible shortcomings or pitfalls to consider when implementing a performance measure evaluation.

It should, however, be stated from the onset that the evaluation of hedging strategies by means of performance measures proved to be largely nonsensical. This reality proved to be an important additional contribution of the study, since the evaluation of hedging strategy returns skewed the return distribution, which led to potentially biased results. The next section provides a short background on this finding.

1.6.4 Chapter 5 and 6 – Methodology and results

The empirical review is in the form of a quantitative analysis and the specific data included in the study take on several forms. Each data set is thoroughly explained in Chapter 5, but some background to the data may be helpful to sensitise the reader to the different data groupings or sets included in the study. Each set of data is associated with the specific objective the application of a specific methodological approach aimed to achieve. The first set of data includes all the factor data for the factors identified in Chapter 2 (Section 2.4), after which a thorough explanation of each of the 12 individual factors included is provided. The factor data differ in the sense that fundamental factors in the form of supply and demand data take on a specific measurement or volume figure value, whereas price data such as exchange rates or the international maize price (United States corn contract) are considered a price per unit of the underlying currency or commodity. Other factors such as weather-related measurements are seen as index-type values. Several factor values are available on a monthly basis, such as supply and demand and weather-related measurements, whereas price data is available on a daily basis. In order to standardise the factor values, the factor data was organised to include a monthly value for each factor from January 2001 up to and including July 2018. Daily price data was transformed into monthly data by taking the last daily value of each month as a representative price for the month. This corresponds with the way a database such as Thomson Reuters (2018) represents monthly price data. The source of each of the factor data sets is specified in Chapter 5 (Section 5.2.3, Table 5.4). The methodological approaches applied to this data set to identify similarities between different production years based on the factor data, were percentile rank grouping analysis and cluster analysis.

The second set of data consists of seasonal contract data for the March and July white maize futures contracts, as well as the respective option volatility values from 2003 to 2018 (16 production years). One of the challenges in this regard was to obtain option volatility data prior to January 2002, even though white maize options were already introduced in March 1998 (Geyser, 2013:3). This requirement was necessary, since the implementation of option-based hedging strategies could not be done without this data. Option volatility data is not recorded in a database such as Thomson Reuters (2018). As a result, the historical JSE daily statistical data files (JSE 2018c), which were available from January 2002, were accessed and a database of daily option volatility for the March and July futures contracts was compiled. The data are in the form of daily closing prices for each season from planting up to contract closure. Thus, the data for the 2010 production year would be from November 2009 up to contract expiry in July 2010.

The third set of data consists of the results of the application of the hedging strategies to the price and volatility data in order to derive a daily hedging strategy realised price. From these daily realised strategy prices for each of the 10 strategies identified and implemented over 16 production years, daily strategy returns were by subtracting the direct and indirect variable cost per metric tonne from the daily realised strategy price and dividing the net value by the input cost. The hedging strategy returns were calculated so they could be evaluated by means of the relevant performance measures. However, as stated earlier, the performance measure ranking analysis of hedging strategies based on these returns proved to be nonsensical. A short discussion of this result, even as part of the introduction, is warranted since an alternative method of evaluating the hedging strategy returns by means of performance measures was considered and evaluated. The alternative method entailed changing the return calculation to the daily returns based on the daily realised strategy price calculated for each strategy. The performance measure ranking analysis results remained nonsensical in isolation. However, the extensive process of comparing the performance measure analysis ranking results with the final realised strategy price, facilitated a meaningful conclusion as to the more optimal strategy to implement, depending on the expected price progression of the main July white maize futures contract price.

All of the data pertaining to the influential price determinant factors, futures prices, option volatility and hedging strategy return data were subjected to a statistical description analysis in order to establish an overview of the data distribution, as well as the normality of the data. The presence of normality in the factor data is not a prerequisite for applying the cluster analysis and percentile ranking and grouping analysis methods to the factor data. However, establishing the normality of the hedging strategy return data was important, since the presence of non-normality could lead to biased results when specific performance measures were applied to the data (Brooks & Kat, 2002:37).

The software used for the analysis also differed on the basis of the methodological approach applied to the different data sets. The percentile ranking and grouping analysis, as well as the final decision-making filter model were applied by means of Microsoft® Excel 2010. The Two-Step Cluster Analysis approach was run by means of IBM® SPSS Statistics Version 25 (2017). The calculation of daily hedging strategy realised prices, as well as the implementation of the performance measure analysis, was carried out by means of Microsoft® Excel 2010.

1.6.5 Chapter 7 – Conclusions and recommendations

The conclusion of the thesis summarises how the study achieved its aims. Each individual objective is also discussed to confirm that it was addressed, and from this an answer to the research question is provided. The conclusions that flowed from the results serve to confirm the relevance of the study and its contribution to the body of knowledge, as well as its practical relevance. Recommendations are also made for future research.

1.6.6 Diagrammatical representation of thesis structure

Figure 1.2 provides a visual representation of the chapter layout to establish an overview of the connections between chapters. All of the relevant links between chapters were highlighted by means of similar colours. The connections identified in Figure 1.2 are already included in the chapter descriptions, but to ensure the reader's understanding of the figure, the links between the main features highlighted in green and yellow are explained in the following paragraphs.

When considering the linkages highlighted in green, Chapter 2 identifies the main factors that existing literature considers influential price determinant factors. However, these influential price determinant factors also form part of studies that may relate to the evaluation of white maize market efficiency in Chapter 3. The relevance of white maize market efficiency is yet again addressed when Chapter 4 considers price discovery and effective price risk management in the light of market participants' reaction to changes in the influential price determinant factors. The logic reaction of market participants to changes in influential price determinant factors are confirmed through an evaluation of the price determinant factors in Chapter 5, which is included as part of the percentile rank grouping and cluster analysis methodology (Chapter 5) and results in Chapter 6.

The linkages highlighted in yellow enhance the readers understanding of the reasons why producers tend to be 'risk averse' to the application of price risk management strategies. Chapter 2 provides the necessary overview of the changes in the South African market structure and agricultural policy which may still be seen as one of the main reasons producers tend to avoid derivative based hedging strategies specifically. Chapter 3 and the different subsections regarding the EMH provide background to the psychological reasons regarding a producer's behaviour or decision-making process which may influence a price risk management decision. Apart from these more psychological reasons, a producer's hedging decision may be influenced by several other external factors which are explained in Chapter 4.

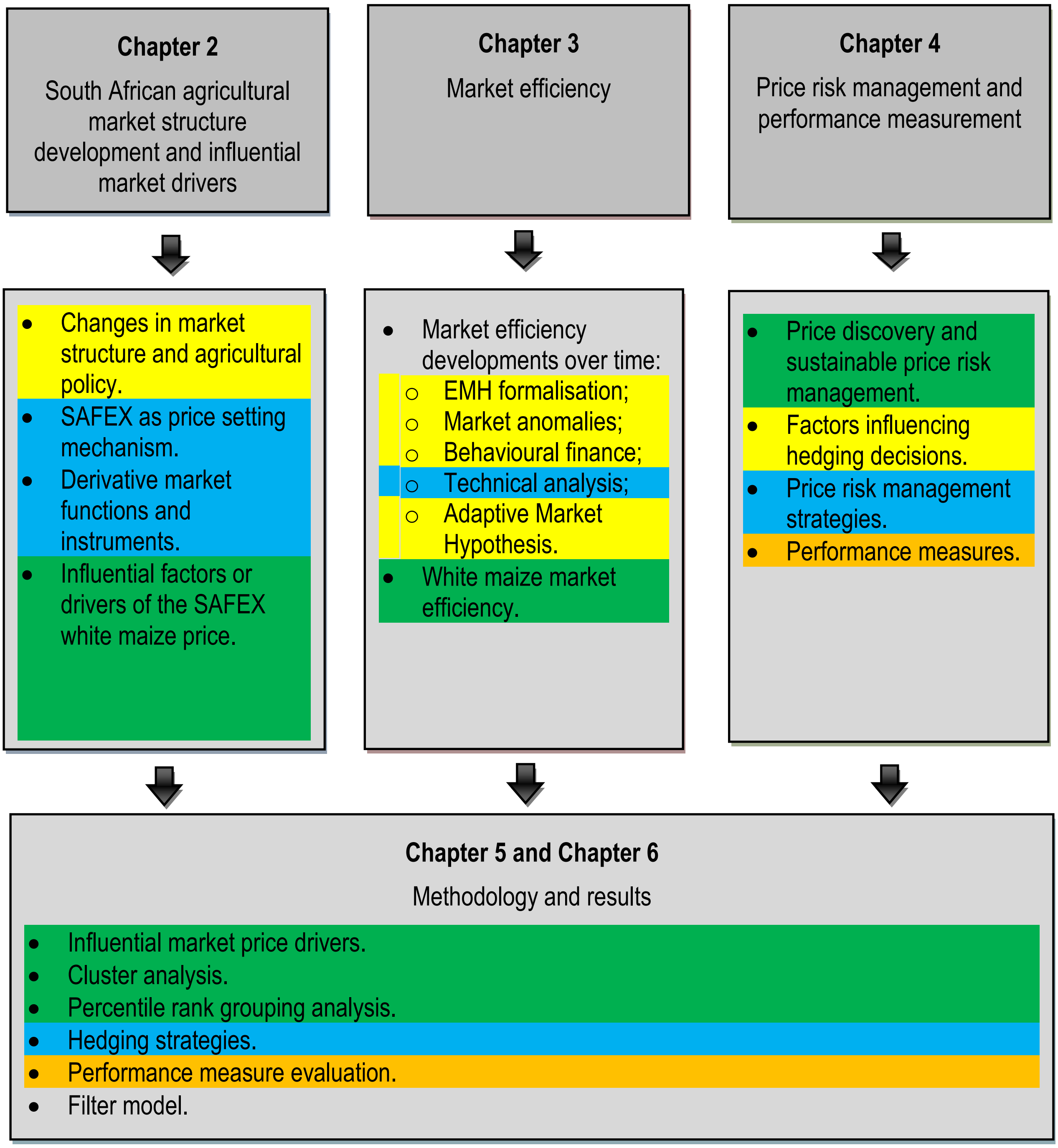

Figure 1.2: Diagrammatical representation of thesis structure
Source: Compiled by author

1.7 Envisaged contribution

This section includes the contributions that this study intended to achieve at onset. These contributions may be broken down into a literature, methodological, and practical contribution.

1.7.1 Literature contribution

The literature contribution in this study is presented as follows:

- Chapter 2: The background to changes in market structure and agricultural policy in South Africa provides an historical overview of legislative changes. Apart from the actual policy implications for the marketing of agricultural products, this review provides meaningful insight into the actual reasons certain decisions were made over time.
- Chapter 3: Developments in market efficiency over time have arguably been dealt with in several instances. Discussions however tend to focus on arguments for and against the Efficient Market Hypothesis (EMH) after the formalisation of the concept of market efficiency. The discussion on market efficiency in this study provides the reader with a historical overview prior to the formalisation of the EMH. This overview provides the required insight into the development of specific concepts, such as market anomalies, behavioural finance, technical analysis and the Adaptive Market Hypothesis (AMH), of which the reader will struggle to find any comparable compilation.
- Chapter 5: The literature overview on hedging strategies in Chapter 4 established the means to include and evaluate several additional hedging strategies that have not been included in previous literature on white maize price risk management strategies.

1.7.2 Methodological contribution

The methodological contribution in this study is presented as follows:

- Chapter 5: The implementation of percentile rank grouping as well as cluster analysis to the white maize influential price determinant factors in order to identify similarities between production seasons has, based on the existing literature consulted and included in this study, not been attempted in this manner.
- Chapter 5 and 6: The application of relevant financial performance measures to the daily realised hedging strategy returns in an attempt to more conclusively rank hedging strategies is not an evaluation method that has been applied in previous literature.

1.7.3 Practical contribution

The inspiration for this study is a result of a recurring discussion by market role-players in an attempt to establish a consensus as to expected price formation for approaching production seasons. Remarks such as “*this season is developing like a specific past production season*” or the other extreme, “*this seems to be another unique production season*” are common remarks in practice.

The author, who has been working in the agricultural derivative market space since 2008, shared this frustration of never really being able to establish a meaningful or applicable framework to base an informed decision on. As may be the case with several students who embark on studies that are based on a problem they face in practice, the plan or problem-solving method is initially thought to be the primary aim with no real need for a thorough review of the literature. In this study, however, the literature review provided substance to some of the more complex aspects that influence price formation. This knowledge in combination with specific aspects applied in practice on a daily basis, facilitated and ensured the structured implementation of the methodological approach which brought about a meaningful result in Chapter 6.

1.8 Notes to the reader

It is important for the reader to note the following:

- The term ‘this study’ refers to this thesis or the physical text.
- All references made to ‘maize’ is from the context of the related literature studies that apply to the focus on ‘white maize’ in this study. The use of the term ‘maize’ is therefore interchangeable with ‘white maize’ throughout the text, unless otherwise specified.
- All references to ‘price risk management’ within the context of this study, should be read as ‘derivative-based hedging’.
- Similarly, the concept ‘marketing plan’ and ‘hedging strategy’ should be viewed as interchangeable. Within in context of the study and with reference to the different strategies (explained in Chapter 5, Section 5.4) specific strategies does not necessarilty make use of any form of hedging by means of derivatives during the planting window. Hedging during the planting window may be referred to as pre-season hedging. As a result, a ‘hedging strategy’ which is implemented by, for instance, selling produce in increments based on a specific procedure or set of rules may be seen as a marketing plan.
- The term ‘maize producer’ is used throughout this study to retain the neutral gender.

CHAPTER 2

South African Agricultural Market Structure Development and Influential Market Drivers

"But, above all, I trust that you will be mindful of the fact that as circumstances change, economic conditions do not remain the same, and that it would not be unreasonable to expect that economic science will seek to adapt itself by modernizing the basic premises."

P.R. Viljoen (1938)

2.1 Introduction

Agricultural commodities are traded in a free market environment, where prices are determined on a daily basis through an exchange-traded platform. Although this has been true for the United States since the establishment of the Chicago Board of Trade (CBOT) in 1848, South Africa only adopted this method of price determination in 1996. Prior to 1996, and specifically since the Agricultural Marketing Act of 1937, prices received by producers of agricultural commodities were determined by various control boards. These control boards acted as the governing bodies for different agricultural sectors and through the legislative power provided by the 1937 Agricultural Marketing Act, they were able to intervene in the market structure as a whole (Geyser, 2013:2-3).

This control came to an end with the deregulation of the various control boards in 1996. Producers were suddenly forced to adopt and apply abstract derivative instruments in order to hedge their associated price risk. This was to be done on the South African Futures Exchange's (SAFEX) Agricultural Markets Division (AMD) formed in January 1995 (Geyser, 2013:3). Naturally, producers were reluctant to make use of the new price determination mechanism, since they had not needed to manage their price risk for the better part of 60 production seasons before 1996. This reluctance was observed in a study by Jordaan and Grové (2007:548), which reported that South African maize producers are reluctant to make use of SAFEX due to a "lack of capacity", "distrust of the market", and "bad experiences".

The question of why South African maize producers are reluctant forms the cornerstone of this literature study. This chapter will start to address this question by providing a thorough background on how the agricultural marketing mechanism and price formulation developed in South Africa. Therefore, Section

2.2 commences by providing a summary of the changes in the South African market structure and agricultural policy. These changes in the South African agricultural market policy also led to deregulation in 1996. More detail on the current free market system is provided in Section 2.3. Arguably, deregulation brought about a whole new price formulation process, which Section 2.4 elaborates on. This includes a discussion of the factors influencing white maize prices, how certain values are calculated, and what the expected change in price direction would be when the value of these factors change. Finally, Section 2.5 provides a summary of this chapter's findings.

2.2 The changes in market structure and agricultural policy in South Africa

The South African agricultural market structure has undergone an array of legislative changes since the early 1930s. The 1937 Marketing Act may be seen as the most influential of these changes, since it provided the foundation whereby control boards determined who produced, handled, processed and traded agricultural commodities. These boards also determined the price that producers and processors would receive, down to the profit margin they could expect. Furthermore, these control boards were mainly composed of producers, which inevitably led to decisions greatly benefitting the producer side of the market, despite the fact that their decisions were subject to the sanction of the Minister of Agriculture. Ultimately, government became obligated to ensure that surplus production was exported at a potential loss, that shortages were replenished through expensive imports, and that potential losses caused by natural disasters were subsidised (Bayley, 2000:xii).

This system was, however, too flawed to survive forever. Macro-economic pressure on South Africa in the 1970s to early 1980s led to the liberalisation of the financial system and subsequent pressure on the government budget to sustain control-board subsidies. As a result, agricultural marketing controls were reformed and the Marketing of Agricultural Products Act of 1996 paved the way for the closure of all control boards. Under the new marketing act, a free market pricing mechanism was deployed and since then prices have been determined mainly by domestic supply and demand, import and export parity prices, and tariffs (Bayley, 2000:xii-1).

To fully comprehend why control boards were instituted in the first place, Section 2.2.1 provides a history of the South African agricultural market, as well as the reasons behind the institution of controlled marketing mechanisms. The mandate of these control boards were endorsed by the controversial Agricultural Marketing Act of 1937. This Act, the arguments for and against the purpose of the Act, the economic implication of its institution, as well as the eventual replacement of the 1937 Act will be discussed in Section 2.2.2.

2.2.1 The early developments in market structure and food security

Commercial farming in South Africa was well established by 1867 after sugar production began in the 1850s. This was soon followed by the commercial development of other products like wheat, fruit, butter, beef and maize[4] for the local market. At the time, these commodities were predominantly produced along the South African coastline because of the suitable climate, and – unlike the interior – access to cost effective transport, mainly by ship. It was only after its initial cultivation in the Eastern Cape during the early nineteenth century that white maize spread inland. As such, white maize played an important role in subsistence farming activities, as South Africans were sustainably producing their own food at this point in time (Wilson & Thompson, 1971:107-113).

In spite of this, agricultural production was not ready to meet the demand for food that came with the discovery of the Hopetown diamond in 1866 and gold alongside the Tati river[5] in 1867. This signalled the start of the diamond and gold rush in Southern Africa, and these discoveries suddenly increased the number of people in the urban areas with new towns developing overnight. Kimberley, for example, did not exist in 1866, but was a town 18 000 people strong by 1877. In the same way, Johannesburg developed from the first street in 1886 to a population of 166 000 by the end of the nineteenth century. Settlements other than these towns also sprouted alongside the Reef, or the Witwatersrand as it later became known (Wilson & Thompson, 1971:113-114).

Consequently, and despite local producers' best efforts, the country could no longer sufficiently supply in its own basic food demands by 1899, and South Africans had to import wheat, maize, meat, eggs, milk and butter at very high prices. Local agricultural producers were also not able to effectively match the supply by foreign producers who gained access to the interior markets through newly established railways. Fortunately, these railways also eventually provided local producers with the means to transport their produce more effectively to markets, which provided them with an opportunity to expand production (Wilson & Thompson, 1971:114-115).

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[4] *Zea Mays*, also known as Indian corn, commonly accepted to have been a domesticated grass (*teosinte)* originating in Central or South America (McCann, 2005:3). Maize was brought to South Africa after Jan van Riebeeck arrived in the Cape and asked for maize seed to be sent to South Africa in 1658 to test its viability in the Cape as a food source for the Dutch East India Company (McCann, 2005:3).

[5] A German trekker found gold alongside the Tati river in the northeastern part of Botswana, between the Shashi and Ramokgwena rivers (Arrelano-Lopez, 2008:72).

However, local producers were unable to fully benefit from the growth in demand. Agricultural production conditions were not always conducive to growth, with producers experiencing a number of natural disasters and resultant price fluctuations at the turn of the nineteenth century. Between 1882 and 1925, South Africa endured an average of one severe drought every six years (De Kiewiet, 1941:189). On top of the droughts, swarms of locusts destroyed grass and crops from time to time, with two mentionable swarms in 1869 and another in 1896 (Collins, 1965:278; Saker, 1965:40). Furthermore, animal mortalities soared in 1861 and again in the late 1880s when horse sickness killed thousands of horses. Animal mortalities were also prevalent amongst cattle, due to redwater[6] in 1871, as well as scab, internal parasites in sheep, and the rinderpest[7] that swept through the country in 1889 and 1896 (Wilson & Thompson, 1971:116).

Besides the various setbacks producers suffered, the South African economy also suffered setbacks between 1873 and 1896. By 1885, the economic advances brought on by the diamond rush became relatively exhausted and commercial recession set in with unsustainably high stock market prices and expensive credit, leading to a banking crisis. The discovery of gold on the Witwatersrand reefs, however, prompted a revival of the South African economy but even the economic advances brought on by the increased population, trade, banking, construction, new railway lines and towns did not lead to commercialisation by South African producers. One of the reasons for this was the fact that South Africa could import maize and wheat from the highly subsidised Midwest of the United States of America at a much cheaper price than it could be produced locally. The commercialisation of farming activities were further halted due to of the vast number of South Africans that were forcefully removed from their land during the South African War[8] (1899 – 1902). This removal was often accompanied by the burning of homes and the destruction of crops[9] (Bundy, 1979:207). After the War, the British

6 Redwater is a parasitic disease commonly spread by ticks, more specifically blue ticks, predominantly amongst cattle. One infected blue-tick female can spread the disease through as many as 2000 infected blue-tick offspring. The parasites destroy the red blood cells of the host, causing anaemia and if not treated accordingly, inevitable death (Mönnig & Veldman, 1986:119).

7 Rinderpest is an acute virus disease in cattle which cause severe inflammation of the mucous membranes. The state is usually compelled to initiate quarantine measures in order to manage the spread of the disease (Mönnig & Veldman, 1986:88).

8 Also known as the Anglo-Boer War (Spies, 1978:9).

9 The burning of farm homes and land, as well as the destruction of crops is otherwise known as the scorched earth policy, which was implemented by Field Marshal Lord Frederick Sleigh Roberts and Major-General Lord Horatio Herbert Kitchener (Spies, 1978:22-29).

authorities resettled producers on their land in order to politically calm the situation, but producers had nothing left and were forced to make use of some form of credit (De Swardt, 1983:3-4). The Transvaal Land Bank emerged to address this need for credit, but mostly for large scale producers (Bayley, 2000:13). As a result, it was only after the War that larger South African producers started to commercialise and exploit the benefits of technological advances brought on by the gold mining stimulus (Bundy, 1979:110-112).

Before and after the South African War, Britain focussed their policy in South Africa around gold mining and other economically viable concerns. In a bid to ultimately politically stabilise the region, sovereignty was given to the former republics which resulted in the formation of the Union of South Africa in 1910. After the formation of the Union of South Africa, local government attempted to promote production by means of maize export schemes. These schemes varied from reduced shipping costs, reduced rail costs for delivery to the harbour, and reduced insurance costs. Provisions for storage, grading and inspection at the harbours were also established (Bayley, 2000:13-15). However, it was only from 1914, during World War I, that domestic production in South Africa showed a significant increase. This was mainly due to production pressure on Western and European counterparts, which limited imported products and created an export market for surplus South African production of maize, amongst other products (De Swardt, 1983:3-4).

Post-war activities brought on a wave of inflation, which initially supported domestic and export prices of South African maize even further. However, this inflationary environment and post-war slump ultimately led to recession in the early 1920s, during which prices tumbled and credit lines available to producers, processors of, and dealers in agricultural products all but ceased. These conditions led to extreme volatility, with the price for maize increasing by 69% from 1919 to 1920, only to decrease by 52% from 1921 to 1922 (Bayley, 2000:15). This situation was so severe that Parliament gave the Land Bank permission to write off large amounts of financing advances which could not be repaid (Davis, 1933:172). These conditions led to market instability and as a result producers called for a suitable market facility and less speculation by traders. As a consequence, the Co-operative Act (Act 28 of 1922) was passed, which enabled government supervision of co-operatives to ensure efficient and accountable collective bargaining power. This, in turn, enabled the Land Bank to prolong its financing facilities to co-operatives with confidence. This new availability of finance allowed producers to improve infrastructure developments – specifically storage facilities and their handling network. At this point, these developments improved producers’ optimism regarding market stability and consequent price increases (De Swardt, 1983:5-6).

Although circumstances regarding marketing and price stability did improve, co-operatives were not able to finance or store large production surpluses without government aid. In an attempt to avoid government subsidisation of export losses due to lower international prices, the Central Agency for Maize Co-operatives stored and held back crops (Davis, 1933:176-177). The aim was to raise domestic prices and wait for the right time to export the surplus at a more acceptable international price level. This strategy worked well for a while and maize prices soared to record price levels for two years. Co-operatives were, however, forced to unload their stocks in 1932 due to the high costs involved in carrying the stock and arguably limited available space to store consecutive crops (De Swardt, 1983:6).

The unloading of stored surplus maize stock could not have happened at a worse time for agriculture in South Africa. During this time, international prices tumbled and the economic buying power of producers declined. This happened after the South African government decided to remain on the gold standard in monetary terms. The direct implication was that most of South Africa's produce was exported to countries no longer on the gold standard, which left South African farmers with an even lower price than the international price, since gold as a currency remained stronger than other currencies. Also, credit extensions contracted after 1930 and a resilient drought plagued the country between 1932 and 1933 (Bayley, 2000:15-16).

Given these circumstances, it is understandable that South African producers longed for some kind of government intervention or assistance. Producers suggested a legal body that would improve their position in determining export prices in general or, specifically, how the Maize Export Control Act was implemented. These developments prompted government in June 1933 to establish a commission of enquiry under the then Secretary of Agriculture, Dr P.R. Viljoen. He was tasked to determine if the establishment of a regulatory body with the powers of achieving "orderly marketing" through, amongst others, the "single channel" sale of produce and compulsory co-operation would be feasible (De Swardt, 1983:12; Tinley, 1940:252).

2.2.2 The 1937 Agricultural Marketing Act

The commission of enquiry and subsequent report by Dr Viljoen in 1934 was arguably an attempt by government to adhere to the cries of agricultural leaders for an investigation into the principles and outcomes of co-operation and agricultural credit extensions. However, the report mainly concluded that it would not be feasible to recommend compulsory co-operation that allows the sale of produce through a centrally controlled body. The report also concluded that the control and fixing of prices would lead to overproduction, the disturbance of the supply and demand balance, and the eventual decline in prices (De Swardt, 1983:12-13).

Not satisfied with the outcomes of the first investigation, agricultural groups prompted another interdepartmental investigation on 12 July 1935, specifically into "the principles in connection with sales through one channel and price fixation". This commission, chaired by Dr Viljoen, investigated the requests and a memorandum was drafted by a young economist, S.J.J. de Swardt, who outlined the agricultural marketing situation at the time as follows (De Swardt, 1983:16-17; Groenewald, 2000:372):

- The demand for maize in South Africa was very inelastic[10]. This resulted in significant price drops, even when only marginal surpluses were produced. Similarly, a season that realised shortages resulted in large price increases.
- The adverse weather conditions in South Africa increased production variability and price fluctuations were accentuated by a relatively small and isolated local market.
- Importers and exporters were also directly influenced by the fact that shortages and surpluses were not always known until the end of a season. For instance, the risk of importing expensive stock and storing the stock in a potential domestic surplus year was considerable, since domestic prices would drop once the actual figures of domestic surpluses became known.
- Unreliable market information also led to speculation and potential market manipulation, which increased producers' discontent with the situation.
- One of the main problems was unreliable production and market information. If it had been possible to establish reliable expected domestic production, consumption, carry-over stock and actual import and export figures, most of the market inefficiencies may have been resolved.

However, the memorandum by De Swardt also pointed out that it was basically impossible to obtain relevant decision-making supply and demand information in order to realise marketing stability. Additionally, he emphasised that, in order to achieve "orderly marketing", it would be imperative that a stable seasonal price be established with price differentials, which would allow for different prices based on delivery dates and transport distances. The memorandum further suggested the establishment of a marketing authority, apart from government, with the necessary proficiency and finance to determine a stable seasonal price (De Swardt, 1983:18). Price determination was to be done by a few capable individuals, able to evaluate the statistical facts of supply and demand, as well as the circumstances of

[10] Demand elasticity also refers to a consumer's willingness to use other products in the place of white maize for the same intended purpose. The use of alternative products would depend on the consumer's money availability, the availability of alternative products, and how important the use of the specific product is to consumers (Geyser, 2007:295).

the day presented to them. It was expected that the result of price changes may be evaluated and contemplated before succeeding price changes were considered. Arguably, the proposed authority would have had to store and finance surpluses from one season to the next, as well as ensure that shortage imports did not influence price stability domestically. It was proposed that the funds needed for such a stabilisation fund be obtained by duties imposed upon certain points in the marketing channel (Bayley, 2000:18).

Shortly after the finalisation of the memorandum draft, Dr Viljoen submitted the proposition to the then Minister of Agriculture, Colonel Deneys Reitz. According to Dr Viljoen, the Minister was very impressed with the memorandum and decided that a Bill be drawn up and submitted to Parliament in 1936. Dr Viljoen made use of appropriate legal advisors to compile an act which would have facilitating powers within the existing marketing schemes. The major difference between this enabling act and previous marketing scheme acts was that it aimed to commission producers to sell through "one channel" at a price pre-determined by a board with authoritative powers (De Swardt, 1983:18).

Despite the Minister's approval, the Bill was strongly opposed in parliament in 1936, ironically enough by the Agricultural Minister's own political party. As a result, the Bill was withdrawn. The main reason for their opposition was their belief that it would only take a while for the market to adjust after the recession and that the process of obtaining market price stability would actually accelerate after South Africa had left the gold standard. They also argued that the process of controlled marketing had been abandoned in countries that had previously employed controlled marketing regimes (De Swardt, 1983:20).

After the withdrawal of the Bill, Dr Viljoen and Mr De Swardt wanted to justify their initial finding and recommendations and set out to obtain the necessary facts regarding international trends towards controlled marketing. In order to accomplish this, they attended the Commonwealth Scientific Conference in London in September and October of 1936 and conducted interviews with senior agricultural officials in the United Kingdom and the Netherlands. However, it was a visit to The Hague (Netherlands) that emphasised the need for a central body under the Minister of Agriculture to control various marketing boards for different commodities. The Dutch marketing model served as a basis for the development of the South African marketing schemes, which were later established under the 1937 Marketing Act.

After these visits, a full report was submitted to Colonel Reitz and relevant farm leaders at the time. A revised Bill was prepared and passed in Parliament without much opposition in the form of the Marketing Act No. 26 of 1937. This Act became the foundation for controlled marketing and regulation in South Africa. Under this act, control boards that consisted of a majority of producers, traders, consumers and representatives of the Department of Agriculture were appointed by the Minister of Agriculture. Control board activities and proposals were evaluated by the National Marketing Council, which also advised the Minister of Agriculture on proposed actions. Bayley (2000:18-20), De Swardt (1983:20-22) and Groenewald (2000:376) indicated some of the far-reaching capacities of the council as being, for instance:

- "One-channel marketing" which enabled only the control board and its appointed agents to buy, sell or store a produced commodity;
- the control of imports and exports;
- the setting or amendment of seasonal prices;
- the managing of pools in which the profits of the sales of produce bought from producers were kept and shares allocated to producers of the basis of their contribution;
- the right to allow or refuse the registration of new traders or processors, as well as the determination of the profit margins they were able to charge; and
- the right to establish designated handling and delivery facilities, managed by the board's agents, and erected by means of compulsory duties imposed upon producers.

Although the intuitive aim of Act 26 of 1937 was to stabilise price variability for both producers and consumers, the methodology of the process and the rights afforded to a select few by the Act raised concerns amongst economists like Davis (1933), Frankel (1934) and Richards (1936), which will be discussed in the following section.

2.2.2.1 Early warnings against and criticism of the 1937 Act

The Agricultural Marketing Act of 1937 may in retrospect be seen as a very controversial act, but in light of the issues and circumstances at the time, even a well-schooled economist like De Swardt, who theoretically did not believe in any form of market meddling, underwent a change of heart. This change of heart came about when he was tasked to investigate the accounting practices of maize traders in order to determine how they complied with their maize export quota obligations. He travelled from town to town through the northwestern Free State during the first three months of 1933. From the utter devastation he encountered, he became convinced that drastic measures could be justified to counter the effects of drought and recession on South African agriculture. But De Swardt's view was not uniformly accepted and there were voices of warning and criticism before the Bill was passed in 1937 (De Swardt, 1983:14).

Initially, Davis (1933) warned against some of the implications of controlled marketing based on the outcomes of, amongst others, surplus export subsidies and surplus holding or storage programmes. He argued that, from these examples, the market rapidly adjusted on either the supply or demand side to take advantage of the schemes, which would inevitably lead to the exploitation of the poor. Additionally, he stated that there was no proof that any form of market and price control would stabilise price adjustments any better than a traditional free market mechanism (Davis, 1933:182-183).

Shortly after the paper by Davis (1933), Frankel (1934:329-331) compiled a tentative list of factors to consider before blindly adopting any method of market intervention. Although the list included thirteen separate factors, the main critique contained in these factors can be summarised in the following arguments. Firstly, such a market system would require significant administrative resources to function. These resources specifically referred to the direct cost of administration as well as the indirect cost brought about by uncertainty in marketing channels due to government intervention, which caused deviations away from the normal supply and demand equilibrium price formulation. Secondly, the exploitation of government support programmes by opportunistic or non-sustainable producers would have to be managed in order to ensure that the burden of export losses not be at the cost of consumers and sustainable producers. Thirdly was the economic reality that price support would encourage production, and consequently lead to overproduction. Frankel (1934) questioned the manner in which controlling bodies aimed to curb overproduction, the administrative and economic cost effectiveness of such programmes, and if any production control plan would be effective at all. Lastly, the extent to which higher and subsidised producer prices would be transferred to processors and consumers should be determined. He argued that local processors would have to compete with international processors who may obtain their raw materials at lower international export value prices, and that the cost of living for consumers would increase. In general, he attempted to point out the economic unsustainability of the proposed intervention programmes, as well as some of the expected implications that ought to be considered before any support plan could be justified.

These initial concerns raised by Frankel (1934) were also supported by Richards (1936), who was more direct in his disapproval of a controlled marketing plan, calling it “cumbersome and unworkable”. Richards (1936:470) argued that it may lead to an “agricultural monopoly” controlled by a privileged group, mainly in order to ensure political power without taking economic consequences into consideration. His economic consequence predictions included production increases with consequent surplus production if price support and intervention plans were implemented. These higher prices would spill over into higher prices for consumers, increased living costs, and, arguably, the cost of future input costs payable by producers, thereby creating a spiral effect of rising costs. He went on to predict that these ever-rising costs to ensure profitable production would be an unsustainable endeavour with significant losses to the government.

However, in order to prevent the predicted outcomes of the Marketing Act, Richards (1936:503) proposed that a thorough investigation into the agricultural problem be launched. Amongst other factors, the following challenges formed part of the proposal:

- Ever increasing production and distribution costs and how they may be reduced by means of improved methods of production and more effective distribution channels;
- the level of domestic consumption and how it may be improved along with the elasticity of demand; and
- the uncertainty surrounding crop estimation and how it may be improved in order to stabilise unsuspected rapid market price adjustments.

These propositions formed the backbone of Richards' (1936) argument that the government was aiming to remedy a problem in the agricultural sector through the Bill without looking into the reasons or cause of the problem in the first place. Richards (1936:477) also blamed the revising committee for not inviting any "professional economists" to provide an expected economic implication perspective. Ironically enough, years later, Groenewald (2000:372-375) stated that the ideas of these economists "*were to become prophetic in hindsight*". The irony is that their ideas were based on economic theory which would have been able to provide a logical expected outcome for the impact of the proposed Bill before implementation.

2.2.2.2 The economic theory of supply and demand, and the effect of price support and production quotas on the latter

The supply of white maize is the amount of product that a producer is willing to sell at a certain price level, assuming that there are no factors influencing the amount of product available to producers. The quantity supply of white maize supply may then be calculated as a function of the price of the product, the (opportunity) cost of resources and inputs needed for production, the (opportunity) cost of producing alternative or related products like sunflowers or soybeans, the technology available to produce, and legislation (for example, import and export tariffs, land tax, land reform and subsidies) (ActED, 2002:7; Pindyck & Rubinfeld, 2005:21). Consequently, an increase in the price of white maize will have an effect on the supply of white maize. For example, if white maize prices increase, every producer would like to produce more, which implies larger areas planted and a potentially greater supply of white maize. Furthermore, as profits from white maize production increase, other producers – not necessarily traditional white maize producers, like chicken meat producers – might decide that it will be more cost effective to integrate vertically and start producing their own white maize which forms part of their chicken feed mixture. Such a decision increases the total supply of white maize. Also, supply may increase when the cost of soil cultivation machinery or equipment decreases, or new cultivation methods that are more cost effective with potential increases in yield, are introduced (ActED, 2002:10; Pindyck & Rubinfeld, 2005:21).

With regards to white maize demand, it is represented by the amount of product that a consumer or processor is willing to buy at a certain price level, assuming that there are no factors influencing the amount of product available to a consumer or processor (Pindyck & Rubinfeld, 2005:20). The demand of white maize may then be calculated as a function of the price of the product, the cost of related products (for example bread), consumer income, and consumer preferences, to name but a few (ActED, 2002:3; Pindyck & Rubinfeld, 2005:21). Consequently, an increase in the price of white maize will have an effect on the demand for white maize. For example, if white maize prices increase, every consumer or processor will buy less, which implies a decrease in the amount of white maize bought. Additionally, demand may also increase when the price of alternative energy sources in feedlot mixes (for example, sunflower oil cake) rises in relation to white maize. This may prompt feedlot managers to use white maize as alternative, which will increase the demand for white maize (ActED, 2002:5; Pindyck & Rubinfeld, 2005:22).

It is important to realise that the demand for and the supply of white maize do not occur in isolation. In any market environment, the trade-off between supply and demand occurs on a daily basis and the price level where producers are willing to sell and consumers or processors are willing to buy is known as a market equilibrium price. The reality regarding market equilibrium is that it only holds, or moves to a new equilibrium based on supply and demand factors, if the market mechanism is fair and competitive. Hence, both producers and consumers have the ability to affect market prices to promote their own cause, but not to the extent where the market may be manipulated by either party (Pindyck & Rubinfeld, 2005:24).

It was for exactly this reason, that Davis (1933), Frankel (1934) and Richards (1936) (Section 2.2.2.1) could anticipate or predict certain outcomes of controlled marketing in agriculture. They realised that if the price paid to producers and the price payable by processors and consumers of white maize were to be determined by a specific entity and not by the market itself, the whole market-equilibrium mechanism would become distorted. There were two rather obvious reasons to foresee certain outcomes. Firstly, a producer-dominated control board would tip the supply and demand balance in their favour, since they would benefit from biased negotiating power, ultimately increasing producer prices (Bayley, 2000:19-20). Secondly, if it were assumed that producers would not act in their own favour, at that time in South Africa there were no econometric demand elasticity[11] figures available for agricultural products. Hence, there was no way for a control board to accurately estimate the effect on demand if prices were fixed at certain levels.

The implications mentioned above are visible in Figure 2.1 and Figure 2.2 respectively. Figure 2.1 provides a graphic representation of price support, where government attempts to increase the price of goods produced. In this approach the price of a good is set above the free-market or clearing price[12] level, which implies that any surplus must be bought by government at the pre-determined price in order to maintain the higher price (ActED, 2002:18; Pindyck & Rubinfeld, 2005:314).

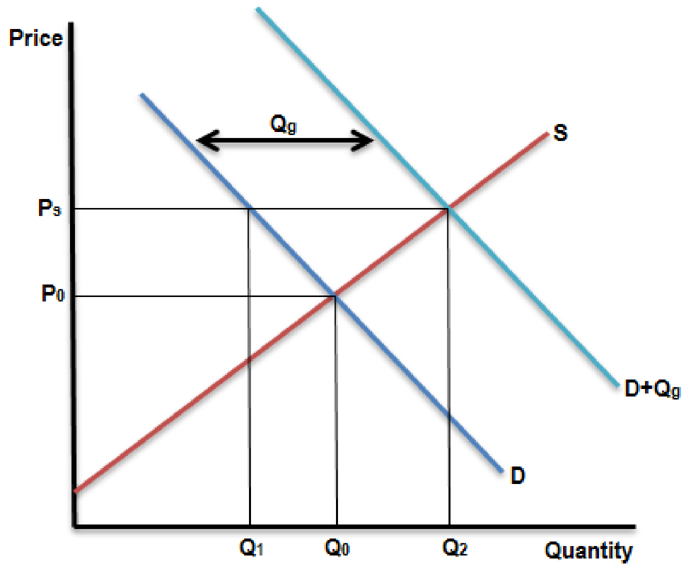

Figure 2.1: ***Price supports***
Source: Compiled by the author, adapted from Pindyck and Rubinfeld (2005:315)

In Figure 2.1, demand curve D and supply curve S represent the market equilibrium demand and supply for white maize, with equilibrium at price level P_0 and quantity Q_0. Therefore, if the price of white maize is set by the government at price level P_s, producers would be able to sell at higher prices and

[11] Elasticity is a measure of the sensitivity of one variable to another. In this instance, it is the percentage change expected in the quantity demanded if the price of the product changes by one percent (Pindyck & Rubinfeld, 2005:24).

[12] The market clearing price is the price at which all goods sells, thus quantity supplied and quantity demanded are equal (Pindyck & Rubinfeld, 2005:24).

more profitable levels. Consequently, consumer demand would fall to Q_1 with some consumers ceasing to buy white maize altogether. Also, when government institutes a minimum price above the free-market clearing price, a surplus will be created (Q_g), which may require additional government intervention. Usually, this entails that government buys the surplus production (Q_g) at the higher fixed price, after which the surplus may be stored, exported or even destroyed. Nevertheless, storage incurs a cost and international prices may be lower than the domestic pre-determined price, forcing government to sell the surplus at a loss. This incurrence of storage costs or export losses may however be more socially acceptable than the alternative, which is the destruction of surplus staple food like white maize. Ultimately, the result of price supports at a profitable level will have a direct and indirect (or welfare) cost to consumers. Directly through the increased price of maize to consumers, including poor households, and indirectly in the sense that government will pay this cost or potential export losses through taxes paid by consumers. Therefore, only producers of white maize will benefit from such a price management method, since they will be able to sell larger quantities (Q_2) at a higher and more profitable price (Ps) (ActED, 2002:18; Pindyck & Rubinfeld, 2005:314-315).

Another possible government intervention is known as production quotas, which is graphically represented in Figure 2.2. This method entails increasing the price of goods by limiting the potential supply (Pindyck & Rubinfeld, 2005:316-17).

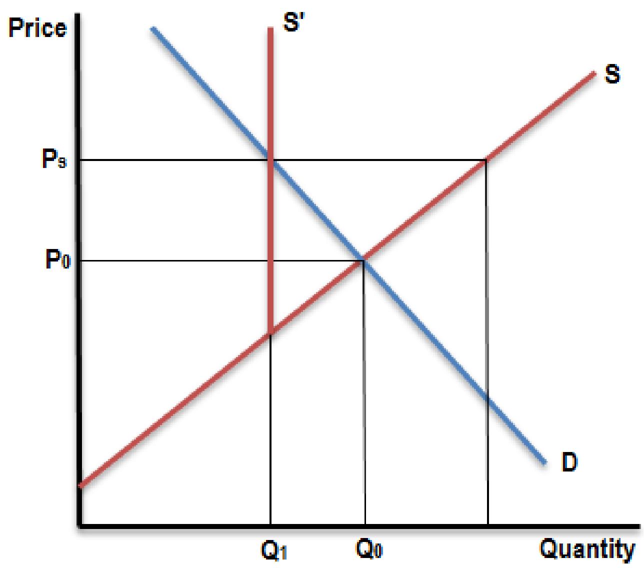

Figure 2.2: Production quotas
Source: Compiled by the author, adapted from Pindyck & Rubinfeld (2005:317)

In Figure 2.2, demand curve D and supply curve S represent the market-equilibrium demand and supply for white maize, with equilibrium at price level P_0 and quantity Q_0. If government decided to implement a programme to reduce the expected number of hectares planted with white maize each season by paying producers an amount of money for every hectare left fallow, the equilibrium scenario would yet again be thrown out of balance. When implementing such a model, government would have to ensure that the incentive paid to white maize producers is large enough. If it is large enough, producers may become indifferent to the profit they might have made by planting, compared to the incentive they will receive if they leave a hectare fallow or use it to produce other commodities. By reducing or increasing the incentive, government may have enough leverage to increase or decrease supply to desired levels. Reduced production would create reduced supply levels from Q_0 to Q_1, forcing the price of white maize to increase from P_0 to P_s and reach a new artificial equilibrium where demand curve D and supply curve S' intersect. Yet again, initial intervention will necessitate continued intervention, since government needs to ensure that the payment to producers to leave land fallow is significant enough to account for the additional profit producers could have made by producing at Ps. This amount may become substantial, since producers have an incentive to produce at the more profitable Ps despite the fact that government is subsidising them not to produce. The added cost of effectively administrating such a system is also important to consider.

After reviewing these two scenarios, it is evident that the consequences of government intervention or price stabilisation programmes should always be considered to ensure sustainable supply and demand stability based on macroeconomic stability. However, economic efficiency is not always considered when government implements or evaluates a new policy. Despite widespread criticism and concerns at the time, the Act was passed in Parliament in 1937 (Pindyck & Rubinfeld, 2005:318).

2.2.2.3 The implementation of the Marketing Act of 1937 and its development from 1938 to 1990

Originally, the 1937 Marketing Act was an enabling act mainly aimed at stabilising producer prices in the wake of overproduction and low international prices. After the implementation of the Act and before South Africa entered World War II in 1939, domestic food supply was sufficient. However, the country yet again experienced severe droughts between 1941 and 1942 and these unfavourable weather patterns considerably reduced maize production (Tinley, 1941:18). Adding to this, shortages of inputs, increased demand, and the inability to import were all consequences of the war. Subsequently, control boards were instructed to maintain control over supply shortages and to ensure that prices did not escalate (Bayley, 2000:21). In order to accomplish this, the government established the Cabinet Food Committee and granted them a form of general law-making power under the War Measures Act, No.13 of 1940. The committee was functional throughout the war and its functions remained in place three years after the war was over (Tinley, 1941:19). Throughout the war and in the period shortly after, prices paid to producers were conservative estimates of production cost.

Inevitably, pressure by producers on government to increase prices by implementing the 1937 Marketing Act started to increase. Following the 1948 election, the United Party was voted out of Parliament and the National Party came to power. From there on, the National Party made use of the control board system enabled by the 1937 Marketing Act, to increase producer prices. Over the next three decades government control through control boards grew, and although renewed warnings and criticism from other economists[13] provoked periodic debates, there was clearly no intent from government to move away from control measures or even to gradually ease the extent of government intervention (Groenewald, 2000:382).

Government intervention during this time occurred in different forms, the most prominent of which were disaster relief, research, interest rate subsidies, and price support through progressively regulated marketing systems by control boards. The number of control boards increased from the 1950s and by the early 1960s more than 90% of total agricultural production was regulated by control boards. With regards to the Maize Board, control was exercised through co-operative agents who received maize from producers and paid them the pre-determined delivery price. The Maize Board would then refund the co-operative the price paid to producers plus financing costs. The co-operative would also store the delivered maize until such time that the Maize Board instructed them to release the product to a buyer. In order to successfully store and transport the produce, the marketing boards initiated a silo-building programme, which was linked to the existing railway system. All of the silos constructed by the marketing boards were done in the name of the different co-operative agents. Consequently, the co-operatives benefitted tremendously from the building of this huge marketing infrastructure. They inevitably became a leading force in the agricultural marketing system, ultimately handling 93% of South African maize production (Bayley, 2000:25-29; Kirsten, 2007:3-4; Vink & Kirsten, 2000:10-11).

Initially, the system of controlled marketing stabilised the agricultural sector and it contributed to an economic growth rate of more than 5% per year up until 1970, from where growth slowed to above 3% until 1980. The main reason for slower economic growth was the oil crisis of the mid-1970s (Kirsten, 2007:4). However, these growth rates still exceeded the population growth rate at the time. Consequently, a healthy, growing economy; stable, profitable price levels established by the Maize

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13 See for example, Tinley (1941), Allwright (1947), Samuels (1947), West (1950), Van Waarsdijk (1954), Groenewald (1964) and Van Biljon (1966; 1974).

Board; and the ease with which credit could be obtained through the Land Bank stimulated mechanisation and biological technology advances in the agricultural sector. The use of farm machinery, like tractors for example, directly led to an increase in the amount of land cultivated to produce maize. Also, combine harvesters simplified and sped up the harvesting process, while improved biological technology improved the yields achieved by maize producers (Bayley, 2000:39; Vink & Kirsten, 2000:10).

Clearly, the controlled marketing environment established by the Maize Board and enabled by the 1937 Marketing Act promoted stability within the agricultural sector. However, in order to maintain stability, the 1937 Marketing Act was regularly amended and eventually consolidated into the new Marketing Act of 1968. The main objectives of this renewed legislation, according to Kassier (1992), was to ensure that mainly Caucasian farmers continued farming; production remained efficient; the margin within the marketing chain was reduced; consumption increased; and price stability persisted. These developments, however, revealed several negative implications for the agricultural sector with regards to marketing and control efficiency. From the studies by Bayley (2000:31-34), Groenewald (1985:30-31), Groenewald (1989:486-487), Groenewald (2000:391-392), Kirsten, Edwards and Vink (2007:12-13), Tinley (1940:257), Vink and Kirsten (2000:9-11), Van Zyl and Groenewald (1988:399) and Vink (2012:8) these implications may be summarised as follows:

i. Government intervention actually increased the costs in the marketing chain and the reality was that when problems occurred, more controls were put in place, demanding increased costs. Some of these costs were:
   a. the direct costs of management and administration of control boards;
   b. the inclusion of the value of land or the cost of rent in the calculation of prices paid to producers; and
   c. the inclusion of profit margins on processing and marketing when cost assessments were conducted. This action was inflationary in itself, since it is doubtful if these costs would have been recoverable in a free market system.
ii. The alteration of prices through the abovementioned costs and controlled marketing system had numerous effects of which the main effects were:
   a. increased agricultural output and consequent surplus production, which had to be stored or exported, resulting in additional costs mainly subsidised by government;
   b. the ratio of maize prices to meat prices became skewed to the point where land better suited for grazing or the production of other crops was cultivated to produce maize.

This, in turn, led to soil deprivation and negatively influenced sustainable animal farming; and

c. consumption of maize decreased as increased maize prices dampened consumer demand. Another factor influencing consumption was that government, for a period of time during the white maize shortage years, forced millers to purchase and mix white and yellow maize, while white maize meal was preferred by consumers.

iii. Inevitable export losses were accumulated due to domestic maize prices being set higher than international prices at the time. By 1954 the Maize Board had set up a stabilisation fund in order to fund these losses in surplus years. Profits from previous years' exports and levies paid by producers and processors were added to the fund. However, by 1980 it had become increasingly difficult for government to subsidise export losses due to budget limitations. Table 2.1 provides a clear illustration of domestic prices received by producers compared to the world market prices at the time to show the export losses that had to be subsidised by die stabilisation fund from time to time.

Table 2.1: Domestic maize prices received by producers from 1981-1988

	Local producers' price in rand per metric tonne (R/mt)		
Marketing year	**White maize**	**Yellow maize**	**World market price in R/mt**
1981-1982	134.15	134.00	132.39
1982-1983	155.05	155.05	137.63
1983-1984	170.05	170.05	204.46
1984-1985	219.50	215.55	258.20
1985-1986	221.45	217.50	264.73
1986-1987	283.59	217.77	191.97
1987-1988	275.00	306.00	211.20

Source: Groenewald (1989)

Ironically, during the 1983-1984 and 1984-1985 marketing seasons when world market prices exceeded local prices, South African producers were unable to produce a surplus. In order to pay for the deficit, government increased local selling prices of maize. This created a situation of cross-subsidisation and in actual fact created a worsening spiral effect, since local demand was dampened by increasing prices, thereby increasing the amount of surplus which needed to be exported.

iv. A dramatic rise in inflation occurred and double digit inflation was a frequent occurrence. The main reasons for inflation could be attributed to:

a. cost-push inflation, since costs were transferred from producers to consumers. Furthermore, government used tax-payers' money to subsidise storage and handling costs of surpluses, as well as export losses; and
b. another source of cost-push inflation was the irrational actions by producers to purchase even larger volumes of certain inputs, despite the fact that prices were set at profitable levels and increased continuously. This phenomenon may be attributed to the fact that farmers cultivated more and more land unsuitable for crop production, thereby increasing the demand for inputs. Factors like subsidisation and prices set at profitable levels further prompted this irrational behaviour. Table 2.2 below provides some insight as to how much producer prices increased in relation to consumer prices and farm input prices.

Table 2.2: Percentage increase in prices from 1973-1982

	Consumer Prices		Producer prices for farm products	Farm inputs
Period	All Items	Food		
1973-1974	11.70%	14.90%	10.80%	18.30%
1974-1975	13.50%	14.90%	9.40%	21.80%
1975-1976	11.10%	7.40%	8.60%	15.60%
1976-1977	11.30%	10.20%	8.80%	12.70%
1977-1978	10.90%	12.90%	6.20%	13.50%
1978-1979	13.20%	15.70%	18.70%	20.60%
1979-1980	13.80%	18.90%	18.00%	16.30%
1980-1981	15.20%	22.10%	13.80%	11.00%
1981-1982	14.70%	11.20%	10.40%	17.60%
1973-1982	12.80%	14.20%	11.60%	16.40%

Source: Groenewald (1985)

Table 2.2 demonstrates that the increase in farm input prices exceeded the price increases observed for a general basket of "all consumer items", when food in particular was isolated as well as the prices producers received. Therefore, despite controlled marketing, the prices received by producers could not keep up with the cost of increased input prices. Over time, producers found themselves in a cost squeeze situation since they effectively received less for their produce, whilst paying more for production cost. The situation created an ever-increasing inflationary environment which was by no means sustainable.

The unsustainability of the situation described above forced the Minister of Agriculture to establish a Committee of Enquiry into alternative marketing arrangements for maize (the Committee Report). The committee was tasked to consider the shortcomings of the marketing system at the time and how changes may affect the maize industry. Additionally, they were tasked to consider the viability of a grain exchange. After completing the task, the committee released a report which stated that the *'status quo'* was to be maintained regarding single-channel marketing. They argued that the majority of producers, processors and consumers support a single-channel system (Groenewald, 1989:473-477). However, the conclusion of the report may not have been as accurate as presented, since the call for deregulation by consumers and the private sector grew stronger. It was also noteworthy that uncontrolled agricultural sectors started to outperform regulated sectors (Bailey, 2000:40; Groenewald 2000:394).

In light of these developments, the committee did suggest some minor changes to the system, which included that producers be given the opportunity to sell directly to processors or end users; and that a system such as a 'trade floor' be established over time. Furthermore, isolation from world markets and political sanctions forced certain forms of deregulation to take place. In terms of maize production, these changes included that the restrictions on the building of grain silos and price control on maize meal were revoked, thereby establishing a more market-related pricing practice (Bailey, 2000:41). However, these gestures of deregulation occurred under the old Marketing Act and still provided policymakers with the means to easily reverse any form of deregulation as they saw fit (Van Zyl *et al*., 1990:728). As a result, the Marketing Act became even more contentious, which prompted entities like the Board on Tariffs and Trade, to pressure the relevant authorities to yet again investigate the sustainability of the statutory powers of control boards.

2.2.2.4 Deregulation under the new Marketing Act, No 47 of 1996

During 1992, the Minister appointed Professor Eckart Kassier as the chairman of what became known as the Kassier Committee. The main tasks of the committee were to investigate all control boards with regards to the implications of their policies on local and export marketing control for producers and consumers. Additionally, the risk environment of agricultural production needed to be determined, as well as the impact of the different risk factors. The Kassier Committee was also unique in the sense that it did not include delegates from agricultural organisations, but consisted more of academics who believed in a freer marketing structure (Groenewald 2000:394-395).

Delegates' inclination towards this free market structure became evident in the findings and proposals of the Kassier Committee when they recommended that pricing policies should become more consumer friendly; prices paid to producers should take location and quality into consideration; and, most importantly, that any form of price support or price regulation should be withdrawn immediately (Bailey, 2000:45). Realising the implications of such propositions for producers, organised agriculture was completely opposed to any of the findings, and dubbed the recommendations 'academic'. Nonetheless, the study by Vink and Kirsten (2000:19) argued that the Kassier report played a key role to effectively initiate deregulation, despite what organised agriculture might have thought at the time.

The Minister became aware of the criticism against the Kassier report, and to ensure that all parties were represented, announced the appointment of the Agricultural Marketing Policy Evaluation Committee (AMPEC) at the same conference where the Kassier report was to be released. AMPEC was headed by Mr Gerhard Basson and, contrary to the Kassier Committee, consisted of representatives ranging from organised agriculture, the Co-operatives Council, Control Board members, the Competition Board, Marketing Council members from the different homelands within South Africa at the time, and consumer representatives. Initially, in a preliminary report entitled 'Agricultural marketing in a democratic South Africa' the AMPEC Committee, to a great extent, supported the Kassier report and even proposed further forms of complete deregulation of market control measures in order to facilitate the use of market mechanisms for price determination, thus a transparent free market system (Groenewald 2000:394-395; Van Zyl *et al*., 1990:728).

Apart from the preliminary report, AMPEC published two formal reports in January and April of 1994. In these reports they advised that market reform was necessary, but that the market interventions of the day may still be required, given that they needed to be adjusted over time. To a great extent both the Kassier and AMPEC reports had a strong link to the African National Congress's (ANC) Agricultural Policy Document, which advocated a move towards free market-related pricing mechanisms. After the second AMPEC report was released, the National Party Minister of Agriculture set up a work group, yet again chaired by Mr Basson, to compile a draft Bill in order to facilitate a revised Agricultural Marketing Act (Bailey, 2000:46).

The first drafts of the Bill were received with market-wide consideration and critique and was presented before the Senate in Parliament in March 1996 by the Minister of Agriculture, Dr Van Niekerk. The Bill was stringently opposed, since it still provided for market interventions and favoured producers and those with longstanding vested interests in the industry. The ANC, being fully aware that the Bill would make it to Parliament, compiled a 'guidelines document' through consultation with different parties involved, and tabled their document as an alternative to the proposed new Marketing Bill. As was to be expected, the ANC's document proposed a completely different approach than that of Dr Van Niekerk, who was part of the National Party at the time. Since there was no consensus in the Senate regarding the Bill, the Senate Chair adjourned the proceedings on the condition that the ANC and NP come to an agreement on the Bill and present it before the Senate in due time (Bailey, 2000:47-48).

However, negotiations between the ANC and NP on the proposed Bill never happened, since the National Party left the 1994 Government of National Unity shortly afterwards. The new ANC-appointed Minister of Agriculture, Mr Derek Hanekom, resumed discussions with organised agriculture on the proposed Marketing Bill. After prolonged negotiations, the ANC and organised agriculture reached a settlement on certain issues and the Bill progressed through Parliament virtually unopposed. Eventually, on 5 January 1997, during the first meeting of the National Agricultural Marketing Council (NAMC), the new Agricultural Products Marketing Act, No 47 of 1996, was enforced (Bailey, 2000:49-51).

Contrary to the 1937 and 1968 Acts, the 1996 Act was aimed at preventing intervention, whereas the previous Acts were known as 'enabling' Acts which enabled controlling bodies to intervene as they saw fit. Another great difference was that the objectives of the 1996 Act was clearly set out, whereas the previous Acts' objectives were vague and the only objective was to ensure 'orderly marketing'. The objectives of the 1996 Act included the promotion of sustainable, more efficient marketing and market access for all, as well as to ensure that export earnings were effectively optimised (Vink & Kirsten, 2000:23). The 1996 Act also contained what was called a 'sunset clause', which stipulated a timetable for the closure of the control boards (Bailey, 2000:52). The Maize Board was consequently closed down by April 1997, and although market participants were exposed to some form of free market price formulation from 1995 to 1997, they were now forced to adhere to a completely new set of rules regarding free market price formulation.

Developments to facilitate this newly formed free market mechanism were not, as may be thought, a new concept in South Africa at the time. A thorough background on the origin of and developments in the new South African market mechanism is explained in Section 2.3.

2.3 The South African futures exchange (SAFEX) as a market price-setting mechanism

In order to provide a background on the development of the commodity derivative market, it will be beneficial to discuss the history and development of the general derivatives market in South Africa (Section 2.3.1). Building on these initial developments, the South African Futures Exchange (SAFEX) was established to facilitate the trading of standardised agricultural commodity contracts within a new free market structure (Section 2.3.2). This standardisation of agricultural product contracts brought different market participants together, who in turn provided the necessary liquidity to the market as well as improved price formulation by trading financial derivative instruments, like futures and options. The functioning of these financial derivative instruments, how they are compiled based on the standardisation of agricultural products, and how they aid in the trading of white maize, is discussed in

Section 2.3.3. The developments and explanations addressed in the subsections form an important cornerstone of the study, since it explains how the market changed after deregulation, as well as the different aspects a market participant should understand in order to effectively take part in it. Ultimately, it provides an overview of the dramatic changes that were implemented after deregulation, therefore explaining why maize producers may have found the transition difficult after 60 years of market regulation.

2.3.1 The development of the general derivatives market in South Africa

The development of the general derivatives market started on 8 November 1887, when Benjamin Wollan established the Johannesburg Stock Exchange (JSE) and listed his own company, Johannesburg Chambers and Company. Since the initial establishment, a great number of companies listed. DRDGOLD Limited listed in 1895, making it the oldest, and South African Breweries (now SAB Miller) listed in 1897, making it the second oldest listed company on the JSE to date. From these initial and subsequent listings, the JSE grew to become one of the top 20 largest exchanges in the world, based on market capitalisation[14], and Africa's largest (JSE, 2016).

However, initial trading on the exchange was limited to the domestic market and it wasn't until the 1960s that South African entities obtained the right to take part in international markets. Entities like the South African Sugar Association (SASA) and several wool traders were now able to trade sugar and wool on foreign forward markets, whilst a copper trader named McKechnie Brothers were able to trade copper on the London Metals Exchange (LME). The Maize Board also made use of international exchanges to hedge their price risk during the mid-1980s. They specifically made use of the financial derivative instruments on maize, provided by the Chicago Board of Trade (CBOT), to hedge the value of the maize they were obligated to buy from producers during a specific season. By hedging this value, the Maize Board tried to ensure that they did not pay domestic producers more than the international price of maize during delivery (Falkena *et al*., 1989:24).

Apart from the Maize Board's hedging activities, Rand Acceptance Bank started their own informal market structure in 1987. The platform provided the opportunity to trade futures contracts for the JSE All Share and Industrial indices, as well as certain commodities (for example, gold and the Kruger Rand) (Geyser, 2013:2-3). These developments formed the basis for the formalisation of the industry by

14 Market capitalisation is the total market value of a share. It is calculated by multiplying the issued shares with the market price of that share. Accordingly, the total JSE market capitalisation is the sum of all shares multiplied by their respective values at a certain point in time (JSE, 2014a).

the JSE and 21 banks that came together to develop and define a formal futures exchange. The result was the formation of the South African Futures Exchange (SAFEX) and a clearing house[15], the SAFEX Clearing Company Pty Ltd (SAFCOM) (Sharenet, 2014).

The main aim of the establishment of SAFEX was to provide a central platform where market participants could effectively trade certain commodities through financial instruments (for example, futures and options), in order to manage their respective associated price risk (CFTC, 2014). Furthermore, SAFCOM ensures that members attract no additional counterparty default risk by ensuring that all registered members are able to pay all relevant costs associated with trading contracts on SAFEX. Therefore, SAFCOM acts as a counterparty to market participants and maintains all operating functions of SAFEX (SAIFM, 2011:66).

The establishment of SAFEX and SAFCOM could not have occurred at a more appropriate time, given the fact that it coincided with the process of deregulating agricultural market boards, as was explained in Section 2.2.3.4. The established platform set the stage for the founding of the Agricultural Market Division (AMD) of SAFEX in 1995. The AMD provided market participants with an alternative market mechanism to formulate a free market price for commodities and to manage their associated price risk. Over time, several commodities were listed on SAFEX (AMD) to facilitate this function. Some of these listed commodities were however delisted due to inactivity, whereas others are actively traded by market participants. Table 2.3 provides a summary of the main agricultural commodity contracts listed on SAFEX since 1995.

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15 Primarily, a clearing house ensures that all contracts traded on the JSE are matched between counterparties and that trading activities are done in accordance with the rules and regulations of the JSE. A clearing house also plays a supporting role since *ad hoc* JSE duties and responsibilities may be transferred from the JSE to the clearing house (JSE, 2014e:8).

Table 2.3: Listing of agricultural commodities on SAFEX

Contract Name	Date Listed	Activity
Beef	March 1995	Delisted: January 1999. Trading volume less than 3% of total contracts.
Spud (potatoes)	October 1995	Delisted: January 1999. Trading volume less than 3% of total contracts.
White Maize Grade 1 (WM1)	March 1996	Trading actively
Yellow Maize Grade 1 (YM1)	March 1996	Trading actively
Wheat (B)	November 1997	Trading actively
White Maize Options	March 1998	Trading actively
Yellow Maize Options	March 1998	Trading actively
Sunflower (FH)	February 1999	Trading actively
Cape Wheat	February 1999	Delisted: December 1999. Trading volume less than 3% of total contracts.
White Maize Grade 2 (WM2)	July 2000	Trading actively when applicable
Yellow Maize Grade 2 (YM2)	July 2000	Trading actively when applicable
Cape Wheat	July 2000	Delisted: November 2002. Trading volume less than 3% of total contracts.
Soya (SB)	April 2002	Trading actively
Cape Wheat	May 2012	Trading

Source: Geyser (2013:3); Scheepers (2005:24); Hartwigsen (2013:53)

Since the first contacts were listed on the AMD, the division underwent continual development and renewal in order to provide the necessary market structures required by participants. The first significant structural change came about in 2001, when the JSE Securities Exchange bought SAFEX and it became a separate entity of the JSE, known as the Agricultural Products Division (APD) (JSE, 2013). Then, in 2009, the JSE obtained the right from the Chicago Mercantile Exchange (CME) to trade cash-settled Chicago Board of Trade (CBOT) contracts for corn and soybeans on the JSE in rand per metric tonne. The final structural change to date was when the APD renamed itself in 2010 to become the SAFEX Commodity Derivatives Division. Since then, the products list was expanded even further to include other cash-settled commodity contracts like crude oil, gold, platinum, silver, and copper (Geyser, 2013:3; JSE, 2013).

These systematic developments in SAFEX were to improve the market platform where buyers and sellers could meet in order to trade a specified underlying commodity. Although, to facilitate this function it is imperative that certain standardised contract specifications are in place for each commodity contract traded on SAFEX. If certain specifications are not contractually defined, market participants will not know what their obligation to the contract is prior to trading the underlying instrument by means of the futures contract (Geyser, 2013:7; JSE, 2012a). These contract specifications are furthermore clearly defined for different future contracts with specific physical underlying assets or commodities. For the purpose of this study, the focus in the following sections are on contract specifications and derivative instruments pertaining to white maize specifically. The reason for this is that SAFEX white maize futures contracts have been the most traded and liquid contracts over time (JSE, 2013:2). Figure 1.1 in Chapter 1 confirmed that the market volume of white maize traded has remained higher than the other main soft commodities.

2.3.2 White maize contract specifications and location differentials

The contract specifications of any futures contract should portray a detailed description of the terms and conditions associated with the trading of the underlying commodity through such a futures contract. Specifications like the specific underlying commodity, the size of the contract, the quality, how prices will be quoted, delivery and expiry dates, as well as delivery location should be properly defined in order to improve the price risk-management function of derivative instruments (JSE, 2012a:5). The basic specifications with regards to the white maize futures contract (WMAZ), as it is specified by SAFEX, are summarised in Table 2.4 and Table 2.5.

Table 2.4: Basic contract specifications for white maize traded on SAFEX

Futures Contract	White Maize (100 metric tonne or 10 metric tonne available)
Underlying Commodity	"Maize" means white maize from any origin, of the grade "WM1" as defined in the South African Grading regulations, that meets all phyto-sanitary requirements and import regulations, but is not subject to the containment conditions for the importation of genetically modified organisms.
Quality (Grading) Specification	All grades of white maize will be free from: (i) a musty, sour or other undesired odour; glass, metal, coal or dung; (ii) any substance rendering it unfit for human consumption or processing thereof for food or feed, like poisonous seeds; (iii) it should be free of insects and stones which cannot pass through a 6.35mm round-hole sieve. If stones pass through the sieve, there may not be more than one gram per 10kg of white maize. The moisture content should not be greater than 14%. Deviation standards per grade are set out in Table 2.5.
Contract Size	WMAZ = 100 metric tonnes. / WNCI = 10 metric tonnes.
Marketing season	Calendar year spans from 1 May to 30 April the following year.
Expiry Dates and Times (Last trading day of contract)	12:00pm on the sixth last business day of March, May, July, September and December. Physical deliveries against contract from the first business day to the last business day of expiry month.
Settlement Method	Physical delivery of SAFEX silo receipts giving title to maize in bulk storage at approved silos at an agreed storage rate. The origin must be clearly identified.
Quotations	Rand per metric tonne.
Minimum Price Movement	Twenty cents per metric tonne.
Daily Limits	R100/mt (extended limits R150/mt)

Source: JSE (2018a)

Table 2.5: White maize grading standards

	White maize maximum possible deviation		
	WM1	WM2	WM3
1. Foreign matter	0.30%	0.50%	0.75%
2. Defective kernels above and below the 6.35mm round-hole sieve.	7%	13%	30%
3. Other colour maize kernels	3%	6%	10%
4. Collective variation for 1, 2 and 3. Provided that each individual deviation is within specified limits.	8%	16%	30%
5. Pinked maize kernels.	20%	20%	No specification

Source: NDA (2014)

These contract specifications in Table 2.4 and the grading specifications in Table 2.5 form the basis from which other specifications, like JSE costs and trading fee structures, may follow. These are all fairly clear to understand and easy to standardise. However, the method by which delivery location of white maize on SAFEX is standardised may not always be as straightforward to understand. There are two methods by which locality can be standardised. Firstly, all white maize produced throughout South Africa is traded at par. In this instance, all delivery points are seen as homogenous with regards to their location and their ability to logistically distribute produce. Secondly, a single reference point may be selected, meaning that delivery of produce at any of the approved SAFEX delivery points is subject to a transport cost to the selected reference point (Geyser, 2013:7).

SAFEX chose to adopt the second method, mainly because it had to optimise the current market structure given the historical remnants of the single marketing system. During the regulated marketing era prior to 1996, all infrastructures like the silo and rail network were planned and developed to optimise the efficacy of the single channel marketing system. Even the milling capacity of the different areas was regulated in order to match the demand of that area. From these developments it was decided that the reference point for SAFEX would be Randfontein, due to the existing milling capacity, as well as railroad links to the rest of South Africa (Geyser, 2013:7; Roberts 2009:3). Therefore, the transportation of white maize to Randfontein could be facilitated by the existing railroad network with links to the silo network throughout South Africa. Also, the distribution of processed white maize products to the greater metropolitan cities of Johannesburg and Pretoria could easily be done from Randfontein. However, this did not mean that all white maize produced throughout South Africa had to be delivered to Randfontein specifically. The delivery process remained linked to the existing silo network, and in order to facilitate the delivery system, all silos in South Africa could become registered as delivery points against the SAFEX white maize contract. Since delivery against the Randfontein

SAFEX contract could now be done at all registered silos, some form of transport cost to Randfontein would have to be accounted for. This transport cost system became known as the location differential system and the differential of each registered silo was calculated on a yearly basis to coincide with each new marketing year. When a producer delivers his produce to a registered silo, his price at that location would be the SAFEX market price minus the specified differential. Alternatively, a miller or buyer of maize would then pay the SAFEX market price minus the specified differential, bearing in mind that he would then be liable for the physical transportation cost to the mill or processing facility (Roberts, 2009:4).

However, the transport differential system, as it is implemented in South Africa today, has been an important point of discussion and indifference over the past few years. For instance, a prominent organised agricultural organisation, Grain South Africa, remains sceptical that the system promotes transparency (Roberts 2009:2; JSE, 2012b). In order to adhere to the request, the JSE requested an independent study to be performed by the National Agricultural Marketing Council (NAMC). A report was compiled by Dr MC Roberts and presented to the NAMC in February 2009. The report clearly indicated that the *status quo* was to be maintained regarding the implementation of location differentials, since the impact of doing away with differentials would be greater than the cost of keeping them implemented. Roberts (2009:2) did, however, acknowledge that the cash market for white maize in South Africa is not transparent or competitive and proposed that SAFEX implement some sort of electronic silo certificate exchange where physical stock in silo storage may be traded on the market. In this manner, the exchange would be able to improve transparency, since the premiums paid at certain locations would be public knowledge.

The JSE adhered to this recommendation by Roberts (2009:2) and announced in May 2010 that they intended to implemented an electronic silo certificate auction from July 2010. This platform would then allow market participants, who hold a long (intending to buy) futures position, to bid a premium on stock offered at a specific registered silo. The stock is offered by the holders of silo receipts who wish to deliver their stock against a short (intending to sell) futures position to close out their contract (JSE, 2012c). Prior to this development, all stock delivered at a registered SAFEX silo and against a short futures position was randomly assigned to the holders of long positions in that specific contract or delivery month. However, this system of random assignment remains in place as a fall-back system if no bid is made on stock on offer. Over time, the JSE has continued to develop the system in order to further improve cash price transparency and, ultimately, price discovery (GrainSA, 2012).

Along with ongoing developments by the JSE towards a transparent cash market system, they conducted a series of workshops together with the NAMC and the Agricultural Advisory Committee on further improvements to the process of determining location differentials. One important outcome of these workshops was that a revised method for the calculation of the location differential rates (LDRs) was developed (JSE, 2012b). The JSE usually acquires inputs from silo owners and more recently included the inputs from road transporters in this regard. The main objective is to collect accurate road and rail rates (JSE, 2012b). In order to facilitate the calculation of inputs, the JSE also invited all market participants to provide their input to the annual adjustment of road and rail tariffs. After these rates are collected they are applied to a specific formula in order to standardise the rate at which a transporter would be able to transport a load from a specific silo to Randfontein.

However, this specific formula has also been revised over time to ensure that all relevant factors and inputs are included. The current formula, which has been in use since the 2012-2013 marketing season to calculate the applicable rand-per-tonne (RPT) rate, is as follows (JSE, 2012b):

$$RPT = \frac{Distance \times RLF \times RPK}{Payload}, \tag{2.1}$$

where:

- $Distance$ denotes the distance in kilometres from Randfontein;
- RLF denotes the return load factor;
- RPK denotes rand per kilometre; and
- $Payload$ denotes the amount of product in metric tonnes.

Therefore, feedback from the transport industry would usually include the distances from each registered silo to Randfontein. These distances are, however, also confirmed by an independent logistics entity. Another formula input which is determined through the inputs of the transport industry and logistics firms is called the return load factor. The return load factor is calculated by means of a kilometre sliding scale and may be seen as a more controversial aspect, since the factor assumes that only one leg of the trip is done by an empty truck and that no return loads were available. This would mean that a transporter would not be able to charge a payload rate for the leg of the total distance the truck is empty for. The return load factor therefore accounts for this transport “loss”. Arguably, not all return loads will be empty and these occurrences will differ from transporter to transporter, depending on available contracts. In order to account for these occurrences of potential available return loads, the return load factors are also revised annually. The applicable return load factors for the 2017-2018 marketing season are reported in Table 2.6.

Table 2.6: Relevant return load factors for the 2017-2018 marketing season

Distance	RLF
< 300 km	2
301 - 325 km	1.9
326 - 350 km	1.8
351 - 375 km	1.7
376 - 400 km	1.6
401 - 425 km	1.5
426 - 450 km	1.4
451 - 475 km	1.4
476 - 500 km	1.4
501 - 525 km	1.4
> 525 km	1.4

Source: JSE (2018b)

It is to be expected that the return load factors, as well as the distance from each silo to Randfontein, would be fairly stable from year to year, but that the big difference to account for would be the applicable rate per kilometre. All of the different rates supplied to the JSE by the different transporters provide them with an indication of the actual cost. Shorter distances usually justify a higher rate per kilometre and this rate would become smaller and stabilise as the distance becomes greater (JSE, 2012b). One reason for this is that a transporter needs to factor in a fixed cost per day per truck, which is usually spread evenly across the distance in kilometres travelled per day. Given the uncertainty the transporter faces regarding the time it would take to unload a truck, it is usually assumed that only one load per day is accomplished. Table 2.7 reports the applicable rates per kilometre for the 2017-2018 marketing season for different one-way distances travelled.

Despite all of the different considerations the JSE made in order to calculate a relevant road transport tariff, the Western Cape delivery silos remain an exception to this rule. Even with return loads available, the cost of transport would not present a sustainable deduction for producers in these areas. Also, the calculation does not accurately reflect the supply of and demand for transport from the area. After an independent survey was conducted, the differential for the Western Cape delivery points was set at R400/mt. In order to standardise the formula even further, it was decided that the payload per truck would be set at 34 metric tonnes, even though it may vary depending on the type of truck (JSE, 2012b).

Table 2.7: Applicable rate per kilometre for different distances travelled

Distance	RPK (R/km)
0 - 15 km	104.32
16 - 25 km	73.33
26 - 50 km	36.20
51 - 75 km	26.34
76 - 100 km	22.21
101 - 125 km	19.78
126 - 150 km	18.17
151 - 175 km	17.94
176 - 200 km	17.78
201 - 225 km	17.52
226 - 250 km	17.37
251 - 275 km	17.16
276 - 300 km	16.91
301 - 325 km	16.59
326 - 350 km	16.35
351 - 375 km	15.86
376 - 400 km	15.64
> 400 km	15.15

Source: JSE (2018b)

All of these inputs then allow the JSE to calculate a relevant rand-per-tonne (RPT) rate for each registered silo. However, not all white maize is transported by road, since most registered silos are linked to the railroad. Therefore, the relevant ratio of road versus rail transport also needs to be determined. The JSE applies the actual rail rates as published by Transnet and uses a two-year average to determine the out-loading ratios at each silo. Finally, the differential for the specific reference point can then be calculated by including the ratio of white maize transported by road and rail through the following formula:

$$Final\ Location\ Differential = (Road\ rate \times Road\ out{\sim}loading\ ratio) + (Rail\ rate \times Rail\ out{\sim}loading\ ratio). \tag{2.2}$$

The method of calculating the transport differential, as well as the institution of the silo certificate auction by the JSE, clearly indicates their commitment to provide a transparent cash-price forming mechanism to the market. However, it still does not clarify why certain locations justify premiums above the SAFEX-minus-differential price. In order to clarify this and the reason why Roberts (2009) stated that the cost to the market would be greater if location differentials were to be abolished, the following scenario is presented based on Figure 2.3.

Figure 2.3: Rail network and grain silos in South Africa
Source: Afgri (2013)

SASKO Mills is a division of Pioneer Foods, which is a manufacturer of foodstuffs in South Africa. One of their white maize mills that produces white maize meal amongst other products, is situated in the industrial area of Klerksdorp in the Northwest Province (SASKO, 2014). Klerksdorp silo is not a registered SAFEX silo and, therefore, no formal differential is published. However, SASKO Klerksdorp still needs to purchase white maize for delivery at the premises in order to produce the different products at the mill. SASKO must, therefore, make use of other existing market mechanisms to procure the stock they need. Some of their formal purchasing alternatives are represented by nearby registered SAFEX silo locations, like the Potchefstroom and Hartbeesfontein silos, which are indicated by the red and blue circles in Figure 2.3. Randfontein silo, as SAFEX reference point to where all location differential rates are calculated, is also indicated by a red circle. The white maize differentials for these reference points, as well as the distances between the different points and an estimated transport cost derived by Formula 2.1, are reported in Table 2.8.

Table 2.8: Estimated distance and transport cost from purchasing alternatives

SAFEX silo	2017/2018 location differential (R/mt)	Estimated distance and transport cost to SASKO:	
		Distance (km)	Transport cost (R/mt)
Hartbeesfontein	183	33	70.27
Potchefstroom	123	50	106.47

Source: Compiled by the author
Location differentials obtained from JSE (2018). Distance calculated by means of DistancesFrom (2014). Transport cost derived from the JSE road tariff per tonne formula (2.1) (JSE, 2012b).

The location basis calculation done in Table 2.7 shows that SASKO will be able to transport maize to their Klerksdorp mill from Hartbeesfontein and Potchefstroom at a lower cost than the applicable location differentials allocated to Hartbeesfontein and Potchefstroom respectively. In both these cases SASKO might decide to pay a premium for white maize at either Hartbeesfontein or Potchefstroom silos. This is a premium above the SAFEX-minus-differential price for that location. For white maize in the Potchefstroom silo, SASKO has the option to pay a premium of R16.53/mt (R123 – R106.47) and for Hartbeesfontein, a premium of R112.73 (R183 – R70.27). SASKO will be able to apply this logic to all relevant silos around Klerksdorp in order to determine relevant procurement locations. In all instances where the transport cost to Klerksdorp is smaller than the location differential of the specific silo, a premium can be paid. This premium will depend on, amongst other factors, the cost of transport, the supply and demand conditions for the specific region, the cost of handling and storing, as well as the required return on capital to purchase the white maize (Geyser, 2013:58).

Arguably, if supply conditions are favourable, SASKO would prefer not to pay a premium and would rather apply the available premium value to pay for storage and interest on capital required to buy and finance white maize stock in advance. The same concept would apply to all millers or processors throughout South Africa. However, the reality is that many silos in South Africa trade at a discount in the cash market, which entails a deduction greater than the applicable differential (Geyser, 2013:58). Therefore, in favourable supply conditions, producers or the owners of white maize would usually not receive a premium above the SAFEX-minus-differential price. In these instances, the owner of the stock has the option to deliver the stock through SAFEX, in which case the location differential as well as certain SAFEX delivery fees will be deductible. The owner of the stock, therefore, has the option to compare the discount below the SAFEX-minus-differential price offered by a buyer to the delivery fees charged by the exchange. In a sense, the location differential offers the owner of the stock a type of "price stabilisation" relative to the prevailing SAFEX price, since selling the stock at a potentially greater deduction is not the only option available (Geyser, 2013:9). It was for this reason that Roberts (2009:3) argued that the cost to agriculture would be greater than the benefit of eliminating location differentials.

From the scenario presented above and with specific reference to the calculation of location premiums, it becomes evident that every buyer in the market would do their own calculations to determine from where they would be able to procure stock at the weakest possible basis relative to their specific location. This would be a location where the purchase price is closest to, or even less than SAFEX minus the differential, and where the size of the differential at least covers transport and handling cost. Consequently, if location differentials were abolished, the SAFEX price would probably adjust to represent the “worst-case delivery scenario”, which would be the biggest differential applicable (Roberts, 2009:8). In international instances, where the location differential system has been abolished, the decrease in the commodity market price was approximately 75% of the “worst-case scenario” (Geyser, 2013:8). Consequently, maize producers who argue that they are disadvantaged by a relatively large location differential rate will not benefit from its abolishment. In the same manner, producers who are situated closer to Randfontein will not be able to benefit from a smaller location differential and will most likely be subject to a greater deduction captured within a decrease in the market price.

The effect of such a decrease in market price due to a “worst-case delivery scenario” deduction may have a significant implication on producers, especially those in lower location differential areas. If market prices were to drop by R412.50 (R550 x 75%), which is the relevant expected “worst-case delivery scenario” for white maize, most producers would struggle to obtain production finance, since they would not be able to ensure repayment of their input finance (Roberts, 2009:10). The reason is that input finance is not granted based on the basis or location of the producer, but on his production value turnover and eventual revenue. This will be his ability to repay his loan based on the potential crop yield of his land and the associated market price. Therefore, if the differential system is abolished and prices suddenly dropped by R400 per metric tonne, producers would immediately find themselves in a cost-squeeze situation, since the market price would not cover input costs (Roberts, 2009:11).

Furthermore, the moment that location differentials are done away with, the entire market would suffer since it would actually reduce the ability of SAFEX to facilitate transparent price formulation. The reason for this is that the area from where the supply of white maize to the market would occur would be linked to the “worst-case scenario” area where surplus stock is available. This area would then change throughout the marketing season as supply conditions in the different areas change. The ironic effect of this phenomenon would be that basis risk would increase, since the cash price would change as the area changes. This would reduce the market's ability to ensure convergence of the cash and future price of white maize, since arbitrage opportunities would be ample (Roberts, 2009:11).

To summarise - Section 2.3.2 discussed the standardisation of white maize contracts and the reasons behind and motivations for the institution of location differentials, thus illustrating that the JSE is dedicated to sustaining market transparency. Market transparency provides market participants with the necessary confidence and trust to effectively trade an underlying commodity. However, although these standardisation characteristics contribute to the transparency of the white maize market, it only forms the foundations for the trading of white maize through financial derivative instruments. White maize derivative instruments are therefore based on these standardisation criteria, from where they are traded through an exchange platform. The SAFEX Commodity Derivative Division provides this exchange functionality. An explanation of the derivative market function, as well as the different derivative instruments traded on SAFEX, is discussed in Section 2.3.3. This explanation is warranted, since derivative instruments tend to be abstract and difficult to interpret without the necessary experience. Jordaan and Grove (2007:561-562) determined that producers tend to avoid future price risk management decisions altogether if they feel that they lack the necessary knowledge about the tools available to them. Nevertheless, in order to compile and execute a price risk management plan in the form of a hedging strategy, knowledge about the different derivative instruments is essential. Section 2.3.3 aims to provide this knowledge foundation.

2.3.3 Derivative market function and instruments

The term derivative instrument, and more specifically agricultural derivatives, refers to the financial instruments that are based on an underlying agricultural product. These derivative instruments are based on the standardised contract specifications (Section 2.3.2) of the underlying commodity which are usually physically settled contracts (JSE, 2014e:11). Although the derivatives market itself does not determine the market price, it facilitates the participation of market participants through derivative instruments in order to set prices and provide information about cash prices in the future. SAFEX provides this market platform to satisfy the needs of market participants, like hedgers, speculators, arbitrageurs and investors (Geyser, 2013:4-5).

These four groups of market participants collectively provide liquidity to the market. However, the reason for their participation in the market usually differs immensely. The main aim of a hedger for example, is to apply these derivative instruments to protect the value of an underlying commodity against adverse price movements. As a result, hedgers are either producers of the underlying commodity, who may intend to sell, or end users (for example, processors) who intend to buy the commodity, either now or sometime in the future (Falkena *et al*., 1989:4).

Contrary to hedgers, speculators do not wish to hedge, but aim to take a view on expected price changes in order to realise a trading profit. Speculators may consist of position traders, day traders, scalpers and spread traders. Position traders tend to take a longer term view of their expected longer term trend in the underlying commodity price. Day traders, on the other hand, take a shorter term view and usually close out their market position before the market closes. Scalpers are also shorter view traders, although their term may be longer than a day, since they only close out their position once a specific profit target or maximum determined loss is reached. Spread traders consider a view of an opposite futures position across more than one contract, like two different future month contracts, expecting the futures prices to either converge or diverge (Geyser, 2013:4-5).

Arbitrageurs may also be seen as a type of speculator; they are, however, considered as a separate group of market participants. The main difference between arbitrageurs and speculators is that arbitrageurs do not take a view of expected market price movements. Arbitrageurs might take a simultaneous position in the corn contract traded on SAFEX and CBOT markets with the aim of making a profit from any mispricing that may exist between these two markets (Geyser, 2013:4-5). The final group, investors, may deem the commodity market an attractive investment opportunity and decide to purchase futures contracts on white maize instead of physical white maize stock, since they consider the futures market to be more liquid (Falkena *et al*., 1989:20-21). As a result, the participation of all four groups increase the liquidity in the market, thereby increasing the number of contracts traded and the ability of the market to act as price forming and risk management mechanism (Geyser, 2013:4-5).

In order to facilitate the price setting mechanism and to ensure that the underlying commodity is successfully traded on the provided platform, the JSE Commodity Derivatives Division must ensure a complete risk management structure. This structure is established by SAFCOM, as explained in Section 2.3.1 (SAIFM, 2011:92). Within this risk management structure, each clearing member needs to ensure that all members registered adhere to the financial compliance prerequisites as set by the JSE Executive Committee, and that all trades are settled on a daily basis. Ultimately, the clearinghouse assumes all responsibility for default risk, but also ensures that if default risk becomes a reality, they will be able to avoid it by means of a process called margining (Krugel, 2003:22-23).

2.3.3.1 Initial margin, variation margin and marked-to-market

Margining is the process by which the exchange requires each client to pay a “deposit of good faith” or a margin deposit for every transaction carried out. After each client enters into a futures contract an initial margin is required by the exchange. This initial margin is determined by the exchange from time to time and is usually between 5-8% of the contract value (SAIFM, 2011:67). Furthermore, the initial margin should be enough to cover two days of market movement, but the JSE may increase the initial margin in times of high volatility. Therefore, the initial margin requirements may change as the futures contract progresses until it matures and expires (Geyser, 2013:49).

These changes are usually linked to the maximum daily price change for a futures contract. The daily price movement limits are also determined by the JSE and included in the contract specifications (see Table 2.4). Consequently, the futures price of white maize (currently) can only trade a maximum of R100/mt up or down in a single day. However, if a minimum of two white maize futures contracts trade at limits in the same direction for two consecutive days, the price limits will be extended to R150/mt and will remain in place until the price movement is equal to, or below the normal limit. Price movement limits are not applicable to the spot months, in order to ensure that the cash price and futures price can converge (JSE, 2012a:24). On limit days, as well as in the spot months where no price movement limits are imposed, the JSE usually increases the initial margin requirement. This initial margin increase forms part of the risk management action plan the JSE institutes to counteract higher default risk in times of higher price volatility. The JSE furthermore ensures that default risk is managed through a daily calculation of variation margin.

Variation margin is simply the difference between the price level where a futures position was entered into and the prevailing futures market price. The difference may therefore create either a profit or a loss on every contract or futures market position. However, this profit or loss needs to be determined on a daily basis and in order to ensure transparency, every futures contract needs to be compared to a specific representative market price after the market closes. The process by which each contract price is matched to the prevailing market price is called mark-to-market (MTM). The JSE determines the MTM price based on a set methodology across the last five minutes of trading. The methodology is based on a snapshot approach to preserve the price difference relationship between contracts and a time-weighted average approach to reduce the risk of capturing non-representative adverse market movements in the last few minutes of trading. As a result, a random snapshot of the market price in every minute of the last five minutes will be taken. The representative MTM is then calculated based on the following basic rules for each snapshot interval: Evaluate the last traded price. If there was no trading activity, use the previous day's MTM. Otherwise, it will depend on the best offer or best bid in relation to the last traded price. If the best on-screen bid is higher than the last traded price, the best bid becomes the MTM snapshot. If the best on-screen offer is lower than the last traded price, the best offer should be used as MTM snapshot. The average calculation of these five snapshot determinations, the value of which is rounded based on the contract specifications, will be the MTM for that day (JSE, 2017:2).

Furthermore, it is important to realise that the MTM process takes place every day in order to ensure that the margin accounts for all futures contracts resulting in a loss are funded or topped up accordingly. This amount is called the variation margin. If the holder of a futures contract makes a loss, he has to pay the required variation margin; if he makes a profit, he will receive the variation margin. In this way, the JSE ensures that price movements on futures contracts are accounted for. However, if the futures contract holder makes a loss and is unable to top up his variation margin, the JSE will close that futures position, deduct the resulting variation margin loss from the initial margin and pay out the remaining initial margin balance (Geyser, 2013:48-49; SAIFM, 2011:67). The initial margin therefore acts as a buffer which ensures that the risk of non-payment of variation margin is accounted for. It is also important to realise that, once the initial margin is paid to SAFCOM, it is reinvested in an interest bearing account and when the futures position is closed out, the initial margin or remaining initial margin plus interest earned for the period is paid out to the holder of the position (JSE, 2012d:2).

To summarise - the background to the functioning of the derivatives market as set out above, as well the "zero sum game" the JSE applies through margining (in order to ensure counterparty liability and price risk transfer), provides the necessary background and knowledge to aid in the understanding of specific derivative instruments. The two main types of derivate instruments are called futures and options. Futures contracts (Subsection 2.3.3.2) and option contracts (Subsection 2.3.3.3) are now dealt with in detail. This explanation is an important cornerstone for the study, since the hedging strategies evaluated (Chapter 5, Section 5.4) were constructed by means of these individual derivative instruments.

2.3.3.2 Futures contracts

A futures contract is a financial agreement to buy or sell a standardised quantity and quality of a specified underlying asset at a specified future time for the price determined at the time when the contracts were traded (Falkena *et al*., 1989:1; Hull, 2005:21). It is important to note that a futures contract is based on the standardised contract specifications (Section 2.3.2) of the underlying and that the price of a futures contract is determined by the factors (Section 2.4) affecting the price of the underlying commodity (Geyser, 2013:45). The formation of the underlying commodity price by means of futures contracts also fulfils other important functions. Firstly, it determines a published market price, since buyers and sellers of a futures contract agreed on the established price based on the changes in the supply and demand conditions of the underlying. Secondly, it provides hedgers with the means to transfer their price risk from the physical or cash market to the futures market through the futures exchange. Thirdly, it provides liquidity in the market, since market participants can enter and exit the market without seriously affecting the current market price. Lastly, it promotes market participation, since a position can be obtained in the market at a relatively low transaction cost and all transactions are guaranteed by the futures exchange (Geyser, 2013:45-46; SAIFM, 2011:55).

Along with these functions it is also important to realise that for every futures contract established by the exchange, there are two parties involved. These two parties facilitate the way in which the clearinghouse is able to transfer price risk from one party to the other. The one party will be the buyer of the contract, also referred to as the long position holder of the contract in the market. When a futures contract is bought, it is also called a long futures contract. Therefore, the buyer of the contract is the holder of the contract which would enable him to buy the physical underlying sometime in the future (Coopers & Lybrand, 1995:653). The other party will be the seller of the contract, also known as the short position holder of the contract in the market. A sold futures contract is called a short futures contract. Accordingly, the selling of the contract enables the seller to sell the physical underlying sometime in the future (Coopers & Lybrand, 1995:660). The JSE ensures that both of these parties pay the initial margin requirement to account for default risk by either party. However, it should be noted that neither of these parties are obligated by the futures contract to either make delivery or take delivery of the underlying prior to the delivery or futures month, since both sides may offset their contract by obtaining an opposite futures position (Geyser, 2013:47).

Therefore, a long futures contract may be sold by the buyer and a short futures contract may be bought back by the seller prior to the expiration date of the futures contract. However, this process of taking an opposite position in the market may result in a profit or a loss for either party. Participants may buy a futures contract at a certain level and sell that contract back into the market at a later stage. If the futures price increased, a profit would be made from the long position (see Figure 2.4); but if the market price traded lower, a loss would be realised. Alternatively, if participants decided to sell a futures contract short and buy it back at a later stage, a profit would be made if the futures price traded lower, but a loss would be realised if the price increased.

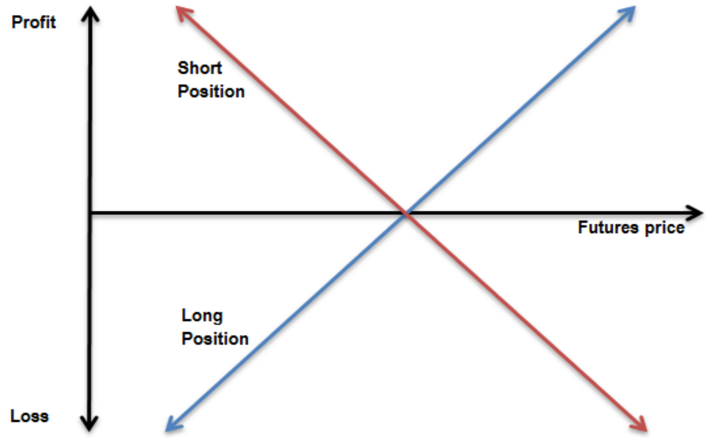

Figure 2.4: Profit and loss diagram of futures positions
Source: Compiled by the author (adapted from Hull (2005:41) and Geyser (2013:48))

The offsetting of futures contracts is also not the only means available to close out either a short or a long futures position. Another way a futures contract may be closed out is by delivering on the contracts. Delivery on SAFEX may only be done by the holder of a short futures position from the first business day of a delivery month up to the second last business day of the delivery month. The holder of the short position should notify the member he trades through of his intention to deliver. The member should then give notice to the exchange before 12:45pm of that same day, upon which a silo certificate from a registered SAFEX silo must be provided to the exchange by the following business day (JSE, 2013). Delivery against the short contract can only be made if all outstanding handling and storage fees, up to and including the delivery date, are paid in full (Geyser, 2013:56). It is important to realise that if a short position holder does not wish to deliver against a short position held in a delivery month, the position needs to be offset or cleared out by the last trading day, which is usually the sixth last business day of the delivery month. If the short position is still in place after the last trading day, the short position holder would be obliged to fulfil the contract by means of physical delivery of white maize to a registered SAFEX silo. Once delivery is made, the JSE may determine to which holder of a long white maize futures contract delivery would be assigned. This is done by means of one of three methods, as described by Geyser (2013:55):

- Firstly, the holder of the short futures position and the holder of a long futures position may have agreed on specific transaction details, such as a basis premium outside the exchange. In this case, both parties would need to notify the exchange in writing from where the exchange would offset the applicable short position against the long position of the buyer at the MTM price of that day. The silo certificate representing the physical stock would then become the property of the buyer once payment at the MTM price, plus basis premium, is made to the exchange. The JSE would then pay the seller this price minus the applicable delivery fees;

- Secondly, if no specific long futures holder is allocated, the exchange would auction the silo certificates on the automated trading platform. All long position holders would then have the opportunity to bid a basis premium for that location from 09:30 – 12:45 each delivery day for the duration of the delivery month. The long position holder with the highest premium bid would be assigned delivery of the specific silo certificate; and
- Thirdly, if no premium is bid by the long position holders, the JSE would assign random delivery to any long position holder.

Despite the methods deployed by the JSE to facilitate the process in order to promote risk management and market transparency (Section 2.3.2), the reality is that only about 2% of white maize futures contracts are physically delivered (Geyser, 2013:47). The rest of the producers who hold a short futures position or processors who hold a long futures position usually apply these positions as hedges in order to limit their exposure to undesirable price movements. These short hedge positions are then cleared by an offsetting position once delivery to a buyer is made, whilst the long hedge positions are cleared by an offsetting position once stock is procured.

Despite this explanation on the working of futures contracts and the built-in price risk management measures they provide, there is another important consideration a buyer or seller of futures contracts must account for. They need to ensure that they have enough cash flow to pay variation margin calls. From Figure 2.5 it is clear that futures positions have a virtually unlimited profit and loss potential. Consequently, a hedger should ensure that he does not run out of cash to sustain the variation margin account, since the JSE would close out the positions on his behalf as explained in Section 2.3.3.1. In this instance, the hedger locks in a loss that may only be recovered if the market price turns in a favourable direction and the physical underlying is sold or bought at the original hedge level in the cash market (Geyser, 2013:64).

The cash flow requirements of hedging or speculating by means of futures and the fixed price realised from the hedging process often prompt market participants to consider option contracts as an alternative financial derivative instrument. Option contracts provide participants with the opportunity to obtain exposure to the market without assuming unlimited risk. Section 2.3.3.3 will shed light on this statement and provide details into the working and applicability of option contracts.

2.3.3.3 Option contracts

An option contract is also a derivative instrument which is standardised by and traded on an exchange. The main difference between a future and option is that an option is not derived from the underlying physical, but rather from the underlying futures contract value (Geyser, 2013:81). An option gives the holder or the buyer of the option (long option holder) the right, without the obligation to buy or sell the underlying at a specific price some time in the future. Effectively, it means that the holder of an option contract obtains the right to decide if a specific futures contract price at a specific time in the future would be favourable (Hull, 2005:181; SAIFM, 2011:126). In order to obtain this right, the holder of the option pays a premium. This premium paid by the holder may be seen as the maximum potential loss if the outcome of the option is unfavourable, while the potential profit is unlimited (SAIFM, 2011:126).

Yet again, in the same manner as with a futures contract, there are two parties to consider. The other party to an option buyer is the option seller, also known as the option writer. Option writers are also seen as market makers since options on different futures prices, which may not be available in the market, are required by option buyers as the futures price change. Option writers then become the seller of that option to the buyer at a specific futures price level, thereby effectively creating a new "option strike price" (more detail in Table 2.9a and Table 2.9b), or a supply to the demand at the specific futures price. The option writer, however, assumes unlimited risk, since he gives up the right to decide whether a futures price is favourable. For this potentially unlimited risk, the option writer does receive a premium. Therefore, the option seller needs to fulfil the option contract obligations if the holder of the option decides to exercise his right (Geyser, 2013:81).

From this explanation of the risk assumed by either party of an option contract, buying option contracts seem to be the perfect type of derivative instrument with potential limited loss and potential unlimited gain compared to a futures contract. The reality is that options are complex and their mechanics not always fully understood which may lead to catastrophic losses (SAIFM, 2011:126). However, grasping the basic concepts relating to the different types of options – how they are structured, and how they may be applied successfully by the different parties in the market – will aid in the understanding of the motivation for undertaking option contracts. Therefore, when considering the use of option contracts as price risk management instrument, it is essential to fully grasp the main building blocks.

Geyser (2013:81) explains two of the main building blocks pertaining to options as follows:

- The first important decision or step for a market participant is to establish an appropriate expiry or futures hedging month. Option contracts for white maize can only be traded in the main hedging months of March, May, July, September and December. Accordingly, options do not have a near month or cash month. The timeline of an option contract relative to its underlying futures contract is presented by Figure 2.6.

- The second consideration is the futures price level at which an option is bought. The SAFEX price at which an option is bought is also called the strike price of the option. Option strike levels on SAFEX are also only traded in even R20 increments. If the strike price of the option is favourable to the holder of the contract, the holder will exercise his option.

When considering these two input variables for white maize options traded on SAFEX, maize producers usually make use of the July futures month to buy options, since this is also the month when the bulk of the harvest takes place. Also, SAFEX specifically makes use of American-style options on the standardised futures contracts. This style of option contract gives the holder the right to exercise the option at any time during the life of the option up to and including the expiration date (Hull, 2005:181; SAIFM, 2011:128). This characteristic of American-style options furthermore establishes three main alternatives for exiting an option contract. The first way would be to sell back the option before the option expires, which may or may not result in a profit and will depend on the premium recovered when selling the option (see different outcomes in Table 2.9a and Table 2.9b). The second method happens naturally when the option expires worthless. In this instance, the price development of the underlying was not favourable to exercise the option. The third method is where the holder of the option decides to exercise his option. This option holder may decide to do this on any date before or on the option's expiration. Alternatively, if the option's strike price is favourable, the exchange would automatically exercise the option on the option expiration date and randomly assign the exercised option against any short holder of the same strike option (JSE, 2013:8). After a favourable strike option is exercised, it is converted to a corresponding futures contract, which would follow the same "life cycle" route as depicted by Figure 2.5 and explained in Section 2.3.3.2. The type of futures contract an option is converted to will, however, depend on the type of option contract.

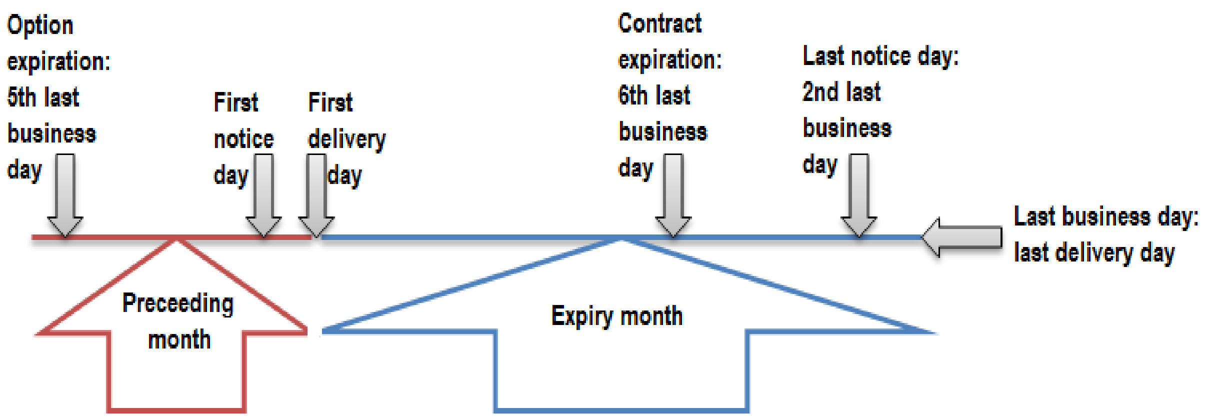

Figure 2.5: ***Different contract days pertaining to an option and futures contract life cycle***
Source: Compiled by the author (adapted from Geyser, 2013:53)

There are primarily two types of option contracts, as explained by Geyser (2013:81) and Hull (2005:181-182). One type is called put options. A put option would give the holder of the option the right, but not the obligation, to sell a futures contract at the option's strike price level on or before the options expiration date. In this case the holder would have a right to decide if he would like a short futures contract at the strike price of the option by the expiration date of the option. The second type is called call options. A call option gives the holder of the option the right, but not the obligation, to buy a futures contract at the option's strike price level on or before the option's expiration date. In this case, the holder would have the right to decide if he would like a long futures contract at the strike price of the option by the expiration date of the option. These rights of the long option holder and the potential obligation of the short option writer are presented in Table 2.9a and Table 2.9b, respectively.

Table 2.9a and Table 2.9b show that the outcome of an option will depend on the relation between the existing underlying futures contract and the option strike price. This characteristic of an option is also known as an option intrinsic value and may be seen as one of the main factors that influence the option premium value. However, the intrinsic value of an option premium will not be the same for the buyer and seller of an option and will also differ for put and call options. In general, it will depend on whether the option is deemed "in-the-money", "at-the-money" or "out-of-the-money". If an option is deemed "in-the-money" or "at-the-money" and it would be favourable for the holder of the option to exercise the option, the intrinsic value of the option would be equal to the difference between the underlying futures contract price and the strike price of the option. If an option is deemed "out-of-the-money" and the option holder would probably not exercise the option, the intrinsic value of the option would be zero (Hull, 2005:206).

Table 2.9a: Outcomes, rights and obligations when buying or selling a put option

Put option position	Rights or obligations	Underlying futures price change prior up to and including option expiration date	Outcome
Buy (hold) put option = Long put	Right to sell futures contract at option strike in future. Pay premium.	Futures price above option strike.	Option "out-of-the-money". Will expire worthless. Max loss is the full option premium.
		Futures price at option strike.	Option "at-the-money", option automatically exercised upon expiry and holder receives short future at strike. Full option premium cost paid.
		Futures price below option strike.	Option "in-the-money", option automatically exercised upon expiry and holder receives short future at strike. Full option premium cost paid
Sell (write) put option = Short put	Obligation to buy futures contract at option strike price if long holder exercises option. Receive premium.	Futures price above option strike.	Option "out-of-the-money", max gain is the full option premium.
		Futures price at option strike.	Option "at-the-money", option automatically exercised upon expiry and writer receives long future at strike. Full option premium received. Loss potential unlimited.
		Futures price below option strike.	Option "in-the-money", option automatically exercised upon expiry and writer receives long future at strike. Full option premium received. Loss potential unlimited.

Source: Compiled by the author, adapted from SAIFM (2011:129) and Geyser (2013:82-84)

Table 2.9b: Outcomes, rights and obligations when buying or selling a call option

Call option position	Rights or obligations	Underlying futures price change prior up to and including option expiration date	Expected outcome
Buy call option = Long call	Right to buy futures contract at option strike in future. Pay premium.	Futures price above option strike.	Option "in-the-money", option automatically exercised upon expiry and holder receives long future at strike. Full option premium paid.
		Futures price at option strike.	Option "at-the-money", option automatically exercised upon expiry and holder receives long future at strike. Full option premium paid.
		Futures price below option strike.	Option "out-of-the-money". Will expire worthless. Max loss is the full option premium.
Sell call option = Short call	Obligation to sell futures contract at option strike price if long holder exercises option. Receive premium.	Futures price above option strike.	Option "in-the-money", option automatically exercised upon expiry and writer receives long future at strike. Full option premium received. Loss potential unlimited.
		Futures price at option strike.	Option "at-the-money", option automatically exercised upon expiry and writer receives short future at strike. Full option premium received. Loss potential unlimited.
		Futures price below option strike.	Option "out-of-the-money", max gain is the full option premium.

Source: Compiled by the author, adapted from SAIFM (2011:129) and Geyser (2013:82-84)

Another factor which is a prominent determinant of the option premium is known as the time value of an option. This value represents the amount of time left until the option's expiration date. The more time left until its expiration date, the greater the option premium would be, since the difference between the option strike price and the underlying futures price may vary over time. Also, a longer time period increases the probability that the option might become "in-the-money", thereby becoming profitable to the buyer and an increasing risk to the writer of the option, which needs to be accounted for through the premium income value. Therefore, the time value of an option decreases as the time to option expiration runs out, leaving only the potential intrinsic value of the option at expiration. This time value decay of an option, however, does not occur linearly but rather exponentially, as illustrated by Figure 2.6. During the beginning of an option's life, the time value remaining is rather constant, but starts to decay exponentially during the last three months until it reaches zero at option expiration (Scheepers, 2005:24-25).

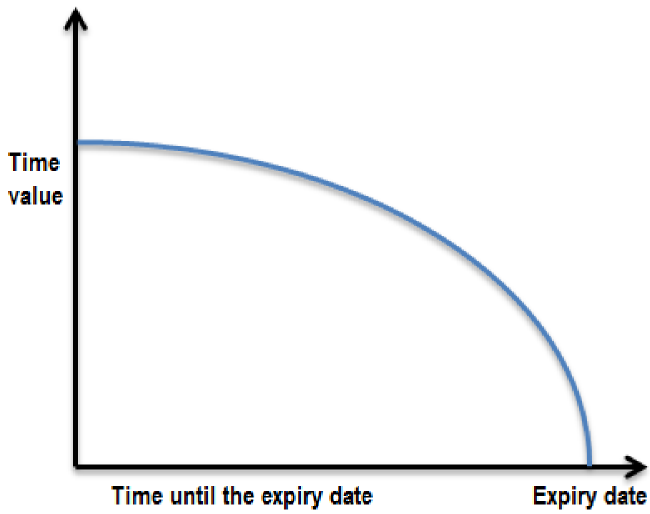

Figure 2.6: Option time value decay
Source: Scheepers (2005:25)

The last main factor that is also a prominent determinant of the option premium is known as option volatility. This volatility refers to the price volatility of the underlying futures market or the manner in which closing futures price levels vary from one day to the next. The implication of increased futures price volatility is that the probability of the option strike becoming "in-the-money" also increases. Volatility might therefore be seen as a risk factor represented in the option premium, since an option writer's risk increases if the option becomes "at-the-money" or "in-the-money", especially closer to the option expiration date in times of higher volatility (Geyser, 2013:87-88). Also, when evaluating the inherent risk associated with option price volatility, option traders will need to consider two types of volatility. The first type is known as the historical volatility, which can be expressed as the annualised standard deviation of the changes in the underlying futures price over a specific time period. This time period is generally accepted as being 252 trading days within a calendar year, since price changes only occur when the market is open and prices react to new information. Consequently, the volatility per annum may be calculated by applying the following formula (Hull, 2005:270):

$$Volatility\ per\ annum = VPTD \times \sqrt{n}, \qquad (2.3)$$

where:

- $VPTD$ denotes the volatility per trading day or the percentage change in price from one daily closing price to the next; and
- n denotes the number of trading days per annum (generally between 250 and 252).

The second type of volatility is called implied volatility. This type of volatility is derived from market participants' perception of volatility, by evaluating the actual volatility at which regularly traded options are traded in the market. Traders tend to apply implied volatility rather than historical volatility to calculate the price of a less active option strike. The reason for this is that historical volatility is no guarantee of future volatility and option writers need to minimise this risk by writing options at the highest possible volatility to ensure a large enough risk premium (Geyser, 2013:101-102).

To summarise - the intrinsic value, time value and underlying futures volatility are the main variables to consider in the calculation of the option premium value on SAFEX. The method and formula to calculate a reasonable option premium value from these variables will, however, be discussed in Chapter 5 (Section 5.4.1), since these calculations will form part of the methodology and empirical study. The specific method and formula for pricing these options is the Fischer Black model (1976), which is an adaption of the original 1973 model by Fischer Black and Myron Scholes. The model was adapted since the original Black and Scholes model (1973) was developed to price European-style options, which requires a risk-free rate in the calculation. SAFEX, however, facilitates American-style options and adopted the adapted Fischer Black model which is better suited for the pricing of commodity-type contracts (JSE, 2012e:A1). This adaption and application of the Fisher Black model by SAFEX is just another example of how they aim to simplify the price formation environment for market participants.

Nevertheless, market participants should never blatantly regard option contracts as an easy or less risky alternative to futures contracts. Despite the fact that options provide flexibility in uncertain market conditions to achieve price risk management aims, the reality is that options, and especially the combination of different types of options within an option strategy, remain complex and have been the cause of several severe financial losses suffered by market participants (SAIFM, 2011:126). The circumstances leading to such losses can usually be attributed to insufficient knowledge of the outcome of different options within a strategy (see Table 2.9a and Table 2.9b), as well as unexpected underlying futures price movements due to changes in the fundamental factors affecting the supply and demand of the underlying commodity. These factors are discussed in detail in Section 2.4.

2.4 Influential factors or drivers of the SAFEX white maize price

The process of evaluating certain influential factors and establishing the individual or combined effect of each of these factors on present and future supply and demand of white maize is referred to as fundamental analysis (Geyser, 2013:11). According to Wisner (2011), the role of fundamental analysis is to create a ‘big picture’ by means of the influential factors in order to estimate possible scenarios or outcomes of marketing seasons. The reason for a bigger, longer term approach is that markets tend to overreact in the short run, deviating from expected fundamental price movements. Ultimately, supply and demand for white maize controls price setting.

When considering supply and demand, it would be meaningful to begin by considering a white maize balance sheet in Section 2.4.1. White maize balance sheets provide an overview of supply and demand-side figures at a point in time. Supply side figures typically include figures, like production area (hectares), the expected production per hectare, the potential imports, and carry-over stock from a previous production season. Demand-side figures usually include the use or processing of white maize for humans, animals, bio-fuels, and potential imports. These supply and demand figures are significantly affected by certain factors, such as local and international macro-economic conditions (spendable income, interest rates or exchange rates), legislative and political influences, as well as the impact of weather phenomena (Section 2.4.2). Hence, the impact of actual or expected changes in these factors is quantified predominantly through changes in the respective balance sheet figures they affect.

2.4.1 White maize balance sheet

As a result, a commodity balance sheet may be seen as a comparative analysis where the sources of current and expected supply are weighed against the current and expected demand, in order to determine if stock levels will be sufficient (Geyser, 2013:12). However, a white maize balance sheet does not always consist of confirmed figures, since the balance sheet is compiled from various inputs, like crop estimates, as well as overlapping planting and marketing seasons, which prompts the setting of different scenarios. From these scenarios, a consensus forecast of the supply and demand balance for the coming marketing season may be established and, as the season progresses, the actual figures improve this forecast until the marketing season ends.

The marketing season for white maize begins 1 May and concludes on 30 April of the following year (JSE, 2012a:9). However, white maize in South Africa is traditionally planted from October in the eastern parts until late December in the western parts of the country, from where the harvest is collected from May to August of the following year (JSE, 2010:10). Table 2.10 provides a timeline of the

Crop Estimate Committee (CEC) dates and the traditional planting and harvesting schedule for white maize.

Table 2.10: CEC reports and production season timeline

Month	Crop Estimate Committee reports	Production and marketing developments
October	Intentions to plant estimate for coming/new season released.	Planting commences in eastern parts of RSA.
November	Finalisation of previous season area and production figures.	Planting commences in central and western parts of RSA.
December		Planting traditionally concludes.
January	Preliminary area planted.	Critical pollination stage in production cycle for maize. Mid-summer traditionally drier and warmer.
February	Revised area planted and 1st production forecast.	
March	2nd production forecast.	
April	3rd production forecast.	Previous season marketing year ends.
May	4th production forecast.	New season marketing year begins. / Eastern parts of country start harvesting.
June	5th production forecast.	Central and western harvest in full swing.
July	6th production forecast.	
August	7th production forecast.	Harvest concludes.
September	Final production estimate.	Field cultivation commences.
October	Intentions to plant estimate for coming/new season released.	Planting commences in eastern parts of RSA.
November	Finalisation of previous season's area and production figures.	Planting commences in central and western parts of RSA.
December		Planting traditionally concludes.

Source: Compiled by the author (adapted from SAGIS (2018a) and JSE (2010:10))
Note: RSA denotes the Republic of South Africa

This timeline presented in Table 2.10 shows how new information regarding the expected crop is released throughout the season on a regular basis when the CEC releases any expectations or production estimates or when weekly export and delivery reports are released by SAGIS (South African Grain Information Service). Thus, at a certain point in time, the latest production estimate, along with relevant figures of supply and demand, may be combined to compile a commodity balance sheet, from where important calculations in the form of current or expected stock levels can be made. Table 2.11 shows a typical white maize balance sheet compiled by the NAMC (National Agricultural Marketing Council) based on SAGIS (South African Grain Information Service) and CEC (Crop Estimate Committee) information which is published on a monthly basis.

Table 2.11: White maize supply and demand balance sheet

	White Maize	White Maize
Marketing season	**Pre-final 2017/18**	**Projection 2018/19**
CEC (Crop Estimate)	9 916 000	6 879 960
CEC (Retention)	-	200 000
Minus early deliveries current season	-	117 369
Plus early deliveries following season	-	200 000
Available for commercial market	9 916 000	6 762 591
Supply (m/t)		
Opening stock (1 May)	597 837	2 428 653
Producer deliveries	9 268 593	6 679 960
Imports for South Africa	-	-
Net early deliveries	-	82 631
Surplus	21 751	10 000
Total Supply	9 888 181	9 201 244
DEMAND (m/t)		
Processed for local market		
-human	4 459 504	4 600 000
-animal and industrial	2 061 649	2 150 000
-gristing	12 813	12 000
Withdrawn by producers (own use)	35 885	30 000
Released to end consumers	30 125	32 000
Net receipts (-) / disp. (+)	7 583	5 000
Deficit	-	-
Local Demand	6 607 559	6 829 000
Exports		
-products	42 038	60 000
-whole maize	809 931	550 000
Total Demand	7 459 528	7 439 000
Ending Stock (30 April) (m/t)	2 428 653	1 762 244
- processed p/month	544 497	563 500
- months' stock	4.5	3.1
-days stock	136	95

Source: Compiled by the author, adapted from NAMC (2018)

Table 2.11 specifically reflects the July 2018 supply and demand estimate based on the latest SAGIS demand figures and projections as well as the 6th production estimate figures for the 2017-2018 season released by the CEC. It includes the figures for the different forms of supply and demand up to the date when the balance sheet was compiled. The supply side of a white maize balance sheet is usually made up of the stock left over from the previous marketing year (opening stock), the expected production to be received in the current season, as well as any imports received. The demand side will include all white maize processed in the local market for human, animal and industrial, gristing, as well as the export of whole and processed maize (Geyser, 2013:12). The core of these figures represents actual and estimated figures for supply and demand from the beginning of the marketing year up to the balance sheet compilation date.

From the established cumulative figures, market participants will be able to compile an array of scenarios for different outcomes relating to supply and demand figures. These figures are then used to progressively estimate what the final figures might be at the end of the following marketing year, and so determine what the ultimate stock levels may be. Such a scenario is depicted in Table 2.11, where demand in particular is projected linearly to the end of the marketing year. As time progresses certain figures – for instance the crop estimate and the different demand figures – become final and the progressive estimations for the demand factors become more accurate (SAGIS, 2018b).

As a result, more reliable ending stock levels may also be determined once supply and demand estimates become more certain. If the expected ending stocks are too low, futures prices are expected to increase and *vice versa* if the expected ending stock will be able to meet or exceed demand (Krugell, 2003:43). Also, certain relevant ratios such as the *stock availability days* may be calculated to express the number of days for which there will be stock available based on the current demand per day. The significance of this ratio as an indicator for expected price movements is seated in the inverse relationship between futures market prices and the *stock availability days*. If the ratio is low, prices will increase and if the ratio is high, prices tend to be lower (Geyser, 2013:13). Goodwin and Schnepf (2000:765) found that, as demand levels increase relative to available stock, the futures prices become more variable, whereas higher stock levels relative to prevailing demand tends to stabilise futures price variability. Nevertheless, it remains important to realise that a change in *stock availability days* should only be seen as an outcome of the factors affecting the supply and demand of white maize.

2.4.2 Variables that influence supply and demand

There may be any number of factors that have an influence on supply and/or demand, since the effect of a change in one factor may have a direct influence on another factor, which may affect either/both supply and demand. For instance, an appreciation or depreciation of the South African Rand (ZAR) could have either a positive or negative influence on the price of imports or exports. This may include the effect on the import or export price of bulk white maize or processed products, as well as the import cost of production inputs such as fertiliser or agricultural equipment. Since these factors tend to influence each other, it will not always be meaningful to discuss them in isolation. Section 2.4.2 as a whole aims to introduce all the different variables that may influence the supply (Section 2.4.2.1), demand (Section 2.4.2.2), and the ending stock of white maize. The focus of Section 2.4.2 is on quantifiable factors (Section 2.4.2.3) that were identified and covered in existing literature. These factors may influence either/both supply and demand. The aim of this approach is to ensure that the factors identified can be included in the empirical analysis (Chapter 5, Section 5.3.) which aims to link the statistical characteristics of the different factors for different seasons with each other.

2.4.2.1 Demand-side factors

Generally, the demand for white maize in South Africa may be represented by the available stock, the cost and availability of substitute products, as well as alternative uses for white maize. White maize may for instance substitute yellow maize as animal feed if a local shortage of yellow maize exists (Geyser, 2013:13). Interestingly enough, the demand for maize increased in the 1980s when it was found that sweeteners made from maize was a healthier alternative than those made of sugar cane (Hinebaugh, 1985:7-13). Another, more recent application of maize to produce ethanol also increased the demand for maize, especially in the US where the share of corn used to produce ethanol has risen from 5% to 40% over the past twelve years (Actionaid, 2012:6). However, the demand for ethanol is greatly influenced by the price of crude oil. A decrease in the price of crude oil may also lead to a decrease in the demand for maize to produce ethanol (Geyser, 2013:13). As a result, it is not just the demand for white maize that influences the price, but also the demand for substitute products (Heymans, 2008:18).

2.4.2.2 Supply-side factors

Subsequently, supply may be influenced by technological advances, international stock levels, the world price of maize on CBOT as well as weather phenomena. Another important variable will be the Rand/US Dollar exchange rate, which affects the cost of imports (import parity price) and the export price (export parity), (Auret & Schmitt, 2008:107-109; Geyser & Cutts, 2007:296; Moholwa & Liu, 2011:1). It should be noted that each of these factors might have a short-term or a long-term effect on supply. An external factor like technological advances may have an effect over the longer term as higher yields are influenced by improved seed varieties, fertilisers, pesticides and machinery. Other advances in production practices, like minimum tillage, irrigation, and crop rotation also tend to reduce production costs and increase yields (USDA, 2014). Alternatively, weather events or expected events like early frost usually have a shorter term effect, as the market reacts to each event individually within a specific season (Geyser, 2013:13).

2.4.2.3 Quantifiable supply and demand-side factors

From this more general categorisation of supply and demand-side factors, it will always be important to identify how the individual influences of these factors are caused by certain specific and quantifiable factors. Changes in the value of these quantifiable factors tend to have a specific effect on the cash and/or futures price of white maize in South Africa. Over time, these dominant and significant factors were identified in existing literature and the expected change in the South African white maize price due to a change in these factors was also determined.

A first important factor to consider in this regard would be international stock levels of maize, usually referred to as corn. The United States is the largest producer of corn and at least one-fifth of annual production is exported (USDA, 2014). Corn also forms part of global coarse grains for which a World Agricultural Supply and Demand (WASDE) estimate is published every month. Monk, Jordaan and Grové (2010:452-455) found that volatility in the July white maize futures contract tends to spike or increase dramatically when the July WASDE report is made public. Results also showed that volatility actually increase dramatically in the last two trading days prior to the release, as traders and market participants act to position themselves according to expectations. The reason why the July WASDE report has this specific effect on markets, is that it marks the beginning of the US production season and provides information regarding international growing conditions and expected stock levels. Consequently, it is to be expected that the figures presented by the July WASDE report would have a significant impact, since ample supply would stabilise US prices, whereas expected diminishing supply would cause US prices to increase.

This price setting and changes in the US corn price due to changing supply and demand estimates take place on the largest commodities exchange in the world, called the Chicago Board Of Trade (CBOT[16]). According to Auret and Schmitt (2008:108), the CBOT near-month corn contract may be seen as a generally accepted world price discovery mechanism. This general finding was based on their analysis of the significance of certain factors in order to include them as part of an explanatory model for South

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16 It should be noted that CBOT and the Chicago Mercantile Exchange Group (CME Group) merged in 2007 to form the world's largest and most diverse marketplace for derivatives (CME Group, 2015).

African white maize futures prices. Despite this generally accepted assumption on the significance of the CBOT corn contract, they found that the impact of the corn contract on the July white maize futures contracts was not statistically significant at the 5% level, which led to the subsequent exclusion of the CBOT price factor in their final model (Auret & Schmitt, 2008:128). However, a study by Van Wyk (2012:67-68) on the volatility and price spillover from the US corn futures contract to the South African white maize futures contract indicated that there is a spillover of futures contract returns from the CBOT futures contract to the South African white maize futures contract. This spillover effect was found to be marginally negative and statistically significant, which means that negative returns on the CBOT futures contract has a greater effect on the South African white maize futures contract than that of positive returns. These results therefore show that the CBOT futures contract returns should be considered as part of the influential factors in the empirical analysis of this study.

The inclusion of the CBOT futures contract, however, necessitates the consideration of the US Dollar (USD) / South African Rand (ZAR) exchange rate, since the effect on the South African white maize market price will be amplified by the USD/ZAR exchange rate in light of the fact that all imports to and exports from South Africa are priced in US Dollars. The explanatory model developed by Auret & Schmitt (2008:108) confirmed that the USD/ZAR is correlated significantly with the US corn contract traded in Rand per metric tonne on SAFEX, the import parity and export parity of white maize, and the J210, which is the JSE top 20 resources index. Despite these correlations, the USD/ZAR could not significantly explain South African white maize futures contract price changes and was not included in the final model. The import parity of white maize was however included in the final model, which implies that both the USD/ZAR exchange rate and corn futures contract are important, since they are incorporated in the calculation of parity prices.

This finding emphasises how one factor may not necessarily have a significant effect on its own, but when combined with other factors it cannot merely be ignored. Building on this argument, parity prices do not only consider the USD/ZAR exchange rate and the corn futures contract price. The calculation of import or export parity price includes different factors that may have an influence on their own as well as affecting the exchange rate. Import parity specifically represents the price or cost of importing white maize. These costs include the cost of maize at its origin, plus the cost of transport to the harbour and loading cost, insurance and shipping cost to a domestic harbour, any applicable finance cost, the harbour and offloading cost, any applicable import tariff, and, finally, the cost of transport from the harbour to Randfontein (Geyser, 2013:16). All of the costs included in the calculation, up to the landing of imported maize at South African harbours, are usually quoted in US Dollar per metric tonne and must be converted by means of an applicable exchange rate. Prices tend to trade closer to import parity if local stock-to-usage levels become low and the market anticipates that stock may need to be imported to meet local demand (Auret & Schmitt, 2008:109). Prices may even trade above import parity for a while, but as soon as market participants import white maize, the recuperation in the supply of white maize will restore price levels to import parity prices or lower (Geyser, 2013:17).

In the opposite scenario, where the domestic supply of white maize is ample and the market anticipates higher stock-to-use values, prices would trade lower to export parity levels (Auret & Schmitt, 2008:109). This would be the price level at which South African white maize can be competitively exported. Exports from South Africa can be done by means of deep-sea exports through Durban or East London harbours, or by rail and road to the rest of Africa. As with import parity, the calculation of export parity would require some form of dominant international reference price. In this instance, and as a standardisation measure, the price of US No3[17]-grade maize delivered and loaded onto a ship in the Gulf of Mexico is used. Due to the perceived quality difference between US No3 corn and South African white maize, a quality premium is added. This USD-quoted price is then converted to Rand per metric tonne from where the cost of transport to the delivered harbour from Randfontein, any applicable finance cost, and the harbour loading cost is deducted to derive a deep-sea export parity price (Geyser, 2013:18-19). This deep-sea export parity price therefore acts as an indication of the price South African maize should sell for to be competitively priced in the world market. Arguably, the specific destinations exported to influence the specific export parity calculation due to specific quality standards, as well as changing stock levels and location availability across the world.

These location-specific stock levels have a specific but variable influence on all the factors discussed and considered up to this point. Ultimately, a change in value will have a specific effect on South African white maize prices. However, without disregarding the importance of international and local stock levels affecting prices and price ranges, like import and export parity, there is one dominant factor in the form of weather patterns that has a significant influence on all of these factors. According to Goodwin and Schnepf (2000:765,771), one of the strongest effects related to price variation is crop-growing conditions, since favourable growing conditions will usually cause a reduction in maize price variability. Furthermore, weather patterns have an impact on local and international stock levels, since favourable and timely rainfall has a direct influence on stable and increased supply, whereas irregular and rainfall and drier conditions are usually associated with dampened supply and lower stock levels (Kleinman, 2001:114; Geyser & Cutts, 2007:291). The variability of rainfall in South Africa associated

[17] US corn is usually of grade 3 quality compared to their own grading standards and of a lower grading quality compared to South African white maize grading standards (Geyser, 2013:17).

with climatic extremes often leads to significant reductions in potential crop yields, since rainfall is the single most important factor in crop production (Chenje & Johnson, 1994:59.64; Martin *et al.*, 2000:1473). This is of specific relevance to South Africa, since Martin, Washington and Downing (2000:1473) stated that crop forecasts in South Africa are predominantly derived from rainfall forecasts. Their study also found that rainfall forecasts should not be seen as the only predictor of expected yields, but that such a prediction should also include other important climatic variables, like temperature, humidity, radiation and wind, which may improve or worsen yield potential. In this instance, the effect of one variable on its own may not have a substantial effect on South African white maize prices, but their combined effect usually has a significant effect on production estimates and realised yields.

Over time, a proxy for these climatic variables and associated yield forecasts was identified and a collective weather phenomena or weather indicator established in the form of the Southern Oscillation index (SOI). Specifically, the relation between rainfall forecasts and historical yield has been successfully linked to SOI by Nicholls (1985), Rimmington and Nicholls (1993), and Meinke and Hammer (1997). The Southern Oscillation index is a measurement of the shift in sea-level air pressure between Darwin in Northern Australia and the South Pacific Island of Tahiti (AGBM, 2014). The strongest shift in air pressure between these two areas is known as El Niño, and the related phenomenon Southern Oscillation (ENSO). El Niño occurs when the upper sea surface temperature in the tropical eastern Pacific Ocean reaches higher temperatures for a period of more than 5 months. The specific index developed to measure the mean sea surface temperature (SST) and to identify El Niño events is known as the NINO3 index. If the NINO3 index records a value of at least +0.50°C above the average SST for 5 months, an El Niño event is identified. Alternatively, the NINO3 index may also record temperatures below the 5-month average SST. As a result, a warm phase of ENSO is called El Niño, whereas a cold phase is referred to as La Niña (Wang *et al.*, 1999:11071-11072). These phases, illustrated by Figure 2.7, indicate the NINO area (black circles in Figure 2.7), as well as the sea surface temperature variation from the average during an El Niño period in 2015/2016, and a La Niña period in 2017/2018. This distinction between the cold and warm phases of ENSO through the Niño-3 index allowed Cane, Eshel and Buckland (1994) to identify an even stronger correlation between maize yield and sea surface temperatures when compared to the correlation between rainfall and sea-surface temperatures.

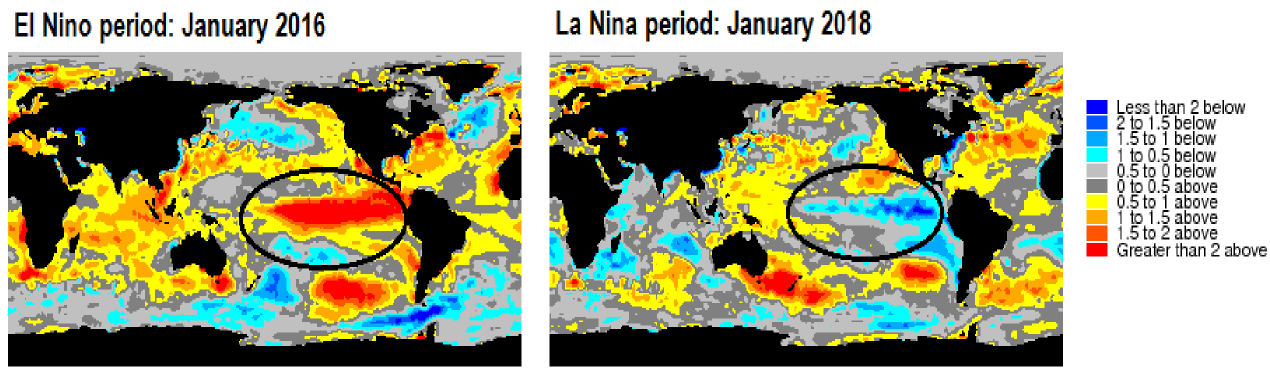

Figure 2.7: Variation of sea surface temperature from the average
Source: The Long Paddock (2018)

These correlations between maize yield, SST and rainfall become clear when the link between the SOI, El Niño and La Niña events is identified. SOI gives an indication of the intensity of these events in the Pacific Ocean. If the SOI value becomes negative or remains negative for a sustained period, an El Niño event may be identified, whereas ongoing positive SOI values indicate a stronger possibility of a La Niña episode. During an El Niño period, the central and eastern parts of the tropical Pacific Ocean becomes warmer and the strength of the Pacific trade winds tend to decrease. The effect of this phenomenon is usually a decrease in rainfall in the Southern hemisphere. Accordingly, a La Niña period is identified by cooler sea surface temperatures, stronger Pacific trade winds, and an increased probability of rainfall in the Southern hemisphere (AGBM, 2014). In South Africa, the onset of rain tends to be earlier and the rainy season shorter with lower than normal cumulative rainfall during El Niño years, while the onset of rain in La Niña years tends to be later with a longer rainy season and higher than normal cumulative rainfall (Moeletsi *et al*., 2011:715). The explanation above emphasises the importance of both El Niño and La Niña events as determinants for the supply of white maize in South Africa, as well as other soft commodities produced in the Southern hemisphere. The first direct effect would be a very high probability of higher grain prices during El Niño-dominated production seasons, whereas lower prices could be expected during La Niña-dominated production seasons. However, it should also be noted that a production season may start with a specific dominant event that may persist or deteriorate as the season progresses.

This unpredictable progression in the state of ENSO, correlated with changing expectations regarding rainfall, which has either a direct or indirect influence on factors such as stock levels and parity prices - ultimately influencing producer prices - was the problem addressed by Stone, Hammer and Marcussen (1996:252-255). The study succeeded in developing a model that categorises SOI patterns and relates them to future rainfall probabilities. The analysis was done for 120 years of monthly data prior to 1996 and classified SOI behaviour into five clusters or phases, called Consistently Negative (phase one), Consistently Positive (phase two), Rapidly Falling (phase 3), Rapidly Rising (phase 4), and Consistently Near Zero (phase 5). This well-established methodology is still applied in Australia by the State of Queensland's Science Delivery Division of the Department of Science, Information Technology and Innovation (DSITI) to determine probabilities of expected rainfall levels for specific locations worldwide. This method also allows the entity to link similar periods with the same SOI phase over time, thereby improving rainfall predictions for the current or forthcoming production season based on similar historic weather developments.

Meyer, Westhoff, Binfield and Kirsten (2006:370-374) also studied the developments in or expectations for a production season in relation to weather. This study was specifically relevant to South African white maize. They proposed an "econometric regime-switching model" where domestic prices in South Africa were determined by three different and specific trade and policy regimes. The first regime was named "import parity", the second "autarky", and the third "export parity". These three regimes depend on the current and expected stock levels of white maize in South Africa, which is greatly influenced by weather patterns. If the current or expected stock levels are low, prices tend to move to import parity, since expected or potential shortages will need to be recuperated. Alternatively, when current or expected stock levels are ample, prices would move to export parity prices so that all relevant surpluses may be exported competitively. In both the import and export parity regimes, factors like international stock levels and maize prices as well as the exchange rate will have a more prominent influence on price formation. However, when the current or expected stock levels are stable and no apparent shortage or excessive surplus is present, the domestic factors influencing the supply and demand for white maize will be the dominant price determination factors.

Ultimately, the fact that not all of the factors discussed above have the same constant influence or impact throughout each production season becomes evident in the studies by Stone, *et al*. (1996) and Meyer, *et al*. (2006). Their results also emphasise that a model which ultimately aims to predict supply and demand conditions in the market should always consider the way through which the influence of one factor may be increased by the joint influence of other factors. Also, the fact that derivations based on a specific factor value should never be done relative to a specific single value, but relative to values that may be linked to certain regimes, intervals or similar developments. If this could be done conclusively, with as many factors as possible confirming similar developments, part of the study objective of linking seasons with a similar seasonal outlook and expected circumstances would be successfully achieved.

2.5 Chapter summary

Over the last 150 years, South African agriculture survived enormous challenges that influenced production sustainability. These challenges ranged from natural disasters in the form of drought and pests to warfare over natural resources at the turn of the 20th century. International events in the form of the first World War between 1914 and 1918 and the second World War between 1939 and 1945 also influenced local and international supply and demand conditions. These sometimes devastating events prompted governing bodies to intervene in the market mechanism through legislative measures. These legislative measures were imposed to take control of the agricultural market mechanism despite the fact that their institution was heavily opposed by prominent economists at the time. Initially, the support provided to agriculture by controlling bodies provided the sector with the necessary stability it so desperately required, but it soon created an unsustainable economic environment of price inflation and forced government subsidisation at the expense of tax payers and consumers. The pure economic consequences of controlled marketing were ignored or disregarded at the time, mostly by governing bodies, in order to realise their own political agendas.

Since the 1980s, political agendas, however changed, and changes in the South African political environment also brought with it systematic changes in the agricultural marketing mechanism. Pressure by stakeholders and parties on governing bodies, which were negatively affected by controlled marketing, finally brought about a sudden and abrupt change from controlled market price setting to a free market price setting mechanism. For white maize in particular, this change occurred from 1996. At that stage the JSE had already established a market price formation platform in the form of SAFEX, where agricultural commodities could be traded. This meant that maize producers had to adhere to a new set of rules, since 60 years of receiving a predetermined profitable price suddenly changed to a system where each producer became responsible for managing their own price risk.

In order to manage this price risk, maize producers are now required to understand how a derivatives market functions through standardised contracts in the form of complex futures and option contracts. Apart from having knowledge of the workings of these financial derivative instruments, they are also required to understand the impact of different factors affecting the expected supply and demand of white maize. These factors range from the expected local supply of maize at each producer's location affecting their respective location basis premium, to domestic stock levels affected by weather conditions and different trade regimes, up to international stock levels, prices, and exchange rates. Changes in these factors all have their own unique effects on white maize prices, depending on the impact a specific change has on current and expected supply or demand levels. The changes in these factors do not occur in isolation or on an individual basis, but create a combined effect. This combined effect may then increase or decrease expected price changes to a greater extent when compared to expectations based on individual factors.

The intricacy of these ever-changing factors emphasise the inherent price risk maize producers must account for by means of derivative instruments. Nevertheless, using derivative instruments to manage their respective price risk does not exempt a producer from all market-related risks. Depending on the type of derivative instrument used by a producer to hedge, the producer becomes exposed to other types of risks of which liquidity risk is the most prominent risk to account for.

Against this backdrop it becomes understandable why market participants may be reluctant to make use of derivative instruments to manage their price risk. The irony is that, although maize producers may be reluctant to make use of derivative instruments, they will eventually just receive the derived SAFEX price when selling their produce, as this remains the main price formulating platform. In spite of this, maize producers do not always trust the futures market's effectiveness and tend to avoid future price risk management decisions altogether, since they feel that they lack the necessary knowledge about the tools available to them. To some extent this also explains their opinion that the market price may from time to time be manipulated by factors outside of the normal supply and demand price drivers. Nevertheless, it was also evident that the JSE is committed to providing a fair and transparent price forming mechanism through the SAFEX Commodity Derivatives Division. In order to address these issues, Chapter 3 discusses the concept of market efficiency in general, as well as a specific focus on South African white maize market efficiency. The aim of the white maize market efficiency focus is twofold. Firstly, to determine whether the inherent distrust producers have of white maize price formation on SAFEX is justified, and secondly, to review the success achieved by different models that aimed to determine price expectations based on the factors that influence white maize price formation.

CHAPTER 3

Market Efficiency

"Be greedy when others are fearful and fearful when others are greedy.' Easier said than done for the vast majority of stock traders. ... On every stock trade there is someone who wants to sell and someone who wants to buy, at least at a particular price. ...the person who is selling thinks that she is getting out just in time while the person buying thinks that he is about to make good money.

... The truth is that the market doesn't really reflect some magical perfect valuation of a stock under the efficient market hypothesis. It reflects the mass consensus of how actual individual investors value the stock. It is the sum total of everyone's hopes and fears..."

– M.E. Thomas (2013)

3.1 Introduction

Work related to market efficiency already began at the start of the 20th century, when Bachelier (1900) first 'unknowingly' tested the random walk model on the behaviour of prices. From there, the theory of efficient markets in terms of the Brownian motion (Brown, 1828), the random walk model (Pearson, 1905) and spectral analysis (Granger & Morgenstern, 1963) were developed, which were formalised to a certain extent in the studies by Samuelson (1965), Fama (1965a, 1965b), and Mandelbrot (1966). The benchmark study by Fama (1970), however, finally formalised the efficient market hypothesis (EMH), including the three associated sub-hypotheses, when he stated that "A market in which prices always *fully reflect* available information is called *efficient*" (Fama, 1970:383). Accordingly, such a market will be deemed informationally efficient when all information that affects prices enter the market in a random, independent and unpredictable manner. This implies that all market participants will attempt to adjust the market price to a revised fair market price equilibrium as soon as any new information arrives. Through the immediate adjustment of market prices based on the new information, it is assumed that the price reflects all current information, as well as the perceived risk associated with owning the underlying asset (Reilly & Brown, 2012:141; Fama, 1965b:56).

Furthermore, the actions of market participants are usually based on a profit-maximisation principle, and decisions to buy or sell on how market participants value the current market price relative to the intrinsic value of the underlying asset. Arguably, each market participant determines the intrinsic value of the underlying asset differently (Marx, Mpofu, De Beer, Mynhardt & Nortje, 2013:4). This also explains why market prices usually "wander randomly about their intrinsic value" and why there usually is a willing buyer or seller at the prevailing market price in a competitive market (Fama,1965b:56). Consequently, based on the different valuations of intrinsic or fair value, Fama (1965a, 1965b) also argued that, as more market participants value an asset, the difference in the current market price and the intrinsic value price at a certain point in time may only be ascribed to systematic or the inherent market risk. However, as with any hypothesis, academics and researchers have accumulated support for and arguments against the EMH over time. In the case of the EMH, specifically, the opposing results are referred to as "market anomalies" (Subsection 3.2.4.2) which later gave rise to "behavioural finance" (Subsection 3.2.4.3) as a sub-division of the field of finance.

The classification of research as part of market anomalies or behavioural finance has therefore also seen a development over time and mainly stems from results which could not be linked to any of the three sub-hypotheses of the EMH. Market anomalies have, for instance, been divided into cross-sectional and time-series patterns. Cross-sectional patterns include the well-known size and value effect, as well as the momentum effect (Table 3.3), whereas time-series patterns include autocorrelation patterns and patterns found around specific weekdays or within seasons (Table 3.4). Fama (1991) addressed opposing market anomaly results and still argued convincingly in favour of market efficiency by pointing out methodological errors made by these studies. However, Fama (1991:1575) admitted that market efficiency in itself was not testable and that returns also reflected investors' "tastes", which were difficult to isolate, but noted that opposing studies had failed to present an alternative model based on expected returns in a real economy.

An alternative methodology to explain investors' "tastes" and, in particular, the sometimes inexplicable gap that occurs between available and realised returns, was presented in the form of behavioural finance. This field of study, as a result, aimed to include the impact of an investor's decision-making process on the return distribution and became more prominent after 1990. Fama (1998:291) subsequently addressed behavioural finance and again pointed out that certain market inefficiencies dissipate over time and also that studies on market inefficiencies do not present an alternative testable hypothesis. Lo (2004, 2005), however, presented an alternative theory that combined the EMH and behavioural finance, called the adaptive market hypothesis (AMH).

In order to explain the developments in market efficiency studies, market anomalies, behavioural finance, as well as the AMH and how all of this pertains to white maize traded on SAFEX, this chapter is structured as follows. Section 3.2 below commences with a discussion on developments in initial market-efficiency theories. However, this section does not attempt to cover the vast literature on the applicable market efficiency tests applied and results obtained. Rather, the aim is to provide only the necessary background to ensure that the developments in market efficiency research are not seen as loose elements; also, to establish a meaningful foundation from where alternative findings and views in the form of market anomalies, behavioural finance, technical analysis, and the development of the adaptive market hypothesis may be built upon.

The concepts of behavioural finance (Subsection 3.2.4.3) and the AMH (Section 3.2.6) are, however, the main points covered to illustrate that the market tends to go through variable phases of efficiency, based on market liquidity and role-players acting on potential market inefficiencies or their interpretations of market information. In times of different levels of market efficiency, different factors may prove dominant and influence seasonal price developments. This characteristic of market efficiency, according to the AMH, may subsequently justify the aim and several objectives of the study **– to link similar seasonal developments to specific white maize hedging strategies over time to ensure sustainable and adaptive price risk management practices**. Section 3.3 continues by providing a thorough review of studies on market efficiency pertaining to agricultural commodities and, specifically, to white maize traded on SAFEX. Finally, Section 3.4 provides a conclusion to the chapter.

3.2 Market efficiency developments over time

This background section considers the pioneering work of Fama (1970) (Section 3.2.1), which paved the way for developments after the dawn of computers made the analysis process much easier and allowed for expansion of the parameters (Section 3.2.2). Section 3.2.3 addresses the more influential development studies leading up to the Fama (1970) paper, which formalised the EMH. Section 3.2.4 includes the rapid expansion in EMH research after 1970, when both supporting evidence and contradicting evidence in the form of market anomalies and behavioural finance were presented. Also, technical analysis (Section 3.2.5) is presented as a way for an investor to detach himself from the behavioural traits inherent in investing. However, the mounting evidence contradicting the EMH in the form of market anomalies, behavioural biases, or technical analysis profitability could not provide a concrete testable alternative hypothesis.

This remained true until the Adaptive Market Hypothesis (AMH) (Section 3.2.6) was developed as an alternative. The AMH applies evolutionary principles to economic contexts and financial markets in order to incorporate the EMH principles, market anomalies, behavioural finance, and the profitability of technical trading rules into one concept to provide a better understanding as to why market prices behave in a certain way during changing economic conditions. Ultimately, by dividing the vast literature on market efficiency into these smaller subsections, a very good overview on market efficiency developments over time may be provided without promoting or abating the importance of any section in particular.

3.2.1 Pioneering studies relevant to the development of the EMH

The first study on the probability of outcomes in games of chance was done in 1564 by a mathematician named Cardano. From the practical analysis process, it became possible to explain the variable and arguably unpredictable character of factors like weather and stock market prices, in the sense that the outcome of a future event was represented by continually changing expectations. These early developments in probability theory was expanded by Brown (1828) when he noticed that submerged grains of pollen in water displayed rapid oscillatory motion under a microscope. The phenomenon was called Brownian motion and formulised in a 1905 paper by Einstein, and by Smoluchowski in 1906. Three years later, Langevin (1908) established an alternative analytical approach when he applied Newton's second law to the particle representing Brownian motion, and in so doing, intuitively described a memoryless stochastic process through which he developed a stochastically differential equation for Brownian motion (Lemons & Gythiel, 1997:1079).

Brownian motion and its relation to the stock market were, however, first noticed by Bachelier (1900). In his study he recognised that, although market prices subsequently reflect changes in past, future and discounted future events, there appears to be no relation between these events and apparent price changes. Bachelier (1900) also recognised efficiency in his opening paragraph, when he stated that *"if the market, in effect, does not predict its fluctuations, it does assess them as being more or less likely, and this likelihood can be evaluated mathematically"* (Dimson & Mussavian, 1998:92).

During the same period, Karl Pearson introduced "The Problem of the Random Walk" in a short letter of enquiry to Nature, published on July 27, 1905. Pearson's letter enquired as to whether any existing formula or solution existed to the following problem: determining the endpoint of a person that starts walking in a straight line, in any direction, for a specific length from a specific starting point and then turns and repeats the procedure *n* times. His aim was to determine the probability of ending up a certain distance or range from the starting point after the person had concluded *n* randomly directed walks (Pearson, 1905:294). Despite these early developments in Brownian motion and the random walk theory, the subject of market efficiency was already intuitively discussed by Regnault (1863), when he could not find any relation between stock market gains and losses. Another clear observation of informational efficiency was made by Gibson (1889:12), who found that a stock's value is enhanced by listing the stock. Once the stock became known to the public, the impact of news on the market price could be reflected much faster due to advances in communication by means of the electric telegraph.

This advance in the flow of information, as well as improved data capturing and analysis methods, improved economists' ability to more accurately observe probability distributions. Mitchell (1915) first observed that the price return distributions are too leptokurtic or "peaked" to be represented by a standard normal distribution (Mandelbrot, 1963:394-395). The data accumulation also permitted economists like Keynes (1923) to propose his theory on normal backwardation in futures markets. Keynes (1930:143) also attributed the backwardation effect to a risk premium present in the futures spot price to compensate producers for price variability in the production period. The same result was reported by Hicks (1946:136-139), who reported that future spot prices are downward adjusted estimates of the expected prices and that futures prices tend to rise as the futures contract reaches delivery or becomes the cash price and nears expiry.

This effect became known as the Keynes-Hicks hypothesis or the "theory of storage", which led to the development of two schools of thought (Cootner, 1960a:396; Fama & French, 1987:55). The first school of thought, which is more in line with the Keynes-Hicks hypothesis, argues that the difference between the expected spot price and the futures price is a factor of an expected risk premium and a forecast of the futures spot price. Studies supporting this theory may also be found in Cootner (1960a), Dusak (1973), Breeden (1980) and Newbery, and Stiglitz (1981). According to the EMH, successive price changes in an efficient market are said to be independent and random, contrasting with the observation that there exists an upward trend in futures prices when it nears delivery (Fama, 1970:394; Telser, 1958:234). Arguably, this school of thought may be seen as some of the studies contemplating a contrasting view to the EMH.

The alternative school of thought, which became known as the "theory of storage" view, explains the price difference between the spot and the futures spot price as being a factor of stock carrying charges in the form of interest, insurance, warehouse or silo costs, as well as a possible convenience opportunity cost[18] (Cootner, 1960b:2-3). This theory was supported in studies by scholars such as Kaldor (1939), Working (1949), Brennan (1958), and Telser (1958). The opposing views became controversial with results supporting each school of thought. This prompted Fama and French (1987:55) to evaluate both views, but evidence was found to support both schools of thought.

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18 A convenience opportunity cost or convenience yield will depend on the holder of the stock, since the stock may then be used at own discretion when needed instead of, for instance, purchasing stock when needed. The current supply and demand factors, as well as stock availability, will influence the convenience yield (Cootner, 1960b:3).

Although the developments in "theory of storage", as well as the Keynes-Hicks hypothesis provide additional insight into the relevant market research at the time, and intuitively provides additional views on informational efficiency, the aim of this research was never to deduce market efficiency. Studies pertaining specifically to market efficiency became more prominent after the 1929 Wall Street crash occurred. Cowles (1933:309) analysed fire insurance companies, leading financial service companies and financial publications during and after the market crash. He concluded that the successful forecast results might have been achieved by pure chance, whereas the probability of unsuccessful forecasts seemed to be even lower than what could reasonably be expected from pure luck (Cowles, 1933:324). Thereafter, Cowles and Jones (1937:281) found results supporting market efficiency, but also certain inefficiencies when they evaluated different indices over varying time frames. They concluded that speculators should not expect to achieve consistent outperformance and large profits by means of forecasting models, but reiterated the fact that they found evidence of price structures in stock prices for certain periods considered (Cowles & Jones, 1937:294).

Clearly, by the mid-1940s there was evidence in favour of market efficiency, as well as evidence against it. The reality was that most of the studies had been to a large extent overlooked until the 1950s when their results and implications were revisited. Also, the developments in electronic computers permitted researchers to evaluate data over longer time series in order to study price behaviour (Dimson & Mussavian, 1998:92). The following subsection elaborates on developments in relevant market efficiency research and how new and improved methods influenced results obtained.

3.2.2 Technological advances and improved informational efficiency research developments

The developments in autoregressive analysis, permitted by more powerful econometric-analysis computerised programs, allowed researchers to analyse the short-term movements or "noise element" in conjunction with the longer term trend. Researchers were now able to more clearly distinguish whether the trend and short-term movements were separate movements, or whether the factors influencing the trend also caused the short-term movements. Kendall (1953:11) established that patterns, which may have been identified by means of previous methods, became less methodical when autoregressive analysis was applied. The analysis found negligible evidence that past prices of a stock predicted the future price and that there was little proof that price changes in one time-series influenced the price changes in another.

Following Kendall's approach, Working (1958) proposed an anticipatory model aimed at providing a better understanding of the true nature of price changes based on expectations. The model assumed price formation through human decisions based on information that would realistically be available to market participants, as well as prevailing real world circumstances (Working, 1958:192-193). When comparing his results, he found significant correlation coefficients between the market price changes of corn and the final production estimate, which was released after the harvest in December each year (Working, 1958:197-198). This research was also one of the first studies to assume that the market consisted of both well-informed and inexpert participants which, in turn, provided an explanation for the time it took for different people to become aware of the impact of information, leading to gradual price change and possible correlation between price changes.

However, Working (1960:916) and Alexander (1961:22) reconsidered previous findings of autocorrelation. They found that certain mistakes had been made in the past when time-series data was analysed for independence by means of autocorrelation tests. Both studies noted that, when original time-series data was converted into specific time-period averages, the conversion may have introduced correlations which may not have been present in the original series. Alexander (1961:26), however, separated price movements over time from the direction of the movement and confirmed that price changes tended to follow a random walk over a longer period, but that a price move in a specific price direction tended to persist.

A study by Cootner (1962:25-27) continued their work, suggesting that well-informed professional market participants tended to buy when a stock became undervalued and sell when a stock became overvalued. The study indicated that these barriers, introduced by the transactions of experienced traders, tended to have a measureable persistence. To a great extent, the proposed model by Cootner (1962) draws a strong link to particles in Brownian motion, since the resistance and support levels created by professional traders act as a type of membrane providing only a small probability of a particle passing through it (Moore, 1962:153). Also, movements against the barriers would most likely cause prices to move in the opposite direction, thereby causing negative correlation and the distribution of price changes over the short period to be highly leptokurtic (Cootner, 1962:28). The results stated that his hypothesis of reflecting barriers fit the data much better and also that the model conforms with chart reading analysis, thereby implying a result in contrast with a random walk hypothesis (Cootner, 1962:26).

Consequently, the early 1960s may be seen as a turning point in time series research regarding the re-evaluation of previous results by means of new methods. Mandelbrot (1963:403) argued that when Gaussian (normal) probability distributions are assumed or applied to the data, a convenience feature exists. This feature permits large price changes to be seen as outliers and eliminated from the dataset so that the returns or price changes may more closely represent a normal distribution. In order to address this issue, he recommended the stable Paretian distribution, especially in speculative markets, to ensure that all returns are included in the distribution and more decisive proof of the independent nature of price changes may be provided. However, using Monte Carlo techniques, Fama (1963:429) found evidence that disagreed with the notion of stable Paretian distributions.

Another important contribution was made by Granger and Morgenstern (1963), where they applied spectral analysis to New York stock market prices. Their results indicated that the model represented a simple random walk to a great extent, but certain long-run movements (24 months or longer) could not be explained. Furthermore, the study showed that factors like seasonal variations and the business cycle were not significant, thus failing to provide additional insight to benefit the investor (Granger & Morgenstern, 1963:16-17).

To summarise – no consensus could be reached regarding the presence of a random walk in market price formulation. Consequently, the random walk hypothesis and its implications became a set of variables which lay the foundations for the characteristics of an efficient market. These important developments are discussed and explained in the following section.

3.2.3 The formalisation period: A random walk to the efficient market hypothesis

In light of the conflicting results regarding the random walk hypothesis, Fama (1965a:34) dedicated his doctoral dissertation to a study which tested the underlying theory of the random walk, as well as the model's empirical validity. Fama (1965a:35) stated that the independence of successive stock price changes, as well as the specific probability distribution price changes resemble, may be seen as two separate hypotheses forming the random walk hypothesis for stock prices. When considering the assumption of independence between successive price changes, he stated that although there may be dependence in the way market participants estimate a fair value for a stock or even in the way new information comes to the market over time, the reality is that superior analysts, either fundamental or technical, aim to benefit from these dependencies, ultimately eliminating them by acting on them. Furthermore, he argued that as several analysts value stock in order to determine its intrinsic value, prices tend to change instantaneously when new information comes to the market, since prices may under-adjust to successive intrinsic value changes just as much as they may over-adjust, thereby causing a random change towards a randomly changing intrinsic value estimate (Fama, 1965a:37-39). From these results, Fama (1965a:90) also made a first contribution to the efficient market hypothesis based on the independence of price changes when he stated: *"...a situation where successive price changes are independent is consistent with the existence of an "efficient" market for securities, that is, a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values".*

Later on, Fama (1965b:55) revisited his doctoral findings and focused on the implications of the random walk theory for technical (price chartist) and fundamental (intrinsic value) analysis. Fama (1965b:56) formally defined an efficient market on the basis of the random walk hypothesis when he stated: *“An "efficient" market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants.”* Based on this definition and his analysis of mutual fund performance, he concluded that mutual funds that make use of skilled analysts do not necessarily perform better than a randomly selected portfolio of stock with the same risk and return characteristics (Fama, 1965b:59).

The foundation set by Fama (1965a,1965b), wherein the random walk model was linked to the efficient market hypothesis, set the stage for a switch of emphasis in this field of study. Within the same year, Samuelson (1965:42) proposed a general martingale theorem for speculative prices. The martingale property does not imply that the distribution of future prices does not depend on past prices, but only that the expected future returns are independent of the returns of past prices. Consequently, the price changes in a martingale series may be dependent on each other, but this dependence would still not provide a market participant with the means to increase expected profits. Intuitively, this means that a random walk is a martingale, but that a martingale is not necessarily a random walk. Samuelson (1965:43-46) proved that properly anticipated prices fluctuate randomly around the fair return, consequently forming a martingale rather than a random walk. This martingale property of price changes was confirmed by Mandelbrot (1966:248-250), when he evaluated the martingale properties of forecasted agricultural prices based on weather. Results showed that, as the number of successive good weather days increase, deviations around the expected price increase as uncertainty regarding expected weather changes increase, thereby increasing overall volatility.

Despite all of these influential papers by Fama (1965a, 1965b), Samuelson (1965) and Mandelbrot (1966), the period leading up to the comprehensive review of theory and empirical work on market efficiency by Fama (1970), may still be characterised by inconclusiveness and new developments. Fama and Blume (1966:240) for instance, compared the filter rule – as proposed by Alexander (1961) – to the process of serial correlation in order to determine the degree and direction of independence in price changes. Their findings indicated that both methods would be equally sufficient to indicate the level and direction of dependence (Fama & Blume, 1966:241). Following these results, Levy (1967a:46) reviewed random walk research results and stated that stock market efficiency remains an open matter. Granger (1968:255) also revisited previous literature and disagreed with the finding by Mandelbrot (1963) and Fama (1963), arguing that the variances of a purely random series of individual price changes are infinite. An additional study by Fama, Fisher, Jensen and Roll (1969:1-2), conducted a market efficiency study which examined a price change process – whereby prices adjust to new information -- and found that the results are in favour of an efficient market (Fama *et al.*, 1969:20).

Notwithstanding all of the studies discussed above, market efficiency remained a statistical statement based on empirical tests of independence and price adjustments based on new information. However, the subject of market efficiency became a coherent theory of asset prices when Fama (1970:383) published his classic paper on the efficient markets hypothesis. One of the main contributions of the study was the formalisation of a joint hypothesis, wherein three different forms or "information subsets" of market efficiency was provided. Fama (1970:383, 388) distinguished between a weak form, semi-strong form, and a strong form efficient market, but noted that the joint hypothesis definition, which states that all possible information is always fully reflected in the current market price, is an "*extreme hypothesis*" and should not be interpreted as "*literally true*".

The weak form, initially proposed by Roberts (1967), conforms to statistical tests of independence and asserts that current or future price changes cannot be predicted from past prices. Fama (1970:389-404) reviewed existing literature on empirical tests of informational efficiency and found that statistical tests of independence studies strongly supported the hypothesis. He stated that, although some studies found evidence which did not conform to the strict implications of the hypothesis, they would not be able to outperform a buy-and-hold strategy if trading costs were taken into account.

Fama (1970:409) also reached similar conclusions regarding the semi-strong hypothesis. The semi-strong form included weak-form efficiency with the additional criteria that asset price changes also fully reflected all publicly available information, like the influence of political and economic developments and company performance figures. Lastly, the strong form included the weak form and semi-strong form, but postulated that even if a market participant had access to private company information, he would not be able to benefit from this information, since it would already be reflected in the current market price. Arguably, the strong form could be seen as a benchmark hypothesis against which the other forms may be evaluated.

In conclusion – the research and contribution of the joint hypothesis by Fama (1970) provided a stable foundation from where further research could develop. However, this did not mean that the market efficiency concept was duly accepted without question. The possibility of market inefficiencies remained and results continued to support and disprove the hypothesis. The main difference of the more recent contributions to the field of research was that researchers were now able to determine different levels of efficiency, thereby providing an incentive for security analysts to acquire and act on valuable information, inevitably contributing to market efficiency through their actions. These developments and results in the study of market efficiency are discussed in the following section.

3.2.4 Modern developments in the joint efficient market hypothesis

The research pertaining to market efficiency and the joint hypothesis in particular expanded tremendously after 1970. The reason for this may have been that, prior to 1970, the relevant research focused on the development of models, different tests, and the identification of relevant probability distributions. This groundwork in methodology provided researchers with the means to apply these methods to different types of time series in order to test for market efficiency. To address the relevant research, the current section and subsections do not attempt to cover all research applications of the EMH tests to different types of time series, but rather to present a composite overview of findings on the established methodology from 1970 to date. Accordingly, in order to present a composite overview of EMH-related developments, Section 3.2.4.1 addresses the research leading up to the mid-1980s, when the mounting evidence of cracks in the EMH armour became known as market anomalies (Section 3.2.4.2), leading to an alternative view of financial economics, called behavioural finance (Section 3.2.4.3).

3.2.4.1 Testing the joint EMH and related assumptions

Following the Fama (1970) paper, Kemp and Reid (1971:29,31) immediately argued that the use of indices to determine independence of price changes could be misleading, since they only provide an indication of the average market movement. They also pointed out that the results obtained by previous studies may have been caused by an over-generalisation of the random walk hypothesis by means of indices, since the valuation of each individual stock revealed its own price change plot which were noticeably non-random. Within the same year, Hirshleifer (1971:561) evaluated the value of information to investors' risk-reward perception from an economic point of view. He found that investors have a substantial incentive to use resources in order to acquire both public, but especially private information in advance, but that the information needed to be made public in order for price changes to occur so that a gain may be realised. However, Hirshleifer (1971:573) stated that only a portion of the expected profit would be realised and that the resource cost of acquiring the information would outweigh the potential profit. Over time, several studies addressed either previous findings or specific aspects relating to the joint hypothesis. The findings from these studies have been summarised in Table 3.1.

The literature summarised in Table 3.1 was, to a great extent, concerned with formal market efficiency tests and how the specific tests within each sub-hypothesis may or may not hold under different conditions or present some form of biased result for different reasons, such as model and/or variable misspecification. An alternative approach started to develop, whereby researchers started to question the validity of the assumptions pertaining to the EMH. The EMH assumptions bear reference to the definition and imply that the market consists of a large number of profit-maximising participants who independently value new information coming to the market in a random fashion, prompting market participants to rapidly adjust market prices according to the rational implications of the new information. (Reilly & Brown, 2012:140). Yet again, it is more meaningful to represent some of these findings by means of Table 3.2.

Table 3.1: Joint EMH research findings

EMH Form	Source	Aspect addressed or aim of study	Finding
Weak form EMH-related studies.	Black & Scholes (1972:399-340, 416-417)	The aim was to determine if option traders were efficient in calculating and adjusting option prices from new information influencing futures prices, since their model used historical volatility as an input to value options.	Results showed that the model overpriced an option when volatility was high and under-priced when volatility was low. A superior trader would have been able to profit from this mispricing if a less informed trader had applied the model to price an option, thereby implying that the option market appeared to be rather inefficient. However, when transactions costs were included, it was evident that this profit opportunity practically disappeared.
	Samuelson (1973:369)	Re-evaluated Samuelson (1965) to determine the expected price when the prices are properly adjusted to include dividend payouts.	Results were consistent with Samuelson's (1965) study and dividend discounted prices followed the same process of a random walk.
	LeRoy (1973:436)	Also reviewed Samuelson (1965) to determine if the martingale property of price changes remained if the expected portfolio rate of return was that of a risk-averse investor.	In the restricted case or risk aversion, the martingale property did not hold. This result did, however, not prove market inefficiency, but only that investors demanded a rate of return consistent with the associated risk of their investment.
	Cooper (1974:887)	Revisited the results by Sprinkel (1964), who found that changes in money supply can be used to predict stock prices.	Results showed that stock returns actually lead money supply changes and that the market was efficient, since the expectation of future money supply was incorporated into stock prices prior to money supply changes.
	Fama (1975:269)	Determined if short-term interest rates may be used as a predictor for inflation and focused on the efficiency of the short-term bond market.	Results indicated that the short-term bond market correctly anticipated future rates of inflation in order to set one to six-month nominal interest rates.
	Lucas (1978:1443)	Reviewed the conditions under which price series did not present martingale properties and therefore presented evidence of irrational behaviour.	Confirmed results by LeRoy (1973) by means of a different methodology. Reiterated that conformation of martingale properties did not present evidence of market efficiency. Also, results depended on the econometric model applied. Specific models could be constructed to include rational agents and present

EMH Form	Source	Aspect addressed or aim of study	Finding
			martingale properties, whereas other models with the same rational agents did not necessarily portray this characteristic.
Semi-strong form EMH-related studies.	Scholes (1972:206)	Event study which evaluated the effect of new information in the form of new share issues on price changes.	The empirical results indicated that no abnormal profit would be possible, since the price change would be too small to justify the sale and potential repurchase of existing stock.
	Kraus & Stoll (1972:587-588)	Investigated the effect that large trades and especially significantly large privately negotiated transactions had on price formation.	The study concluded that large trades did have a significant short-term effect on market prices. They also stated that the occurrence could be addressed if the market mechanism in terms of fixed commission were eliminated, thus, allowing other participants to compete by means of block trades in the opposite direction.
	Beja (1977:6,21-22)	Evaluated the effect of information limitations on price changes. They argued that, although market prices may reflect all public information, it would never fully reflect superior or private information, since a fully reflective price would be inconsistent with a genuine trading process.	The study justified a genuine trading process as a model, which incorporated different traders' behaviour or different interpretations of the same information. Hence, implying that the assumption of identical interpretations by other models were a "self-fulfilling" prophecy.
	Basu (1977:680-681)	Contradicted the findings by Beja (1977) that publicly available information may be regarded as low level, inherently inferior information.	Results showed that publicly available price to earnings (P/E) ratios seemed to provide information that was not instantaneously reflected in the stock price. Also, especially low P/E ratio stocks seemed to be inappropriately priced, presenting opportunities for returns above the norm.
	Ball (1978:103)	Evaluated returns after a company announces their earnings figures, despite the fact that this type of information is regarded as public information.	Results showed that excess returns are achievable. As a likely explanation to the market inefficiency, the study considered the possibility of potential misspecification of the variables used in the model applied, since earnings variables was used as proxies for other unobserved variables.
	Brenner (1977:57-58, 66)	Questioned model specification when an inappropriate model was used to estimate the different parameters in price forecasting models.	The study found definite model misspecification, which was caused by correlation between the observed factors and advised the testing of several alternative models to ensure the legitimacy of the analysis and conclusions regarding market efficiency.
	Brenner (1979:917-918)	Built on Brenner (1977) and evaluated several pricing models to determine if they would render the same result in terms of market efficiency.	Results showed that different pricing models led to different results regarding market efficiency. This study also confirmed that the applicability of the data to the model should be confirmed in order to ensure that the resulting market efficiency test was not biased by the misspecification of a model.
Strong form	Grossmann	Argued that, if a market were	The study concluded that, in order to prevent

EMH Form	Source	Aspect addressed or aim of study	Finding
EMH-related studies.	(1976:574,529)	completely informationally efficient there would be no incentive to acquire new information and the market mechanism would all but cease.	this, informed investors would need to be able to hide their information advances within the ”noise” of price changes, which would be improved by speculative participation and liquidity.
	Grossmann (1977:432)	The model was built around the findings of Hirshleifer (1971) and aimed to show that investment professionals invest in information in order to acquire abnormal gains. This information is reflected in the price, allowing other uninformed traders to get the information by merely observing market price changes.	Results indicated that markets can become informationally over-efficient, meaning that informed traders would not be able to earn a return on their information acquisition if all information were represented by the current price.
	Black (1986:529)	Building on Grossman (1976) and reiterated the importance of “noise”.	The study admitted that, although ”noise” makes it more difficult to empirically test for market efficiency and may contribute to observed market inefficiencies, it makes trading and price formation possible, ultimately preventing any benefit from the observed inefficiencies.

Source: Compiled by author

Table 3.2: Joint EMH assumptions research findings

EMH Assumption	Source	Finding
Information is freely available and costless.	Grossman &Stiglitz (1980:393, 399-340,404)	The study found that when market information is available freely, the market would most probably be characterised by low trading volume, since all traders have homogenous expectations based on the same set of costless available information. The study concluded that it would never be possible for a market to be completely informationally efficient. If prices at all times completely reflected all available information there would be no incentive for investors to apply resources to obtain and analyse any form of additional information.
	Bray (1981:576)	Introduced a model which assumed that commodity producers were also the agents who marketed their produce on the futures market based on their information of expected output and spot prices. The study assumed that, although there might not be sufficient incentive to acquire costly information on the spot price, there would always be incentive for producers to acquire information about the futures price in order to make an informed decision about future trades.
Prices adjust rapidly to a new fair market price value based on the implications of new information.	LeRoy & Porter (1981:557)	Presented an alternative approach to test if markets were efficient in times or periods of high volatility. Results showed that stock prices were more volatile than what would be expected from an efficient capital market model, despite the fact that no return serial correlations were observed.
	Shiller (1979:1193)	Found that long-term interest rates were much more volatile relative to short-term rates, implying that conventional tests of market efficiency may be biased.
	Shiller (1981:303-304)	Confirmed the results from Shiller (1979) from an alternative angle by showing that stock prices presented greater volatility than that which may be justified from subsequent changes in dividends.
	Potterba & Summers (1986:1142)	Found that the effect of volatility changes and the corresponding influence it had on risk premiums deteriorated rapidly, leaving no significant lasting effect on stock market prices.
	Haugen, Talmore & Torous (1990:987)	Found significant effects of increasing and decreasing volatility on stock market prices. They concluded that, when volatility changes occur, they have a short-term impact; but since they occur frequently, market participants regularly adjusted their risk premiums. This caused excess volatility when market prices were re-evaluated through the investor's required rate of return.
Rational expectations of market participants.	Milgrom & Stokey (1982:26-27)	Found that if all traders were rational and their beliefs of market changes based on new private information were similar, they would have no incentive to act on it. Ultimately, this would lead to reduced market efficiency.
	Tirole (1982:1180)	Showed that rational traders could not expect a speculative gain if markets were in equilibrium. Also, unless speculators were able to obtain access to privileged information or obtain "insurance" in the market in the form of hedging their position and transferring the risk to another party, speculation was an inconsistent process which did not always adhere to rational expectations.

Source: Compiled by author

From Table 3.1 and Table 3.2 it becomes evident that the only aspect separating the two tables is the focus or aim of the studies. Research that aimed to test the assumptions of the EMH may also be linked to a specific form of efficiency studies, depending on the model and type of data reviewed. Ultimately, the objective of all these studies – which was to prove or disprove some aspect pertaining to the EMH – was to find proof of irrational behaviour or predictable market movements. As time progressed additional studies emerged, which found proof of irrational behaviour or predictable market movements that was inconsistent with the EMH framework. These discrepancies became known as market anomalies, where different types of inconsistencies or repeating occurrences were observed within different markets or periods. The following subsection elaborates more on these discrepancies.

3.2.4.2 Market anomalies

When deviations from the EMH are derived, the discrepancy cannot always be attributed to a specific form of the hypothesis and is usually interpreted as evidence of market inefficiency. This interpretation may, however, not necessarily be valid given the fact that changes in the empirical model applied or altering influential factors or data used in the model may change the outcome of the study (Brenner, 1979:917-918). As a result, research started to focus on the identification of specific discrepancies in different datasets by means of different methods. Discrepancies became known as anomalies, which may be divided into two broad categories.

The first category includes cross-sectional return patterns, like the value effect, the size effect, and the momentum effect. These effects are collective terms for financial ratios, which measure the cash flows or value of a firm, like the earnings-to-price (E/P) ratio and book-to-market ratio or market capitalisation and financial leverage of the firm, which may be used to explain the expected return of an asset. Pioneering research in this regard was presented by Basu (1977) and Ball (1978), who showed that the E/P ratio may be regarded as a proxy for risk and expected return. As a result, if cross-sectional patterns are able to explain returns, expected returns might be predicted based on changes in these values or patterns, which relates to market inefficiencies. Acknowledged research related to cross-sectional patterns may be summarised constructively by means of Table 3.3.

Table 3.3: Cross-sectional pattern market anomalies

Cross-sectional pattern	Source	Ratios evaluated	Finding
Size effect	Banz (1981:3-4)	Market capitalisation	The study coined the term, "size effect", when results indicated that the returns of smaller firms' stock realised higher risk-adjusted returns than the returns of larger firms.
	Rogalski (1984:836)	A relation between Monday effect (Table 3.4) and January effect (Table 3.4) to firm size was observed.	For the months other than January, both small and large firms experienced negative returns on a Monday, whereas small firms experienced greater returns than large firms on a Monday, Thursday and Friday during the month of January.
	Chan & Chen (1991:1467)	Evaluated the size effect and corresponding economic reasons why small firms and large firms had different risk-return characteristics.	Found that smaller firms tended to struggle more with managerial and production efficiency, resulting in greater leverage and consequent higher risks. As a result, the difference in risk and return between small and large firms was explained by the price reaction of high leveraged firms to economic news. Also, the size effect explained the dispersion of returns for portfolios constructed from either large or small firms.
Value effect.	Rosenberg, Rein & Lanstein (1985:12)	Book value to market value (BV/MV).	Found that there exists a positive relationship between expected returns and the BV/MV of a firm. As a result, portfolios formed on the basis of higher book-to-market values are associated with higher expected returns.
	De Bondt & Thaler (1987:571,575,579)	Book value to market value (BV/MV).	Reiterated the positive relationship between expected returns and the BV/MV of a firm. Also confirmed that small firms tend to realise excess returns, which could be linked to investor overreaction based on earnings achieved.
	Griffin & Lemmon (2002:2318)	Revisited Fama & French (1995) due to excess high BV/MV returns.	Found contrasting results to Fama & French (1995). Low BV/MV stocks did not show sustainable profitability. They argued that excess returns should be attributed to low BV/MV stocks which are overvalued and high BV/MV stocks which are undervalued, since investors overestimate potential future returns for low BV/MV stock.
Value effect and size effect.	Reingagum (1981:19)	Earnings-to-price (E/P) and market capitalisation.	Confirmed that the E/P ratio may be regarded as a proxy that explains risk and expected return, particularly within portfolios which are based on a specific firm size or market capitalisation. However, when the returns were adjusted to account for firm size, the E/P value anomaly was not as prominent.

Cross-sectional pattern	Source	Ratios evaluated	Finding
Value effect and size effect.	Fama & French (1992:428-429)	Conducted an extensive evaluation of the combined influence of market capitalisation, leverage, E/P and BV/MV on the cross-section of average returns.	Results confirmed that the size effect and BV/MV effect dominates the other variables significantly in explaining expected average returns.
	Fama & French (1995:132,153-154)	Revisited Fama & French (1992). Aimed to evaluate if excess return for high BV/MV firms may be attributed to a greater risk of distress.	Confirmed that BV/MV and size factors influence stock prices and that high BV/MV stocks are more subject to financial distress. Lower BV/MV stock also showed more sustained profitability.
	Van Rensburg & Robertson (2003:10)	A regression analysis of 24 different fundamental and technical attributes, including P/E, leverage, size and momentum was evaluated.	Results showed that a two-factor model, including size and price-to-earnings (P/E), was an adequate model to significantly explain the expected earnings achieved on the Johannesburg Stock Exchange (JSE).
	Auret & Sinclaire (2006:32)	Following the same regression analysis approach as Van Rensburg & Robertson (2006), but only including the five most significant variables, as well as the BV/MV ratio as an alternative variable.	Results indicated that BV/MV was more significant than size and P/E. Also, when combining BV/MV, P/E and size in a separate three-variable model, BV/MV completely dominated the other two, rendering them insignificant. However, given the high level of autocorrelation induced by the BV/MV ratio, the final result and model confirmed that size and P/E significantly explained average returns on the JSE without inducing autocorrelation.
	Basiewicz & Auret (2009:24)	Re-evaluated the cross-section of returns on JSE, expanded the data sample, and included trading costs.	The study found no relation between size and value on the JSE and confirmed that the BV/MV ratio was the strongest predictor of stock market returns, whilst the E/P ratio seemed to be the weakest.
Momentum effect	De Bondt & Thaler (1987:557)	Return reversals	Results showed that firms which initially performed poorly realised higher returns than firms which initially performed well over a 5-year rolling window analysis.
	Jegadeesh & Titman (1993:89-90)	Return continuation	Found that firms that tend to perform well in the short-term period of six months to a year will continue to perform well for a corresponding similar period.
	Rouwenhorst (1998:283)	Return continuation	A portfolio of strong performing stocks outperformed the returns achieved by a portfolio constructed of poor past performers.

Cross-sectional pattern	Source	Ratios evaluated	Finding
Momentum effect, size effect and value effect	Grundy & Martin (2001:30)	Return continuation	Found that strategies based on the momentum continuation effect are more profitable. Also found that the momentum effect could not be attributed to industry trends or size and value effects.
	Subrahmanyam (2005:661)	Combined BV/MV and the momentum effects	Found that BV/MV and momentum were significant in explaining excess returns. Concluded that momentum proxies for risk may be used as an additional factor when empirical pricing models are applied to determine expected returns.

Source: Compiled by author

The second category includes time-series patterns, like return predictions by means of autocorrelated past returns for individual stock and portfolios, as well as patterns in returns around days of the week, weekends or seasons. Some of the research in this regard originated from findings by Fama (1965a:74), who identified slight autocorrelation in past returns. Methodology usually involves tests for autocorrelation of higher frequency time intervals for both individual stock returns, as well as portfolio returns when determining if the expected returns are time-varying. Mainstream research that relates to time-series patterns may be summarised constructively by means of Table 3.4.

Table 3.4: Time-series pattern market anomalies

Time-series pattern	Source	Finding
Autocorrelation	Niederhoff & Osborne (1966:914)	Found that if two price changes occured in the same direction, the odds of a price change in the same direction doubled when compared to the odds of finding a pattern when prices alternated in different directions.
	Potterba & Summers (1987:27-28)	Found positive autocorrelation over shorter periods and negative serial correlation over longer periods.
	Fama & French (1988a:247)	Results showed that negative autocorrelation was generated by the slow mean-reverting components of stock prices and that they influenced return variations.
	Lo & MacKinlay (1988:61)	Strongly rejected the random walk hypothesis for weekly stock market returns of especially small market capitalisation stocks. This rejection did not necessarily indicate market inefficiency, since the random walk process along with a mean reverting process could not completely account for stock price behaviour.
	Conrad & Kaul (1988:423)	Departed from the EMH assumption that expected returns would remain stationary. The study found changes in the variation of expected returns across sub-periods and that the size of the variance decreased systematically as the size of a portfolio increased.
Day of the week effect or weekend effect	Cross (1973:68)	Found that the S&P Composite Index performed better on Fridays than on Mondays. Also, there was no significant price change relationship between any of the other business days of the week.
	French (1980:68)	Confirmed that the average return for Mondays was negative, whereas average returns for all other trading days were positive. Results could also not explain the effect as a closed market effect; only as a weekend effect, whereby average returns are lower for a Monday.
	Rogalski (1984:835-837)	Confirmed the weekend effect. Stated that all the negative returns actually occured between a Friday closing price and a Monday opening price.
	Keim & Stambaugh (1984:834)	Confirmed that returns for indices and individual stocks were positive towards the end of a week and negative on the corresponding Monday.
January effect	Branch (1977:207)	Presented January as a trading rule when he found that tax selling of stocks that were performing poorly at the end of the year might be the reason why the market tended to excel at the beginning of the year in January when these or similar stocks appeared more attractive.
	Marsh, Brown, Keim & Kleidon (1982:2)	Evaluated the January effect for the Australian stock market, for which the tax year ended on 30 June and not 31 December. Results confirmed a January effect. The study concluded that they were still at a loss to explain the January effect, since Australian evidence of the effect could not be reconciled with the tax selling hypothesis.
	Keim (1983:14)	Found that the risk-adjusted returns of the size effect (see Table 3.3; small firms relative to large firms) may be attributed to the January effect.
	Roll (1983:26)	Confirmed the size effect relation to the January effect. Attributed the effect to tax-loss selling.
	Rogalski (1984:836)	Found a relation between the Monday effect or weekend effect and

Time-series pattern	Source	Finding
		the month of January in the sense that both these effects actually produce positive returns for the month of January. The relationship was non-existent in the other months of the year.
	Haug & Hirschey (2006:78)	Noted that the January effect in small capitalisation stocks had been "*remarkably consistent over time*" despite the 1986 tax reforms, which resulted in the new tax period being from January-December to November-October.
	Dzhabarov & Ziemba (2010:93)	Found that, amongst others, the January effect for especially small capitalisation stocks still had value on the US market.
	Auret & Cline (2011:29)	Results showed no significant evidence of either the value, size or the January effect on the JSE.
	Darrat, Li & Chung (2013:157)	Found no significant evidence with regards to the January effect on the JSE. Results, however, exhibited robust evidence of lower returns on a Monday and Tuesday. Also, a beginning-of-the-month effect was observed, whereby the returns for the second and third day of a month were greater than any other day of the month. These effects all but ceased to exist after the sub-prime credit crisis of 2008. They concluded that an improvement in JSE efficiency occurred after global sub-prime crises, which "*filtered out*" any seasonal effects.
Window dressing as possible explanation for the January effect	Lakonishok, Shleifer, Thaler & Vishny (1991:231)	Confirmed the finding that portfolio managers sell the shares that performed poorly prior to year-end in order to avoid disclosure of non-performing stocks or to make their holdings look good in order to increase investment in the fund.
	Eakins & Sewell (1994:78)	Could not confirm any of the window-dressing assumptions and questioned earlier findings of the hypothesis.
	Potterba & Weisbenner (2001:353-354)	Found that changes in capital gains tax did not provide the necessary incentive to apply window dressing, but that it may influence the decision of individual investors to participate in year-end tax-loss selling. Also, they were able to prove that tax-motivated year-end selling contributed to the January effect. However, they could not establish the profitability of tax-selling with regards to its contribution to observed returns.
	Steyn & Smit (2004:37)	Found that year-end, as well as quarter-end unit trust pricing behaviour tended to confirm the window-dressing hypothesis for the JSE.

Source: Compiled by author

Apart from these two general groupings of past return predictability patterns, another approach, which presented evidence of return predictability from other observed variables, seemed to provide even more conclusive evidence of time-varying expected returns. Among these observed variables were expected inflation, yield spreads between long and short-term interest rates, as well as the dividend-to-price ratio. With regards to the statistical relation between inflation and stock returns, papers by Lintner (1975), Bodie (1976), Nelson (1976), Fama and Schwert (1977), Jaffe and Mandelker (1977), Gultekin (1983), and Kaul (1987) found a negative correlation between stock returns and inflation. These results also contradicted the finding by Fisher (1930), based on the hypothesis that there is a positive one-to-one relationship between expected nominal interest rates and expected inflation. Fama (1981:545) confirmed the negative relationship but found that the relation became insignificant when real variables like base growth rates were included in the regression model.

Related research pertaining to yield spread observed that variables also did not lag in vigour. Shiller, Campbell and Schoenholtz (1983), Campbell and Shiller (1984), Mankiw and Summers (1984), as well as Campbell (1984a) showed that the yield spread between long-term bonds and short-term bonds significantly predicted the excess return obtainable from long-term bonds. Furthermore, Campbell (1984b:33) found that measures constructed from interest rates on US Government securities were able to predict market price risk premiums. Keim and Stambaugh (1986:387-388) built on this result when they found that risk premiums changed in relation to variables that reflected asset price levels. For instance, the difference (spread) between long-term and short-term bonds yields showed an inverse relationship with asset price levels.

Fama and French (1989:23) also contemplated the term structure of expected returns on stocks and bonds in comparison to the business cycle. They specifically evaluated whether dividend yields and the default spread[19] may forecast bond and stock returns. A strong relation to business conditions was established in the sense that expected returns were lower during favourable business conditions, while unfavourable business conditions could be associated with higher returns. The inclusion of dividend yield was especially applicable at the time, since both Campbell and Shiller (1988) as well as Fama and French (1988b) confirmed the relevance of the dividend-to-price (D/P) ratio, or dividend yield to forecast expected returns. Interestingly, the result was not linked to the specific market anomaly, but rather to rational investor behaviour, stating that increased expected returns during poor business conditions would induce a switch from consumption to investment (Fama & French, 1989:48).

Consequently, the developments in research findings regarding market anomalies and the EMH at the time set the stage for a revision of new and potentially improved findings in order to justify or adjust the status quo. The situation inevitably prompted Fama (1991) to write a second review paper on the renewed findings after his 1970 paper. Fama (1991:1575-1576) focused his review on the different anomalies he found interesting and addressed them within the three categories or forms of market efficiency.

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19 The default spread or the default premium is the difference between the yield on a market portfolio of corporate bonds and the yield on top AAA grade bonds (Fama & French, 1989:24).

Firstly, in terms of previous papers on the weak form hypothesis, Fama (1991:1577) covered the literature on the predictability of returns. In terms of the predictability of short-term returns from past data by Black (1986), Lo and Mackinlay (1988), as well as Conrad and Kaul (1988), he admitted the relevance of the research on a statistical basis (Fama, 1991:1580). For a longer term basis of return predictability, Fama (1991:1586) – amongst others – reviewed the work by Fama and French (1988a), as well as Poterba and Summers (1988). Based on these results, he contemplated the fact that most of these tests were done by means of sample-specific conditions, which may cause spurious results and should be dealt with sceptically until the predictability was confirmed out of sample. Ultimately, Fama (1991:1610) stated that, until it was possible to distinguish between investors' "tastes" and technology shocks, the full link between expected returns and variables that seem to influence expected returns could not be drawn. In order to accomplish this, he argued that it would be necessary to construct a synchronised model that related the different aspects of returns to the variation of expected returns. He did, however, admit that such a model – relating behaviour of expected returns to the happenings in a real economy would most likely be impossible, thereafter concluding that return predictability may also never be conclusively proven.

Secondly, in terms of semi-strong efficiency test papers or event studies, Fama (1991:1600) more exclusively reviewed studies on corporate finance events, like market price responses to investment and financing decisions, as well as corporate governance changes. Fama (1991:1602) admitted that some event studies showed that the variation in returns after an announcement increased, but countered the observation by stating that these tests were still not able to determine whether the excess variance was due to under or over-reaction to new information, or whether the variance was irrational. He concluded that these event studies provided the best type of evidence on market efficiency and that the literature prompted him to believe that prices adjusted swiftly, and thus efficiently, to new firm-specific information.

Lastly, when considering the strong-form efficiency tests in terms of the access to private information possibly leading to abnormal returns, Fama (1991:1607) mentioned that new research in the field had been sparse since his 1970 paper. Also, since these tests usually made use of performance evaluation in order to link potential access to private information to superior performance by fund managers, the validity was usually confronted with criticism, like an inferior model of market equilibrium or model implementation problems. This realisation, along with the precondition for strong form efficiency that trading and information were costless, compelled Fama (1991:1575) to admit that the extreme version of the EMH was false and that market efficiency in itself was not testable. However, he suggested that the alternative version by Jensen (1978:3), that market prices reflected information up to the point where the cost of acquiring the information exceeded the benefit of acting on the information, made more economic sense.

Arguably, these observed anomalies could not always be explained from an EMH perspective and in order to provide a potential explanation, a field of study called behavioural finance began to surface. Behavioural finance addressed the statement by Fama (1991) that investors' "tastes", which are reflected in an investment decision, should be isolated to fully explain expected returns. Within behavioural finance, the decision-making process of market participants is explained by means of psychology-based theories. Accordingly, behavioural finance assumes that market information and the actions of other market participants influence the decisions of individual participants, ultimately affecting certain market movements. The development and findings in the field of behavioural finance are discussed in the following section. The relevance of market anomalies and behavioural finance to the objectives of this study cannot be overstated. The existence of market anomalies as contrasting evidence to the concept of market efficiency provides the necessary foundation in favour of the study objective of linking different seasons by means of statistically significant factors based on historical data. The formation of historical price data may, as a result, also have been influenced by the decision-making process of producers. This decision-making process may also have been influenced by the developments in influential factors throughout each season. It is therefore important to understand more about the psychological influence of decision making, since it may have a direct influence on producers' decision criteria (Section 4.2.1) when price risk management decisions are made.

3.2.4.3 Behavioural finance

Since the initial development in market price behaviour research (see Section 3.2.1), the EMH has become a benchmark theory for rational expected investment returns. Research mainly aimed at disproving the EMH through the identification of market anomalies also began pointing out that the EMH did not include the impact of investor decision-making in the investment management process. As a result, the field of behavioural finance developed from the notion that investors make fundamental mistakes in their investment management process. The development in research pertaining to behavioural finance may, however, be traced back to the research by Kahneman and Tversky (1979:263), when they developed an alternative to utility theory called prospect theory. They argued that expected utility did not hold under risky conditions, since people tended to make choices inconsistent with expected utility theory when confronted with the same choice presented to them from different angles. Also, people had a tendency to assign more weight to outcomes that were more certain as opposed to outcomes that were probable. Thaler (1980:39) supported the findings presented by Kahneman and Tversky (1979), and proposed that the prospect theory be considered as a basis for an alternative descriptive theory, since circumstances when consumer behaviour was inconsistent with economic theory definitely occured. Later on, Tversky and Kahneman (1981:453) built on their 1979 paper by introducing the concept of "decision framing". They showed that human psychology influences decisions, causing shifts of preference when the same problem is framed in a different way. They also concluded that psychological dependence on preferences during decision making presented serious concerns for the assumption of a rational choice or behaviour.

From these foundations, the notion of behavioural finance was coined by De Bondt and Thaler (1985) when they evaluated specific price movements in an attempt to determine if the price movement may have been attributed to a market overreaction. They found that the market tended to overreact to dramatic or unexpected news or information which sometimes caused market prices to trade much lower than the fair market price, based on the impact of the news. Their results showed that if stocks were identified as poor performers which made losses over a three to five-year period, they showed improved returns relative to the market in the subsequent years, even though they were inherently more risky to consider as part of a portfolio (De Bondt & Thaler, 1985:804). In a follow-up paper, De Bondt and Thaler (1987) presented additional evidence in support of their hypothesis that market participants tended to systematically overreact. Their proposition of behavioural actions explaining certain irrational price changes presented researchers not only with a possible explanation, but also with an alternative research angle that could prove or disprove previous findings by means of different methodological approaches. Marsh and Merton (1986:484), for instance, re-evaluated the variance-bound methodology which Shiller (1979, 1981) applied to derive his finding of irrational volatility. They found it to be unreliable and that Shiller's (1979, 1981) findings did not present proof of market inefficiency at all.

Arguably, market inefficiency induced by irrational behaviour may not necessarily be empirically testable or proven, but may definitely be clearly observed through extreme market price movements, such as the stock market crash on Black Monday, 19 October 1987. Black (1988:274) attributed a part of the excessive decline in the market on Black Monday to a physiological factor brought about by participants' distrust in the market mechanism, causing them to withdraw from the market. Black (1988) pinned the greatest reason for the decline on the argument that investors' tastes were changing, actually causing increased volatility in a rising market, whereas volatility normally decreased when market prices rose. Consequently, the market rose more than it should have, since the expected return was overestimated. Upon the realisation of this mistake, market prices were adjusted to conform to the actual expected rate of return, inevitably causing another sudden change in investors' tastes and the ultimate sell-off (Black, 1988:272). French (1988:282) also conducted a study on the specific stock market crash, but attributed the decline to the fact that investors overvalued the intrinsic fundamental value of stocks due to the high level of “noise” in the market. This realisation caused investors to react to the market movement and to the actions of other parties rather than consulting an updated calculation of an equilibrium market price based on relevant information.

Over time, different causes of behavioural finance were also identified in order to provide explanations as to why investors tended to make irrational financial decisions. These various causes aimed to demonstrate how human emotions and different cognitive dispositions influence investors during their decision-making processes. The different causes may also be grouped into two main decision processes, namely prospect theory and a heuristic decision processes. Heuristics, as initially developed by Tversky and Kahneman (1974), entails a decision process whereby investors arrive at their own conclusion, usually by trial and error, leading to generalised rules of thumb; while the prospect theory, also developed by Kahneman and Tversky (1979), formed a basis for the development of several states of mind that may influence investor decisions.

Under the heuristic decision process, there are different principles by which investors may arrive at their own conclusions. These principles include representativeness, availability, overconfidence and anchoring. Firstly, the heuristic of representativeness may also be called similarity, since it is linked to recent success from an investment’s point of view. Investors tend to be optimistic in a bull market and pessimistic in a bear market. Accordingly, investors tend to believe that based on recent success (or failure), the success (or failure) will continue in the future, irrespective of prior probability of outcomes, sample size, or any form of predictability or regression analysis (Tversky & Kahneman, 1974:1124-1127; Andreassen, 1988; De Bondt, 1993).

Secondly, availability refers to the instances where people base investment decisions on instances or information to which they can relate from their own frame of reference. Thus, they subjectively base their assessment on a frequency within a class, the likelihood of an event, or the frequency of co-occurrences on the ease with which they can retrieve information relating to the decision at hand (Tversky & Kahneman, 1974:1128). Initial and confirmatory studies relating to this type of human behaviour was done by, amongst others, Tversky and Kahneman (1973), Carrol (1978), Folkes (1988), Schwarz, Bless, Strack, Klumpp and Rittenauer-Schatka (1991), MacLeod and Campbell (1992), Waenke, Schwarz and Bless (1995) and Schwarz and Vaughn (2002).

Thirdly, people tend to be overconfident regarding their ability and knowledge, causing excessive trading, as well as potential under-reaction to new information. Daniel, Hirshleifer and Subrahmanyam (1998:1839) proposed a theory which stated that price under and overreactions in a security market was caused by investor overconfidence with regards to their perception of private information and biased self-attribution. The concept that overconfidence may be the reason why business entry mistakes are made was initially proposed by Roll (1986). However, the concept was never tested until Camerer and Lovallo (1999:306) created an experiment to measure the effect of economic decisions as opposed to personal overconfidence. They found that overconfidence and optimism cause excessive participation (and consequent lower profit) when people bet on their own skill and knowledge rather than random processes. Odean (1999:1280) confirmed that when trading volume in equity markets become excessive it may be attributed to overconfidence. He stated that rational investors would assess expected trading profits and not make trades if the cost of trading may exceed the expected returns. On the other hand, when investors are overconfident, they tend to overestimate expected profits, resulting in returns that do not cover costly trading. Another overconfidence study was done by Barber and Odean (2001:261) when they tested the psychological research, which found that men tend to be more overconfident than women in areas such as finance.

The last heuristic, as identified by Tversky and Kahneman (1974:1128), is known as anchoring, which is followed by adjustment. Anchoring is the process by which investors tend to rely too heavily or have a tendency to anchor their mindset to a specific piece of information, even if the information at hand does not logically address the decision at hand. Investors tend to believe that market price changes due to new information are only temporary and will soon follow some historical trend. This causes under-reaction to trend changes with an eventual adjustment by investors, which is usually too late and typically insufficient (Kannadhasan, 2006:4). A related heuristic that follows from anchoring is known as conservatism. The concept was proposed by Edwards (1968) and follows that investors do update their beliefs as new evidence becomes available and is observed, but are usually slow to react. Thus, they tend to anchor in the status quo of information. Basu (1997:3) also found evidence of conservatism and showed that earnings reflected negative news up to six times faster than positive news, resulting in positive news causing much more persistent earnings changes over a longer period.

Apart from these heuristics, several other states of mind developed from the prospect theory, which can influence an investor's decision process. A first concept, state of mind, or phenomenon became known as loss aversion. Kahneman and Tversky (1979:268-269) found that investors seem to be risk-averse when faced with decisions regarding the potential of definite gains, but become risk-seeking when these decisions are substituted with the prospect of losses. Consequently, an investor would be willing to endure greater losses in the hope that the price will rise above the initial purchase level. Rabin (2000), and Schmidt and Zank (2002) agreed with these findings.

A second observation on behaviour, called regret aversion, was presented by Kahneman and Tversky (1979), Quiggin (1982), as well as by Loomes and Sugden (1982), and Bell (1982). Within this concept of behaviour, an investor comes to the realisation that his current course of action is not optimal and that the outcome may have been improved by an alternative course of action. Ultimately, the investor regrets the poor investment choice he has made and in order to avoid this type of emotion or feeling of regret he tends to avoid the same decision in the future, even if the future decision would have been optimal. Also, investors avoid recognising a loss from a poor investment decision by holding on to poorly performing investments (Loveday, 2012:3-5).

A third behavioural state of mind is known as mental accounting. The concept was developed by Tversky and Kahneman (1981:456) and specified by Thaler (1985:199). It involves an evaluation of the consumer decision-making process which specifically focuses on their perception of gains and losses, purchase decisions, and budgetary rules. From an investor's point of view, it entails the cognitive process through which individuals "*organise, evaluate and keep track of financial activities*" (Thaler, 1999:183). This cognitive decision-making process involves categorising or labelling at three levels, namely budgetary expenditures, wealth or savings investing, and income. Interestingly, mental accounting violates the economic principle of fungibility which states that these categories or accounts should be substitutable. However, from the behavioural perspective of mental accounting, they are not interchangeable; leaving Thaler (1999:203) to conclude that mental accounting is an important aspect of the decision-making process.

From the research presented above, it becomes clear that the field of behavioural finance has a well-established foundation. Heuristic decision processes and prospect theory form part of cognitive psychology, questioning the strictly rational assumption of the investor decision process, as suggested by the EMH. The implications of these behavioural finance biases may, for instance, cause under or overreaction to new information, neglect of fundamental analysis, the formation of past price trends in the future, and herd behaviour, which – individually or collectively – may cause asset prices to deviate from their intrinsic fundamental value.

This mounting evidence prompted Fama (1998:284) to write a third review paper in which he addressed behavioural finance. However, the focus of his paper did not address individual or specific cognitive biases, but rather approached the findings from a holistic point of view. He argued that observations of under and overreactions may be seen as proxies for market anomalies or behavioural finance observations and that an efficient market would have a roughly even split between under and overreactions. Also, with regard to longer term anomalies, he stated that they became negligible and even disappeared when different models or statistical approaches were used to measure them;

ultimately stating that these observations could reasonably be attributed to chance. Fama (1998:291) to a certain extent challenged advocates of, as he called it, a vague alternative hypothesis, promoting market inefficiency to develop a more robust hypothesis or model for price information that may be subject to empirical testing. He argued that the task would be daunting, since it should incorporate all possible scenarios and circumstances which would ensure that investors always under or overreact in the same way. He concluded that *"the question should be: Does the new model produce reject-able predictions that capture the menu of anomalies better than market efficiency? For existing behavioural models, my answer to this question (perhaps predictably) is an emphatic no".*

Evidently, it is inaccurate to claim that market anomalies and behavioural finance provide concrete evidence of market inefficiency. It would, however, be acceptable to state that these observed price behaviour traits, in all probability, are a result of individual decision-making processes by investors. Consequently, they may provide plausible explanations for certain price formation observations, which are usually just classified as anomalous. Throughout the discussion presented above, it seems that there are inconclusive results for and against the EMH and that an all-inclusive model – which accommodates both market efficiency and behavioural perceptions – seems to be an impossible feat, but the only plausible explanation. Also, despite the fact that investors are not able to realise abnormal returns from market anomalies, they would be able to practically incorporate and benefit from the implications of the observed traits of human behaviour in their portfolio. One of the methods for an investor to observe these traits and to a certain extent identify and detach himself from the "human condition" inherent in investing, may be through technical analysis. The process of technical analysis and how it pertains to behavioural finance, as well as its relevance to the study at hand, is discussed in the following section.

3.2.5 Technical analysis

Technical analysis may be defined as a method to evaluate statistics based on price changes generated by market activity. These statistics are usually portrayed in the form of charts, which are then subjected to chart analysis, pattern recognition analysis, seasonality, and cycle analysis. Technical analysis is also based on three important assumptions. Two of the assumptions stand in direct contrast to the EMH, since technical analysts assume that prices move in trends and that history tends to repeat itself. Therefore, price changes tend to follow the current trend rather than moving against it and market participants tend to react consistently to certain market conditions over time. A third assumption, not necessarily contradicting the EMH, is a very important aspect of technical analysis, which assumes that all relevant fundamental, as well as psychological factors that may affect price changes, are already incorporated in the new equilibrium price (Reilly & Brown, 2012:543-544).

Consequently, the link between the EMH, behavioural finance, and technical analysis may be explained as follows: Although the EMH predicts that all information is available for investors to base their price formation decision on, it still could not explain the reactions or response to the information by investors since, as shown under behavioural finance, investors are not always rational. Accordingly, technical analysis captures this irrational behaviour through the study of market behaviour. Thus, technical analysis incorporates the study of human psychology (Credit Suisse, 2010:3). Human psychology not only includes the different cognitive biases explained in the previous section, but also the human condition of herding. Investors tend the follow the crowd or the mood in the market, they tend to buy when a market is rising and sell when a market falls. Inevitably, they tend to buy near the top of a market movement and sell near the bottom of a market movement. This herding behaviour by investors, which contradicts the basic investment assumption to buy low and sell high, was identified and confirmed by, amongst others, Shiller (1987), Scharfstein and Stein (1990), Banerjee (1992) and Bikhchandani *et al*. (1992). Herding behaviour entails an array of human emotions, as depicted in Figure 3.1, which in turn contributes to the different heuristics and investor states of mind that influence their investment decisions. Investors are, therefore, subject to their own convictions and tend to make decisions based on their own emotional state. Ultimately, in order to separate decisions based on human emotions or cognitive dissonance, technical analysis can play an important role to help investors identify certain market turning points (Benartzi, 2013:3; Credit Suisse, 2010:5-6).

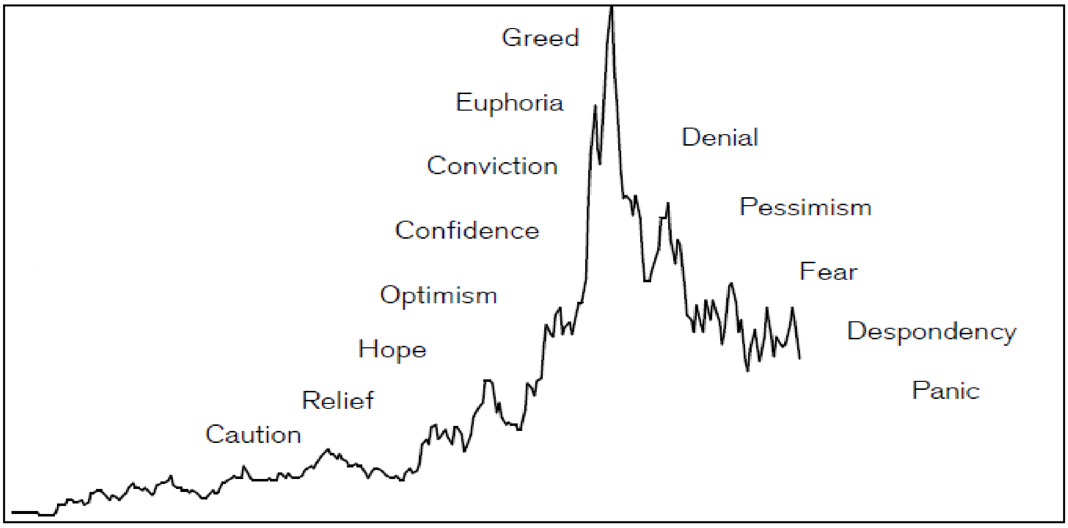

Figure 3.1: Human emotions in a changing market cycle
Source: Credit Suisse (2010:1)

Technical analysis and behavioural finance may, therefore, be seen as synergetic, since both tend to capture rational and irrational return expectations reflected through both fundamental (intrinsic value) and psychological (emotional) factors (Credit Suisse, 2010:5-6). Technical analysis incorporates both through the assumption that the reflected price statistics automatically include intrinsic value and emotional factors, whereas behavioural finance shows that irrational trading causes deviations from the fair (rational) intrinsic value, which cannot always be explained by rational pricing models. The aim of this review is, therefore, to provide an overview of studies wherein returns obtained by means of technical analysis were evaluated.

The initial developers (see Section 3.2.3 and Section 3.2.4) of the EMH and subsequent advocates[20] of the EMH, especially from an academic point of view, tend to immediately write off the possibility of excess returns by means of technical analysis with a statement like, "*technical analysis has no value*". They argue that technical analysis makes use of historical price data to identify patterns or trends, whereas even weak form efficiency states that current market prices already incorporate all relevant information contained in historical price levels and volumes of trade. This conviction by staunch EMH supporters sometimes comes over so strong that they seem to rule out any potential profits obtainable from applying technical analysis. Van Horne and Parker (1968:128) already stated that the random walk hypothesis does not rule out profits from applying technical analysis, only that these profits would not exceed that of a buy-and-hold strategy.

It is, therefore, to be expected that technical analysis research results also report conflicting findings, as is the case with market anomalies and behavioural finance. Technical analysis research pertaining to EMH tests for independence usually consisted of some form of statistical model until Alexander (1961:26) deployed a mechanical filter trading rule that tested percentage changes in market price movements. With this finding, Alexander (1961:26) stated that, although prices may follow a random walk, these random movements tend to persist once they have set off in a specific direction. Mandelbrot (1963:417-418) criticised the findings by Alexander (1961) by stating that it will be easy to make a substantial profit if it is assumed that a trader can always trade at specific turning points or levels, thereby realising biased results. Alexander (1964) reworked his results and took some of these biases into account. Profitability was reduced dramatically but still produced returns slightly in excess of a buy-and-hold. However, the method still neglected to consider commissions and evaluated stock indices instead of individual stocks (Pinches, 1970:106). Fama & Blume (1966:240) also applied the filter rule and included dividend payments. They found that, when trading costs were included, filter transactions did not show any indication of possible increased profits for investors. In related studies, Van Horne and Parker (1968), as well as James (1968), deployed numerous trading rules based on moving averages

[20] Early examples of such statements include Jones (1985:433), Reilly (1985:197), and Haugen (1986:469).

and found no evidence that these technical rules produced returns in excess of a buy-and-hold strategy.

The study by Levy (1967b:69), on the other hand, stated that statistical tests of independence are not able to detect non-linear patterns observable by technical chartists and found that technical analysis is useful to forecast market price movements, since prices follow evident trends and patterns. Nevertheless, Jensen (1967:78) queried the findings by Levy (1967b). He based his disbelief in results on certain errors made by Levy (1967b), which overstated the profitability of the trading rules. However, he was not able to explain the corresponding excess returns even after he had adjusted for risk. He concluded that, in order to verify the persistence of the results obtained by Levy (1967b), the method should be replicated on other data sets for different time periods. This prompted Jensen and Benington (1970:470) to re-evaluate two of Levy's trading rules, which were especially profitable beyond the returns obtainable from a buy-and-hold, over a much longer period. Results showed that, if returns were adjusted to include trading costs, the trading rules could not generally outperform a buy-and-hold strategy (Jensen & Benington, 1970:481).

The filter trading rule foundation set by Alexander (1961) nevertheless remained a benchmark study which soon spilled over to other markets than the stock market to test for excess return by means of technical analysis. For example, Stevenson and Bear (1970:75-79) expanded their analysis to the July corn and soybeans contracts on CBOT (Chicago Board of Trade). Overall, they found that the stop-loss orders strategy and the combination with filters resulted in substantial excess returns when compared to a buy-and-hold strategy. Also, when the strategy was adapted to trade against the market trend, very poor results were obtained in contrast to trading or going with the market trend. Another application, to the foreign exchange market this time, was done by Sweeny (1986:163). He expanded the traditional filter tests by considering risk, transaction costs, as well as post-sample performance. Despite the fact that he did not consider interest rate differentials, results indicated that smaller filters in particular showed superior returns when compared to a buy-and-hold strategy, even after transaction costs had been included.

These studies were not the only studies confirming the profitability of trading rules in futures and foreign exchange markets. For futures markets, Irwin and Uhrig (1984) and Taylor (1986) confirmed technical trading rule profitability after Stevenson and Bear (1970), while Poole (1976), and Cornell and Dietrich (1978) provided a foundation for the profitable results obtained by Sweeny (1986) on the foreign exchange market. Arguably, these early results seem to indicate that technical trading rules applied to the futures and foreign exchange market produced successful and profitable results, whereas limited profitability was achieved in stock markets. Consequently, the conclusion may have been drawn at the time that stock markets were more efficient than the futures or foreign exchange market.

However, these early studies may not have been as thorough as the researchers may have thought at the time. According to Park and Irwin (2004:24-25), several methodological aspects were omitted that could have altered or improved the results obtained by these studies. Firstly, the studies relied on only the filter or moving average trading method, thereby introducing model selection bias. Secondly, the risk introduced by implementing these trading rules was largely ignored. Thirdly, the profits obtained by means of technical analysis were not always tested for significance by some form of statistical test. Fourth is the fact that the process of identifying an optimal filter size may also have been biased, since it was based on a specific data set and did not imply that the result would remain constant for in and out-of-sample data. Fifth, different benchmark returns were used to compare technical profits and no consensus on specific benchmarks for different markets was established. Lastly, the fact that returns for a technical trading rule were usually given as an average across all trading rules or all assets evaluated, made results difficult to interpret. Consequently, specific stocks, futures or currencies which would have realised improved results from specific filters were impaired by the averaging of returns across all filters for a given stock or all stocks for a given filter.

These limitations of previous studies were soon addressed by researchers and a first attempt at a more comprehensive study was done by Lukac, Brorsen and Irwin (1988:623). They found that the trading systems they deployed were able to generate excess return after adjusting for risk. Shortly afterwards, these results were confirmed by Lukac and Brorsen (1990:593), who applied the same method but to an extended number of commodities and other test periods. Other studies that made use of the same type of methodology largely focused on the foreign exchange market. For example, Taylor and Tari (1989), Taylor (1992, 1994), Silber (1994), and Szakmary and Mathur (1997) all provided empirical proof of excess annual returns for currency futures by means of technical analysis; predominantly for the period of 1970 to 1990. Furthermore, Menkhoff and Schlumberger (1995), Lee and Mathur (1996a, 1996b), Maillet and Michel (2000), Lee, Gleason and Mathur (2001), Lee, Pan and Liu (2001) and Martin (2001) confirmed the profitability of technical analysis in the different periods they considered. Nevertheless, the profits obtainable from technical analysis seemed to gradually decrease over time. Olson (2004:85) found that risk-adjusted returns obtainable from technical trading strategies in currency markets declined from just over three per cent in the 1970s to almost zero in the 1990s. Kidd and Brorsen (2004:159) attributed this reduction to structural changes in the futures market, which caused a decrease in price volatility and consequent lower returns for technical analysis.

Despite this apparent reduction in obtainable profits, these studies seemed successful overall in showing that excess returns were obtainable by means of technical analysis. However, they still did not address the issue that results could not be tested for significance. Brock, Lakonishok, and LeBaron (1992:1743) addressed the fact that return distributions were generally leptokurtic, autocorrelated, conditionally heteroskedastic, and time-varying after statistical resampling by means of bootstrapping[21]. The bootstrap results exhibited significant differences between buy and sell returns generated by means of technical trading rules that were not equal to zero.

As a result, the bootstrap-based model stimulated research across markets and different sample periods. Amongst others, Bessembinder and Chan (1995), Ratner and Leal (1999), Coutts and Cheung (2000), and Gunasekarage and Power (2001) provided evidence that technical trading rules produced profitable results for both spot and futures stock indices of emerging markets, even after transaction costs had been taken into consideration. However, almost the opposite result was found for developed markets, with negligible or decreasing technical trading profits that found by studies by the likes of Hudson, Dempsey and Keasey (1996), Mills (1997), Bessembinder and Chan (1998), and Day and Wang (2002).

Notwithstanding this improved methodology, these studies still lacked optimised trading rules and out-of-sample verification, and were still subject to results obtained from apparent data snooping[22]. White (2000:1098-1099) addressed these issues by developing a statistical procedure, called the Bootstrap Reality Check method. This method tests whether the best trading rule performs any better than a benchmark strategy. Initially, Sullivan, Timmermann and White (1999:1649) applied the Bootstrap Reality Check method to the same data period used by Brock, Lakonishok and Le Baron (1992). They were able to add 10 years to the data set that was used as an out-of-sample test period. Results proved to be robust to data mining. However, despite the fact that they were able to find a 'best rule' which realised significant excess returns, the rule did not continue to realise the same results in the

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21 Bootstrapping as a method was developed by Efron (1979). The method forms part of statistical resampling where several samples are drawn from a generated data series to ensure a thorough understanding of the main statistic values from the collective values of the samples. The specific study used an artificial Dow series as a population and evaluated several samples compiled from it. The returns from the application of the trading rules to these simulated series were then compared to the actual Dow Jones series returns based on the same trading rules (Brock, Lakonishok, & LeBaron, 1992:1733).

22 Data snooping (data mining) occurs when the same data set is used more than once to draw a conclusion from the evidence or for model selection. Consequently, any results may be obtained by pure chance rather than by the method applied to obtain the results (White, 2000:1097).

subsequent out-of-sample period. Sullivan *et al*. (1999:1684) argued that the reason for the poor out-of-sample results might have been improved market efficiency, cheaper and more accessible computing power, lower transaction costs, and increased liquidity in the market. Shortly afterwards, Sullivan, Timmermann and White (2003:217-218) expanded the study by including calendar anomalies as trading rules. Different optimal rules were identified that realised statistically significant returns for the sample period, but yet again failed to do so for the out-of-sample test period.

Over time, the success rate of technical trading strategies to realise excess risk-adjusted returns declined to almost zero in the 1990s. This tendency provided academics with a greater argument against the sustainable use of technical analysis. Tian, Wan and Guo (2002:3-4) for example, found that the rules showed no predictable power for the more efficient US market after 1975, whilst the comparatively less efficient Chinese market exhibited predictability and profitability throughout the 1990s. Cai, Cai and Keasey (2005:45-46) extended the study by Tian *et al.* (2002) by including the UK market, Hong Kong market, and the Japanese market, and confirmed that trading rules had had predictive power during the 1970s, but for developed markets profitability had gradually decreased and disappeared by 1990.

This gradual decline in technical analysis profitability after 1990 was, however, not reported universally. For example, McKenzie (2007:69-70) evaluated the efficacy of trading rules for emerging markets, as well as the US market as a developed market benchmark, and found that the level of return persistence for emerging markets was far greater than for developed markets. The results did show that the forecasting ability of trading rules deteriorated after the 1997 currency crisis and that this forecasting ability was strongly related to the depth and consequent liquidity in the market. In addition, studies by Neftci (1991), Nauzer, Kathleen and Rao (1996), Rodriguez, Rivero and Felix (1999), Kwon and Kish (2002), Wong, Manzur and Chew (2003), Vasiliou, Eriotis and Papathanasiou (2008) and Yu, Nartea, Gan and Yao (2013) all provided empirical support in favour of the profitability of technical trading rules. These studies considered various markets around the world, including emerging and developed markets, as well as large and small market capitalisation stocks.

There are also several studies contemplating the applicability of technical analysis from a South African market perspective. Roberts (2009:25) showed that the trend-following systems indicators were able to outperform a buy-and-hold strategy. He noted that a great portion of the returns generated by the indicators could be attributed to market conditions and particularly to the major general market collapse experienced during the sub-prime credit crisis of 2008 (Roberts, 2009:71). The trend following indicators applied in the study was, however, beneficial to the profitability of technical analysis in the aftermath of the credit crisis. If the crash had not occurred, the buy-and-hold strategy would have outperformed the technical strategies even if all technical analysis parameters had been optimised. In a related study, Du Plessis (2012:6) also made use of a single basic technical indicator to compare the result of an active trading strategy to a basic buy-and-hold strategy. Results showed that a buy-and-hold strategy could not be outperformed by the technical strategy.

An alternative approach to comparing a buy-and-hold strategy to technical trading strategies was presented by Mashiqa (2014:12). This study compared the effectiveness of technical and fundamental analysis when making investment decisions, as well as if a complementary relationship between the two processes of analysis existed. Results showed that technical analysis explained JSE returns better than both fundamental analysis and a complementary approach. However, Mashiqa (2014:53) noted that technical analysts should be wary of relying solely on specific fixed technical analysis approaches, since they may not be evident in the data or remain relevant over time.

Another relevant study with specific reference to the SAFEX July white maize futures contract was done by Geldenhuys (2013:11). The aim of the study was to develop a composite technical indicator that could aid producers with the timing aspect of price risk management decisions, with particular reference to hedging decisions. Results showed that a composite indicator, which assigned more weight to the correct type of indicator for the specific market type, provided superior results with the least amount of hedging signals over time and the highest average hedge level obtained over the thirteen production seasons evaluated (Geldenhuys, 2013:110).

From the literature presented above, many studies provided empirical evidence in favour of the use of technical analysis, while some of the opposing studies presented a very convincing case that mostly pointed out the flaws and limitations of the different technical analysis approaches. There also seemed to be a very strong argument showing that the use of technical analysis became unprofitable during the 1990s. This trend was, however, not an indication of the use of technical analysis as an investment decision tool. Several survey studies determined the view by market practitioners on the use of technical analysis. Surveys by Group of Thirty (1985), Brorsen and Irwin (1987), Frankel and Froot (1990), Taylor and Allen (1992), Menkhoff (1997), Lui and Mole (1998), Cheung and Wong (2000), Cheung, Chinn and Marsh (2000), Cheung and Chinn (2001), and Oberlechner (2001) were amongst these studies. All of these surveys showed that technical analysis was used to a great extent in the futures and foreign exchange markets with 30 per cent to 97 per cent of respondents regarding technical analysis as an important factor for identifying trends and turning points, especially in the short to medium time frame of six months.

Despite the fact that these survey studies show that almost all market participants and even professionals in the futures and foreign exchange market make use of technical analysis to at least a small degree, there is no evidence that they behave irrationally or ignore the risk involved when using technical analysis. Menkhoff and Taylor (2007:967) stated that one explanation for the continued use of technical analysis is that it is able to provide traders with information about non-fundamental price determinants. Arguably, technical analysis will most probably remain an important part of an investment analyst's decision-making toolkit. With this in mind it may, therefore, be beneficial to understand the use of technical analysis and how it may be incorporated into economic reasoning before writing off its applicability and utility. The result of such cognitive dissonance by EMH supporters with regard to technical analysis may in actual fact lead to the heuristic of representativeness or anchoring in favour of the EMH.

This does, however, not imply that market practitioners who make use of technical analysis can sit back and rest on their laurels. Technical analysis still does not provide a method that would always work perfectly for all market types, data sets, and different periods. The search for and development of technical trading strategies that can stand the test of time, will remain ongoing in the search for excess returns. To conclude, proof of market anomalies (Section 3.2.4.2), an explanation of market anomalies in the form of behavioural finance (Section 3.2.4.3), and technical analysis (Section 3.2.4.4) which incorporates behavioural finance, were not able to provide a concrete alternative to the EMH as challenged by Fama (1998), but did present proof which should not merely be written off.

As a result, the challenge by Fama (1998) became an important caveat for market anomalies, behavioural finance, and technical analysis. Lo (2004:15-16), for instance, referred to the EMH as "*a deceptively simple notion that has become a lightning rod for its disciples and the proponents of behavioural economics and finance*", causing "*far-reaching consequences for academic theories and business practice; and yet is surprisingly resilient to empirical proof or refutation*". He, however, presented a hypothesis that he called the Adaptive Market Hypothesis (AMH) and introduced it as an alternative hypothesis in an attempt to combine and reconcile EMH and behavioural finance schools of thought. This new approach by Lo (2004) presented a testable alternative hypothesis to the EMH and merits further review of available literature in order to present a potentially complementary, and universally acceptable hypothesis as requested by Fama (1998:291).

3.2.6 The Adaptive Market Hypothesis (AMH)

Throughout the literature review presented above it becomes evident that even market efficiency seems to evolve over time, not just from a definition point of view, but also through new and improved tests of significance and the level of robustness of either EMH tests, market anomaly findings, or behavioural finance conformations. This evolution in itself may best be described by Self and Mathur (2006:3154), who wrote: "*The true underlying market structure of asset prices is still unknown. However, we do know that, for a period of time, it behaves according to the classical definition of an efficient market; then, for a period, it behaves in such a way that researchers are able to systematically find anomalies to the behaviour expected of an efficient market*."

The AMH approach may, therefore, be seen as an application of evolutionary principles to economic contexts and financial markets. Lo (2004:21-22) builds on the "evolutionary psychology" principles presented by Wilson (1975), called "Sociobiology". From there he presented a compelling case from existing literature where the connections between biology and economics were explored. He argued that valuable insights may be derived from a biological perspective ranging from evolutionary game theory, evolutionary economics, and economics as a complex system, to behavioural ecology. From a financial context the link to evolutionary concepts, like the implications of natural selection of futures markets and the long-run prospects of overconfident traders, were also reviewed. As a result, Lo (2004:22) proposed his new AMH as an alternative wherein the EMH and behavioural finance could co-exist. However, the AMH development did not occur overnight and largely stemmed from the work by Farmer and Lo (1999), as well as Farmer (2002), who viewed financial markets as an ever-evolving social and biological environment.

This notion built on the work by Simon (1955), which considered bounded rationality with an economic context. Lo (2004:22) drew the link to evolutionary dynamics and argued that, when faced with changing circumstances and a decision to optimise these circumstances, an individual would not make a decision analytically, but rather through past experiences based on trial and error; and ultimately become subject to natural selection or, more specifically, survival of the fittest. Therefore, many behavioural biases may be explained by evolutionary models wherein individuals learn and adapt to an ever-changing environment by satisfying certain heuristics. Although these behavioural biases may then be labelled as irrational behaviour, they are usually viewed separately from an evolutionary context or certain circumstances. Lo (2004:22) explained this notion by means of the following visualisation: "*The flopping of a fish on dry land may seem strange and unproductive, but underwater, the same motions are capable of propelling the fish away from its predators.*"

With this notion in mind, the contradictions between the EMH and behavioural finance, as well as certain adaptions to changing environmental conditions, like competition, cooperation, market-making behaviour, general equilibrium, and disequilibrium dynamics, may be better understood. From this background and line of thought, Lo (2004:23) formally defined the AMH as follows: "*Prices reflect as* *much information as dictated by the combination of environmental conditions and the number and nature of "species" in the economy or, to use a more appropriate biological term, the ecology.*" Within this context, "species" referred to different market participants, like pension funds, retail investors, market makers and hedge fund managers. If the ecology is then seen as the market, different species in the marketplace are then competing for scarce resources in the form of profit opportunities. If these profit opportunities are ample, the competition in the marketplace may not be so fierce. However, as more market participants become aware of these opportunities, the opportunities become exploited and depleted by increased competition. As a result, the conditions in the marketplace change to a point where certain species or participants become "extinct" (leave the market after suffering a certain level of losses), ultimately reducing competition and causing a recurrent cycle as scarce resources recover over time.

Therefore, competition in the marketplace may be compared with market efficiency, which increases as participation increases and profit opportunities diminish and *vice versa*. Consequently, different investment strategies will undergo cycles of profitability and loss, which may be linked to periods of market inefficiency and periods of market efficiency as market conditions change over time and market participants enter and leave the industry or market. Also, the profitability of investments, businesses and industries, as well as the level of efficiency in the marketplace are, therefore, determined by the impact of the evolutionary forces on financial institutions and market participants (Lo, 2004:23-24).

Lo (2005:31) wrote a follow-up article wherein he stipulated the primary components of the AMH. He briefly stated that market individuals will act in their own self-interest, and will make mistakes from which they will learn and adapt. This adaption and consequent innovation would largely be driven by increased competition, which would lead to natural selection and the shape of the market ecology from where evolution would determine the market dynamics. Arguably, the AMH still remains a qualitative and abstract approach, but a number of practical applications may be derived that are relevant to investment and, specifically, portfolio management. The first is the relation drawn between risk and reward in the sense that it does not remain constant over time, since the market environment and the demographics of investors in that environment change over time. This causes a shift in participants' risk preferences and a consequent varying risk premium. Secondly, contrary to the EMH, opportunities to realise excess profit from arbitrage opportunities do arise under the AMH, otherwise there would be no incentive for market participants to obtain valuable information. However, as more and more participants become aware of the discrepancy, they are usually exploited and the opportunity gradually disappears. This does not mean that all opportunities disappear altogether, just that opportunities come and go as the market environment changes and different market participants enter and exit the marketplace (Lo, 2004:24-25).

The AMH is, therefore, able to accommodate occurrences, like trends, manias, bubbles, crashes and other market anomalies usually associated with extreme market conditions, without assuming that the market will always return to some ideal market equilibrium associated with perfect efficiency. A third, fairly logical progression of the first two implications is that not all investment strategies will always be profitable in all market environments. As profitable opportunities fade or market environments change, different strategies may also be subject to changing business conditions, the adaptability of investors, the number of competitors in the industry, and the magnitude of profit opportunities available. The last two implications are innovation and survival. This implies that, in order to survive, the best way to achieve a stable return is to continuously adapt to changing market conditions. Ultimately, the objective that matters for the evolution of markets and financial technologies is survival (Lo, 2004:24-25).

Lo (2005:32-38) expanded on these applications with more detail as to what aspects may ensure survival. He referred to the proper measurement and management of investors' preferences. This may even involve the measurement of the more fundamental aspects of investors' personalities, like considerations of temperament that may be linked to risk preferences and investment decisions. From these risk preferences, a more relevant asset allocation and decisions about passive or active portfolio management approaches may be drawn. If an investor seeks to build wealth, it would be crucial to actively manage the general investor preference. Also, as the institutional aspects and regulatory environment within the market ecology change, the risk/reward relationship of investors is also likely to change with a direct influence on the risk premium considered. Therefore, as the investor population, investors' preferences, and environmental conditions change – and if these changes can be measured meaningfully – it would be possible to construct an actively managed portfolio that will be more suited to meeting investors' financial objectives. This does, however, not imply that asset allocation will be less challenging, but it does provide a rationale for the consideration of the cyclical nature of risk premiums when deciding to actively manage a portfolio.

Another observation which can be rationalised within the AMH is the mounting empirical evidence showing that market efficiency is not a static phenomenon. Initially, Emerson, Hall and Zalewska-Mitura (1997:75) tracked the degree by which the market efficiency of a developing market changed over time. They found that, if the smoothed time-varying estimate of the autocorrelation coefficient gradually converges to zero, the market becomes more efficient over time. Shortly afterwards, Zalewska-Mitura and Hall (1999:1-2) formalised an econometric tool that tests how markets evolve and become more informationally efficient. By evaluating both developed markets and emerging markets, they found that the level of market efficiency gradually improved as market participants become more experienced and the market systems developed over time. The results of these studies could also indicate the time paths of the different developing markets towards a higher level of efficiency.

Subsequent studies by Rockinger and Urga (2000, 2001), Zalewska-Mitura and Hall (2000), and Schotman and Zalewska (2006) evaluated the evolving efficiency of other Central and Eastern European transition economies by means of the same type of methodology. The method was soon applied to other markets that were not necessarily emerging markets. Jefferis and Smith (2004, 2005) applied the methodology to African Stock markets, Li (2003a, 2003b) to Chinese stock markets, and Pierdzioch and Schertler (2007) to European stocks. All of these studies showed varying degrees of market efficiency over time. Interestingly, Ito and Sugiyama (2009:62) evaluated the degree of time-varying market inefficiency for the US stock market from 1955 to 2006 and found that the relevant inefficiency of what was considered a developed market varied throughout the period. A further application was to show that the rate at which market prices adjusted to new information was also time varying (Chelley-Steeley, 2001, 2003, 2005, 2008; Chelley-Steeley & Lucey, 2008). Also, the varying predictive ability of financial variables within traditional predictive regression models was highlighted by Paye and Timmermann (2006), Rapach and Wohar (2006), Lettau and Nieuwerburgh (2008), and Hjalmarsson (2010). Therefore, the application of methodology that captures the time-varying component of return predictability and subsequent market efficiency essentially shows how stock prices depart from the benchmark set by the EMH.

This ever-evolving change in market efficiency and return predictability as pre-empted by the AMH was also evaluated by Neely, Weller and Ulrich (2009:468-469), when they considered several technical trading rules applicable to the foreign exchange market. They specifically considered the finding that these rules were able to generate excess returns up to the mid-1980s, from where the excess profits deteriorated up to the mid-1990s. Results showed that the initial returns identified by previous studies were in fact genuine and not the results of data mining. Also, as competition in the market increased these profits were in fact exploited to such an extent that the market actually became more efficient and the profit opportunities based on the specific trading strategies all but ceased. Interestingly, the fact that these profit opportunities declined at a much slower rate than what would have been consistent with the EMH, was attributed to institutional and behavioural factors. Neely *et al*. (2009:482) connected the findings to the guidelines and implications of the AMH in the general sense, that markets adapt to evolutionary selection pressures. Another technical analysis evaluation was done by Todea, Ulici and Silaghi (2009:7), when they determined the profitability of moving average strategies. Results showed that even the optimal trading strategies were not profitable throughout the period, but that the profitable periods could be linked to periods when linear and/or non-linear dependencies were observed. The study concluded that market efficiency varied cyclically over time and conformed to the statistical features advocated by the AMH (Todea *et al*., 2009:11).

A related study, which also aimed to identify periods of efficiency versus inefficiency, was done by Alvarez-Ramirez, Rodriguez and Espinosa-Paredes (2012:5643). Results showed that market efficiency gradually improved from 1930 to 1970 and increased to a point where departures from 100 per cent efficiency were no greater than five per cent. This period may also be associated with market efficiency transformational years, when Fama (1970) formalised the EMH. However, the 1987 market crash immediately moved market efficiency to a point even greater than 25 per cent away from 100 per cent efficiency. Interestingly, the Fama (1991) review paper observed the mounting evidence of market anomalies throughout the 1980s. Undoubtedly, the market was under the preliminary and aftermath effects of the crash. Since then, market efficiency has shown signs of deterioration, relative to the 1970 to 1987 period, especially after the credit crisis and subsequent economic recession of the late 2000s. Alvarez-Ramirez *et al*. (2012:5646) also concluded that certain events affect market efficiency negatively, since profit expectations decline and the corresponding bearish conditions usually lead to some form of market evolution. Subsequent events may lengthen and increase the level of market inefficiency, but over time the negative effects are dampened by increased market participation, leading to increased market efficiency. Ultimately, the results were in line with what the AMH postulates, in the sense that market efficiency varies continuously over time and across markets.

From these studies it becomes evident that, although the AMH is still a very new approach when compared to the EMH, the applications of the AMH becomes a viable alternative to the EMH, since it is able to accommodate inconsistencies, like market anomalies and behavioural finance traits that could not be reconciled in the EMH framework. Therefore, when economic conditions are stable and predictable, markets generally function efficiently and the EMH presents a fitting picture of reality. However, when market conditions become more dynamic and behavioural features start to influence price formation, the AMH provides a more integrated framework from where investors could gain valuable insights as to investment decisions during unstable economic conditions and associated market turmoil. Also, it provides a logical explanation as to why market structures are always adapting to changes caused by natural disasters, economic recovery or recession, political implications like regime changes or instability, and even social events like globalisation that can disrupt the market dynamics. Arguably, these markets dynamics are never static; therefore, it will not be wise to assume that factors like expected returns, market volatility, liquidity, investors' expectations and subsequent market efficiency will remain static over time. Those market participants who remain static and not willing or able to adapt to changing economic and subsequent market conditions, will not survive. The inevitable result is that markets are moving through cycles of increased and decreased levels of efficiency.

These characteristics of the AMH provide an important foundation in support of the academic viability of two of the study objectives. These specific objectives are the back testing of hedging strategies for the July white maize futures contract from 2003 to 2018, as well as the potential linkage of similar market circumstances based on influential fundamental factors, to specific hedging strategies in order to determine preferred or optimal strategies given the seasonal outlook and expected circumstances. From a pure EMH perspective, these objectives will be futile, since past data will be used to compare optimal strategies and to link different seasons to each other by means of similar fundamental characteristics. Also, the continuous change in influential fundamental factors within a production season (Chapter 2, Section 2.4), provides the necessary information that a maize producer may base his hedging decisions on. The way that the white maize market price adapts or changes in accordance to changes in these influential factors mostly remain the same or re-occur over time.

The reason for the similarity in the reaction of market participants may be based on certain heuristics which tend to remain fairly constant. For instance, adverse changes in weather conditions will directly affect production conditions and subsequent realised supply at harvest. As a result, a participant's decision-making process in terms of price risk management may be influenced by specific heuristics such as availability or anchoring. They may therefore base their hedging decision on their own personal experience or prediction of the impact of the changes in weather conditions. Despite the initial reaction by market participants to changes in influential factors, it is also to be expected that as a marketing season progresses, and the actual impact of the changes in influential market factors become known, volatility would tend to stabilise and a more efficient market would present itself. Therefore, even in the shorter seasonal cycle of a white maize production season, the implications of the AMH seem to present the model as a logical explanation to the evolution of market efficiency.

This does not imply that the white maize market operates as an inefficient market throughout a production season until the impact of changes in influential market price drivers become more probable or known. In fact, no white maize producer would be able to transfer price risk through hedging or actively manage his hedged position if the white maize market were not at least weak-form efficient or able to facilitate the necessary liquidity. This may render producers unable to deploy any hedging strategy successfully. It is for this specific reason, and to highlight the importance of the literature pertaining to white maize market efficiency, that the relevant literature is presented separately from the rest for the subsections on market efficiency.

3.3 White maize market efficiency in South Africa

When considering the concept of white maize market efficiency on the JSE Commodity Derivatives Market, the notion takes on a whole new perspective. Firstly, because white maize forms an integral part of food security in South Africa, as well as in other African countries (Lyne, Hendricks & Chitja, 2009:1-2). Secondly, because futures contracts fulfil important economic functions which contribute to sustainable food security. These functions include that futures markets provide producers with the means to hedge and manage their price risk through a central marketplace for price discovery (Hasbrouck, 1995:1175; Srinivasan & Bhat, 2009:29). Also, futures contacts may be used by speculators, which in turn provide liquidity and improved price discovery, and a means to store seasonal commodities and reduce volatility (Marshall, 1989:52-54; Phukubje & Moholwa, 2006:199).

However, the premise of white maize market efficiency, which conforms to these attributes, has been questioned both intuitively and analytically. Intuitively, maize producers are afraid that the price will increase after they hedge their expected produce due to excessive speculation and manipulation in the market. Also, producers were found to be reluctant to make use of hedging practices due to bad experiences, either their own or that of others (Jordaan & Grove, 2007:561). Other reasons like regime or institutional changes, farm size, age, education, farm location and – very significantly – the differences in producers' risk perceptions, were also identified by Ueckermann *et al.* (2010:233-234) and Woolverton (2007:5). Arguably, the futures market function of providing transparent price discovery is not a sentiment generally supported by producers.

This intuitive derivation was, however, evaluated analytically by Behar (2011:2) when he tested whether South African maize producers were risk averse, whether their response to price changes had changed since deregulation in 1996, and if their ability to manage price risk had changed since the introduction of a free market system. Behar (2011:14) found little evidence that producers' response to price changes had changed over time or that it differered significantly from the Maize Board fixed price setting regime. The study, therefore, questioned the price discovery mechanism of SAFEX and stated that futures prices were influenced by a number of additional factors that would affect the expected price and warranted caution. However, despite the observation of increased price risk and the presence of more volatile prices since deregulation, the study found robust evidence that SAFEX has provided producers with the means to manage their price risk.

Therefore, it seems evident that SAFEX provides enough liquidity for white maize producers to enter into and to manage some form of price risk management strategy despite the apparent high levels of volatility. However, when it comes to price discovery, producers do not seem to be convinced that the white maize futures price is a reliable estimate of the spot price they may expect during harvest. This questions the effectiveness by which the spot and futures markets incorporate new information into the respective price formation of both contract types. Over the past 22 years since deregulation, a few studies have dealt with the premise of white maize market efficiency. Section 3.3.1 provides a literature overview of these specific studies, their specific findings, and the implications thereof for the market as a whole.

3.3.1 Testing for white maize market efficiency

The study of white maize market efficiency may be regarded as a relatively new and developing field of study. Given the relatively short time span that has elapsed since deregulation in 1996 (Section 2.2.2.4), the South African agricultural market may be regarded as a developing or emerging market. Until recently, the efficiency of white maize with reference to the price discovery function of the market has not been investigated extensively. Interestingly, the US corn contract, which has been trading on CBOT since 1877, is considered to be efficient or, more specifically, weak-form efficient (Yang & Leatham, 1998:111; McKenzie & Holt, 1998:9). However, as volatility increased and predictability of the spot and futures contract convergence decreased from 2006, critics started to doubt the market's efficiency and especially its function of price discovery (US Senate, 2009). Undoubtedly, and consistent with the premise of the AMH, market participation actually increased as reflected in the increased volume of contracts traded on US markets since 2006. A later study by Armah and Shanmugam (2013:67,73) already showed that the market for agricultural commodities provided efficient price risk management opportunities for market participants. Arguably, it is to be expected that, since 1996, the South African white maize market would have progressed to a higher level of efficiency with reference to the AMH.

From a South African perspective, the first study on white maize market efficiency was conducted by Wiseman, Darrock and Ortmann (1999:322). This study was limited in a sense by the availability of reliable spot price data at the time, as well as the fact that only two production seasons had transpired since deregulation in 1996. Initially, it was found that market participants would have been able to realise abnormal profits from past data for the 1997 July white maize futures contract. However, the presence of a long-run relationship between the spot and the futures contract was observed for the following production season (Wiseman *et al*., 1999:332). They concluded that the changes in observed co-integration may be seen as an indication of the elimination of certain inefficiencies as market participants started to come to terms with the new marketing mechanism and liquidity subsequently increased.

A second study of relevance was conducted by Moholwa (2005:9-10) when he evaluated the efficiency of both white and yellow maize traded on SAFEX from 1999 to 2003. The results showed that there was autocorrelation between futures prices, indicating that past prices could have been used to predict future price changes. There was also no indication that this observed predictability deteriorated over time. However, when trading costs and the time value of money was included and the out-of-sample predictive performance was evaluated, he found that it would not be profitable to base trading strategies on the observed predictability. In this light, the market was deemed consistent with an efficient market (Moholwa, 2005:20-21). A related study on the market efficiency of wheat and sunflowers for the period 2000 to 2003 by Phukubje and Moholwa (2006:210-2011) realised mostly the same results.

All of these initial studies admitted that a limitation of their studies was the fact that they had to make use of the continuous or cash contract traded on SAFEX as a proxy for spot prices. The limitation of a spot price is that is does not necessarily include the actual basis or cash prices used in the physical market. McCullough (2010:57) also noted that these studies to a great extent only evaluated co-integration and that the methodology may have been improved by using more sophisticated error correction models in conjunction with the finding of co-integration. She argued that, although the relation between co-integration and error correction was significant, the direction of information flow or the causality between the spot and futures market could also have been established. Following through on this observation, McCullough (2010:9) endeavoured to conduct the first longer term study on white maize market efficiency. This study aimed to determine the relationship between the spot and futures market, as well as to establish which contract was the point of price discovery.

The study examined the spot prices, as well as a constructed white maize futures contract price series as realised through trading on SAFEX. Three main conclusions were drawn after applying an array of techniques to determine stationarity, co-integration, and causality. The first was that co-integration existed between the spot and futures series, confirming the presence of a long-run relationship to ensure that information passed between the spot and futures price so that price discovery may take place. Secondly, the relationship between the spot and the futures market in terms of the direction of information flow was also established. These tests confirmed that price discovery was evident in these markets but that it was in actual fact the spot market that led the futures market (McCullough, 2010:126). Thirdly, an additional finding was established through the specified application of the error correction models in the sense that the SAFEX futures market for white maize did not contain a risk premium, meaning that the futures market could be regarded as an unbiased predictor of expected spot prices (McCullough, 2010:69).

Arguably, the study by McCullough (2010) provides a very compelling case in favour of at least weak-form market efficiency, especially when information transfer between the spot and the futures market is considered. Also, the effectiveness of the white maize futures contract as an unbiased predictor of the expected spot price dampens doubt that the futures contract may be used to effectively hedge price risk. However, this notion of effective hedging may only pertain to traders or potential storing of white maize, since the futures contract evaluated was a combination of the futures contracts traded on SAFEX and not specifically the main producer hedging month of July. Furthermore, as admitted by McCullough (2010:131), no forecasting function was evaluated, despite the fact that the econometric analysis showed that the spot prices were in fact influenced by past prices and futures prices were only slightly affected by their own past values (McCullough, 2010:119). In light of the finding that spot prices lead the futures market in price discovery, a very logic derivation would be that if a forecasting model for spot prices could be established, expected futures prices would most likely also be predictable.

A study which leaned towards this notion was conducted by Auret & Schmitt (2008:105), who derived an explanatory model for white maize futures prices. In its simplest form, this explanatory model is a forecasting model, which incorporates the relationship of various sources of information in the form of variables in order to attempt to explain white maize future price changes. The constructed model showed signs of autocorrelation and it was decided to include a third independent variable in the form of the one period lag of the white maize futures price series. The new model showed an improved confidence statistic, meaning that a higher portion of the variation in die white maize price was accounted for in the model. The eventual model was, however, subject to the presence of autocorrelation (Auret & Schmitt, 2008:125-126). Despite the presence of autocorrelation, Auret & Schmitt (2008:129) evaluated the forecasting ability of the model on a 12-month out-of-sample data series and found the results of the model to be surprisingly accurate.

Another study providing evidence of certain predictabilities in the white maize futures market was presented by Kirk (2007). The aim of the study was to determine if there was an observable seasonal component in white maize futures prices. The study provided two interesting results from the empirical analysis. Firstly, that the white maize futures price tended to peak in the March contract and dip in the July contract of each season. Secondly, that the white maize futures price exhibited contango behaviour (Kirk, 2007:84). A related study by Heymans (2008), also evaluated the seasonal component in the white and yellow maize contract prices traded on SAFEX. The main aim, however, was to determine if different white and yellow maize contract combinations ranging from the spot contracts to the different futures contracts moved together in order to derive a pairs trading strategy. The study found seasonal patterns for both the white and yellow maize contracts, which conformed with the expected reactions of the market to changing supply and demand conditions. The white maize seasonal pattern showed peaks during January, which correlated with uncertain conditions during planting and showed a price drop during July and August, which correlated with the main harvest and delivery period (Heymans, 2008:122). From these seasonal patterns, different contracts could be paired to derive a trading strategy. Furthermore, the trading strategies were enhanced by combining fundamental, technical and the seasonal analysis tools to determine entry and exit points (Heymans, 2008:196). Results showed that, by identifying seasonal patterns and market entry and exit points by means of technical analysis, it would be possible to profit from the implementation of a pairs trading strategy (Heymans, 2008:204).

These findings, which showed that past futures prices may be used to predict futures, the fact that a regression model could explain the variation in the white maize price on a satisfactory level, the observations of seasonality, and the profitability of technical analysis trading strategies on the white maize futures price definitely places a question mark over the variability in the level of white maize market efficiency. Arguably, these findings may also conform to the AMH to a great extent since influential factors and the level in which they influence prices in different phases of the production cycle may definitely cause variability in the level of market efficiency. As a result, and since the AMH encompasses the EMH, the fact that efficiency-specific studies confirmed the premise of weak-form market efficiency, maize producers will be able to use the futures market as a price risk management mechanism. Also, since the futures market may be regarded as an unbiased predictor of expected spot prices, producers may as a result be able to effectively deploy various hedging strategies.

3.4 Chapter summary

Throughout the literature review on market efficiency, the aim was to systematically, and mostly chronologically, work through the mainstream research concerning the EMH, market anomalies, and behavioural finance. Market efficiency as a notion has foundations as early as the beginning of the 20th century. However, the concept of the EMH developed over time to include improved methodologies and alternative angles to the same research problem as well as advances in technology and analytical techniques. Especially during the past four decades the focus shifted from confirming the random behaviour of prices, to an effort to understanding and explaining the behaviour of asset prices. Through these studies, several conflicting results appeared pertaining to unexplainable market anomalies and the striking resemblance which could be observed between the human cognitive decision-making process and the formation of asset prices.

Arguably, there will always be some form of bias, which may be identified from the studies presented in order to disprove various results on market efficiency. Even Fama (1991) admitted this when he stated: "*To be fair, and to illustrate that efficiency issues are never entirely resolved, I play the devil's advocate. (Attacks on efficiency belong, of course, in the camp of the devil.)*" From this statement Fama (1991) discussed various anomalies and signs of irrational market price behaviour, which could not always be explained rationally at the time. The statement nevertheless also shows the reluctance by staunch EMH supporters to admit that markets do not always conform to the EMH.

Bias towards a specific conviction also became prevalent in the opposing views of market anomalies, behavioural finance, and the profitability of technical analysis, where each notion presents a compelling case in favour of its own assumptions. In this regard, especially the EMH has been subject to a fierce attack on the rationality of its assumptions. However, despite this criticism on the assumptions of the EMH it remains a cornerstone and important reference point from where improved research on financial economics can occur. Arguably, the identification of market anomalies and the notion of behavioural finance would probably not have developed, at least to such a great extent, if the EMH had not presented a testable hypothesis. It was exactly this premise which prompted Fama (1998) to say, in laymen's terms: Prove the EMH wrong, and provide an alternative, testable hypothesis which incorporates market efficiency as well as the inconsistencies presented.

This challenge was duly accepted and to a great extent adhered to with the development of the AMH. The AMH in actual fact presents a scenario where the EMH is not written off but incorporated to provide an all-inclusive explanation of the behaviour of price changes over time. According to the AMH, the market will always react to eliminate market inefficiencies in order to return to an improved state of efficiency. Therefore, when anomalies or behavioural properties are identified, the exploitation of these supposed excess return opportunities will in actual fact remove their existence. However, the time it takes for these opportunities do disappear will not be a fixed parameter. Consequently, market participants need to approach market efficiency from an all-inclusive point of view in their quest for excess return. For instance, when anomalies are presented, attempt to gain from potential excess return opportunities by exploiting them. When behavioural heuristics are presented, equate yourself with the expected outcome of the influence of such behaviour on market prices and act accordingly.

As a result, the AMH provides the necessary foundation which supports the objectives of the study to evaluate and compare white maize hedging strategies and identify the potential link between seasons based on influential market factors. From this analysis, the aim would be to find similarities between seasonal developments based on influential factors, and to link these similar seasons to specific optimal hedging strategies. In terms of the specific hedging strategies deployed, the AMH intuitively implies that hedging strategies will not be profitable if the strategy is not able to adapt or adjust to changing market conditions as well as the reaction of market participants to changes in influential market factors.

These reactions to changes in influential factors by market participants also to a great extent influence a producer's hedging decision as well as the hedging strategy they deploy. The following chapter aims to determine which aspects influence a producer's decision-making process with regards to hedging and also include several possible hedging strategies evaluated over time. The way in which optimal hedging strategies were identified from these studies is discussed to show that these methods were not always able to conclusively rank hedging strategies. In order to address this shortcoming, the chapter included a review of another, more objective method in the form of performance measures which may be applied to rank hedging strategies.

CHAPTER 4

Price Risk Management and Performance Measurement

"I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meagre and unsatisfactory kind; it may be the beginning of knowledge, but you have scarcely, in your thoughts, advanced to the stage of science, whatever the matter may be."

- Sir William Thompson (Lord Kelvin) (1883)

4.1 Introduction

The primary functions of any agricultural commodity market are to ensure efficient price discovery, and to provide a platform for effective price risk management (Working, 1962:454, Garbade & Silber, 1983:289, Koonz, Hudson & Garcia, 1987:338-339). In order for efficient price discovery to occur, the market must reflect the impact of new information on the cash or futures price in a timely manner (Zapata, Fortenbery & Armstrong, 2005:4). The size and rate of adjustment in which the market price responds to new information should, however, not differ significantly for the spot and the futures market since it will influence effective price risk management (Mckenzie & Singh, 2011:77).

Effective price risk management will, therefore, be possible if the co-movement between the spot and the futures market remain stable. Armstrong, Zapata and Fortenbery (2003:4) stated that price discovery in the US corn market occurred in the futures market and spilled over to the cash market. For the South African white maize market, McCullough (2010:120) determined that price formation occurred in the spot or cash market, which led to price formation in the futures market. This finding implies that a certain level of market efficiency exists to ensure that the price risk management or risk transfer can occur effectively in the futures market (McCullough & Strydom, 2013:30).

Despite the fact that literature provides the necessary confirmation that the market price efficiently incorporates new information (Chapter 3, Section 3.3.1), which may facilitate effective price risk management, it does not imply that producers are willing to adopt the use of derivative instruments to hedge against future price variability. Their use of derivative instruments remains low, even in the US where futures markets have been well established (Goodwin & Schroeder, 1994:936). Optimal hedge ratios (hedged production in relation to produce sold in cash market) for US producers vary between 53 to 75 per cent (Bown, Ortmann & Darroch, 1999:298) and evidence shows that producers still hedge sub-optimally (Dorfman & Karali, 2008:1). One reason why producers' use of derivative instruments and hedging optimality remains low may be attributed to the introduction of government support programmes[23] after the 1996 Farm Act, which has been widely utilised by producers (Zuniga, Coble & Heifner, 2001:1). The result of these programmes is that producers view insurance price levels, such as the loan deficiency programme insurance level, as a free put option. This reduces the necessity to make use of derivative instruments to manage price risk. Price protection or insurance products even resulted in actions where producers became speculators by buying call options when prices fell below insurance levels (Zhang, 2007:93).

Producers' reluctance to make use of derivative instruments as price risk management mechanism could however also be linked to several other reasons and factors that influence their decisions. These reasons and factors have been confirmed by literature (Table 4.1) and are mainly a combination of geographical location (basis implications), farm size, farming status, enterprise specialisation, farming experience and formal education, producers' own perceptions of grain prices and hedging effectiveness, indebtedness, as well as alternative means to reduce risk. Nevertheless, the study by Ueckermann, Blignaut, Gupta and Raubenheimer (2008:234) found that a producer's use of hedging will increase if meaningful expected market trends, as well as geographical characteristics (such as climate variables), yield expectations and production patterns are accounted for in a proposed hedging strategy. Strydom, Grové, Kruger and Willemse (2010) and Venter, Strydom and Grové (2012) also found that it would always be profitable (sound practice) to deploy some form of a hedging strategy. This result emphasised the inconclusiveness regarding the ranking of different hedging strategies over time.

In general, hedging strategies were ranked based on the average hedge level achieved or the outperformance of a specific benchmark in the form of the average seasonal price (Section 4.2.2.1 and Section 4.2.2.2). When a risk measure was included it was merely the smallest standard deviation in average hedge level realised or outperformance of a set benchmark. Strydom *et al*. (2010) and Venter

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23 Support programmes include three primary types of payments. These are direct payments, loan deficiency payments and counter-cyclical payments. Direct payments provide enrolled farmers with an annual fixed income support that is not linked to the specific season. Loan deficiency payments provide price level insurance when market prices drop below loan rates. Counter-cyclical payments is a type of insurance where partaking producers are compensated when the market price drops below the average seasonal price (Zhang, 2007:13-14).

et al. (2012) improved on the basic ranking criteria by applying a cumulative distribution function (CDF) measure. They nevertheless concluded that the choice of hedging strategy would depend on the risk preference of a producer. As a result, the ranking of hedging strategies remained inconclusive. This shortcoming in literature methodology or results is one of the aspects this study aims to address through the inclusion of performance measures as ranking criteria.

However, this does not imply that performance measures as ranking criteria would resolve all inconclusiveness once and for all when comparing hedging strategy performance. Several advantages and potential shortcomings of performance measures should be evaluated and considered to reach an applicable conclusion. For instance, performance criteria – which are predominantly used to rank financial results – usually assume that a return distribution conforms to a normal distribution (Amin & Kat, 2003:5). With regard to the return distribution of white maize, Jordaan, Grové, Jooste and Alemu (2007:318) already determined that the volatility in white maize prices follow a highly leptokurtic distribution. A highly leptokurtic distribution will not adhere to the characteristics of a normal distribution, which may lead to biased results and varying ranking (Van Heerden, 2015:210). Consequently, the specific measurement deployed to rank the results of hedging strategies should account for the non-normal distribution and be able to evaluate returns on a risk-adjusted basis.

Against this background, this chapter is structured as follows. Section 4.2 begins with a background study of the factors that influence price discovery. This includes literature on the willingness of role-players to adopt derivative instruments, as well as the findings which could influence more sustainable price risk management decisions. The section also includes hedging strategies that pertain specifically to commodity markets, which may be deployed as applicable strategies to evaluate. Section 4.3 discusses relevant performance measurements that may be used to more conclusively rank hedging strategies. The evaluation of performance measures from literature forms the foundation for the applicable method(s) to deploy in the study in order to more conclusively rank the outcomes of the different hedging strategies evaluated. Finally, Section 4.4 provides a conclusion to the chapter.

4.2 Price discovery and sustainable price risk management

Agriculture all over the world remains a sector affected by real and significant risks on a daily basis. The outcomes of risk management decisions are rarely known when the decision is made to proactively manage expected risks. Kaan (2001:1) stated that the general groupings that lead to uncertainty and consequent risk, are the high probability of unfavourable events in agriculture, and the reality that the outcome of these events could cause income fluctuations which has the potential to disrupt and even close down an agricultural business. These unfavourable events range from variable rainfall patterns, price variability, unavailability of labour at critical times, unexpected mechanical breakdowns, and changes in government policies (Akcaoz & Ozkan, 2005:662). Several risk responses were consequently developed to address different risk categories. These included production responses through diversification or financial responses by improving liquidity in order to absorb the outcome of risk events. Another risk response may be seen as a marketing response which aims to transfer price risk through hedging by means of financial instruments.

The financial instruments that may be linked to agricultural commodity markets include future and option (Chapter 2, Sections 2.3.3.2 and 2.3.3.3) derivative contracts (Mahalik, Acharya & Babu, 2009:2). The main reason why these financial instruments may be used for price risk management is that they are ideally suited to apply as hedging instruments and consequently contribute to price discovery (Srinivasan & Bhat, 2009:29). The effectiveness of derivative instruments to reduce price risk through an established exchange has also been confirmed by Asplund, Forster and Stout (1989:25). This means that producers should be able to use the futures market as a decision platform from which to make informed production and marketing decisions when they evaluate the price they can expect when their produce is ready to harvest.

The applicability of the futures market to establish effective market access is, however, continuously questioned by especially the producers of agricultural commodities, which inevitably influences them to refrain from using the price risk management platform available to them (Asplund *et al.*, 1989:25). The reasons why producers are reluctant to address price risk management through derivative instruments may differ significantly between producers and is not necessarily linked to potential beliefs about price formation effectiveness. Section 4.2.1 touches on the effectiveness of price formation in the international and local market, as well as the main reasons why producers tend to avoid price risk management through derivative instruments. Section 4.2.2 follows with a discussion of strategies that may be used to hedge price risk in the international (Section 4.2.2.1) and local commodity markets (Section 4.2.2.2).

4.2.1 Price formation and the factors influencing hedging decisions

Initial studies, such as the Keynes-Hicks hypothesis or “theory of storage” by Keynes (1927,1930) and Hicks (1939,1946), on the reasons for the differences between the spot and futures market, may be seen as pioneering studies on the reasons for price formation. Thereafter, several studies already mentioned in Chapter 3 (Section 3.2.1) also evaluated price formation and potential reasons why prices form in a specific manner. These studies, to a great extent, evaluated the impact of market price formation on hedging from an end user or processor’s point of view, since price risk management practices (such as hedging) by means of derivative instruments was predominantly done by these parties (Paul, Heifner & Helmuth, 1976:iii).

On the other end of the market spectrum at the time, producers mainly made use of forward contract pricing, since their limited knowledge of derivative instruments and the cost of trading made them reluctant to utilise these instruments (Hirshleifer, 1988:1207). The costs of trading derivative contracts included brokerage commission and margin calls, which influenced cash flow and incurred interest charges (Collins, 1997:497). The relevance of the influence of the cost of hedging with derivative instruments was later confirmed by Arias, Brorsen and Harrari (2000:375), who found that producers would hedge if the tax or liquidity benefits of hedging outweighed the cost. Riley and Anderson (2009:7) added that the cost of hedging increased over time due to higher volatility of prices induced by an external market, such as the use of corn (US yellow maize) for ethanol production.

Another reason for producers' reluctance to make use of derivative instruments was their subjective beliefs about futures prices, as identified by Danthine (1978), Holthauzen (1979), Feder, Just and Schmitz (1980). Producers, for instance, do not necessarily take the futures price into account when making production decisions and tend to only make hedging decisions after production output becomes more certain. However, if futures prices are relatively certain at the time decisions have to be made, producers prefer to acquire additional inputs to expand production rather than managing their price risk, even if production output is uncertain at that point in time (Moschini & Lapan, 1992:618).

This general tendency of producers to avoid price risk hedging practices was initially noted by Working (1953:318). Survey studies by Shapiro and Brorsen (1988) and Mishra and Perry (1999) also showed that less than half of producers included had used futures and/or forward contracts, whereas as much as 75 per cent were seen as risk-averse. Main reasons for avoiding hedging practices were attributed to a disbelief in the markets' ability to provide a platform for sustainable price risk management. Over time, several predominant factors that influence producer's willingness to make use of derivative instruments were identified. These predominant factors are summarised in Table 4.1 below.

Table 4.1: Factors influencing producer's adoption of derivative instruments

Factor	Source	Result
Geographical location	Makus, Lin, Carlson & Krebill-Prather (1990:628)	Certain regions were more willing to make use of futures and options. Producers in these regions were positively linked to the existence of marketing clubs.
	Musser, Patrick & Eckman (1996:75)	Location had an influence in the specific marketing year due to unusual weather events occurring over different areas. Location may, therefore, be linked to yield risk, which may influence a producer's willingness to hedge in the short run.
	Sartwelle, O'Brien, Tierney & Eggers (2000:109)	Producers who were closer to end users or processors were more likely to make use of options and futures.
Farm size	Shapiro & Brorsen (1988:151)	Producers with larger farms were more likely to hedge.
	Makus, *et al*. (1990:628)	As farm size increased, producers became more likely to make use of derivative instruments to hedge. Producers who fell in the largest farm size category were, however, less likely to hedge. A possible explanation was that producers in this category were less indebted and less likely to hedge.
	Goodwin & Schroeder (1994:943)	An increase in farm size directly increased the probability that a producer would make use of hedging instruments.
	Musser, *et al*. (1996:75)	Large-scale farmers were more willing to make use of derivative instruments to hedge a significant portion of expected produce.
	Sartwelle, *et al*. (2000:108)	Cash market sales decreased in relation to forward marketing and derivative hedging as farm size increased in absolute and relative terms.
	Franken, Pennings & Garcia (2012:331)	Producers with larger farms relied on spot sales and proportionally hedged significantly less by means of options and futures. This finding was, however, influenced significantly by age and the debt-to-asset ratio. Larger farms with more debt were more likely to hedge, whereas older producers with less debt were less likely to hedge.
	Welch, *et al*. (2013:7)	Larger producers tended to be in a more financially sound position to fund margin requirements, but also needed to manage price risk more rigorously due to the higher level of exposure and therefore use options and futures for hedging.
Farming status	Makus, *et al*. (1990:626)	As farming status became a full-time partaking, for instance from share landowner to full-time producer, the use of derivatives increased.
	Dorfman & Karali (2008:10)	Producers who were more dependent on rented land usually hedged less of their production than land owners.
On farm grain storage	Sartwelle, *et al*. (2000:109)	Directly led to a decrease in hedging by means of options and futures, but to an increase in the use of forward contracts.
Grain enterprise specialisation	Asplund, Forster & Stout (1989:32)	Producers who made use of consulting and specialised computer services were more likely to hedge.
	Goodwin & Schroeder (1994:943)	Producers who invested in additional inputs to improve yields were more likely to make use of hedging instruments.
	Sartwelle, *et al*. (2000:108)	Increased specialisation directly led to an increase in the proportion hedged by means of forward contracts.

Factor	Source	Result
Grain enterprise specialisation	Katchova & Miranda (2004:95)	Producers who specialised in specific types of commodities were more likely to adopt derivative marketing contracts. They were, however, also more likely to hedge proportionately less of total production and tended to hedge more frequently.
	Woolverton & Sykuta (2009:844)	Producers who irrigated and specialised in a specific commodity were more willing to hedge.
Farming experience	Shapiro & Brorsen (1988:151)	More experienced producers were less likely to hedge. The finding was consistent with human capital theory, which states that an increase in experience, as well as education, directly leads to a decrease in risk aversion.
	Makus, *et al*. (1990:626)	Used age as a proxy for experience and found the factor not significant. An increase in age did relate to a higher probability of derivative instrument adoption.
	Goodwin & Schroeder (1994:943)	Age and experience were found to be highly correlated. Older (more experienced) producers were less likely to participate in training courses and make use of hedging instruments.
	Musser, *et al*. (1996:75)	Age and education were significant in the short-run, but did not have a significant influence on long-term use of hedging instruments.
	Sartwelle, *et al*. (2000:109)	As years of farming experience increased, producers showed a decrease in probability of making use of derivative instruments to hedge.
	Woolverton & Sykuta (2009:845)	Pre-planting hedging decisions were not significantly affected by experience, but producers with more experience hedged less prior to harvest.
	Franken, *et al*. (2012:334)	Older producers were unwilling to refrain from conventional cash market marketing methods. One reason was that they had less time left until retirement to become accustomed to marketing by means of derivative instruments.
	Welch, *et al*. (2013:7)	Older producers were less likely to make use of options and futures to hedge. They tended to view the inherent risk and cost associated with options and futures trading as too high.
Formal education, training courses and sources of information	Shapiro & Brorsen (1988:150)	Not a significant factor, although all respondents had attended a class or seminar on derivatives which may have led to biased results.
	Makus, *et al*. (1990:628)	Membership of a marketing club increased the probability that a producer would make significant use of derivative instruments. As a producer's level of education increased from secondary to tertiary, the probability of using options and futures increased substantially.
	Goodwin & Schroeder (1994:943-944)	A producers' willingness to make use of derivative instruments increased significantly with each additional year of training or formal education. The effect of seminars was found to be highly significant and led to positive changes in producers' willingness to adopt the use of hedging instruments.
	Katchova & Miranda (2004:95)	A producer's adoption of derivative marketing strategies increased when they formed part of an advisory service that provided written marketing plans.
	Dorfman & Karali (2008:9)	Different sources of additional information had a significant influence on a producer's use of derivatives to hedge. Consultants or field days were identified as sources that had a positive effect on the amount of production hedged, whereas magazine articles had a negative effect.
	Woolverton & Sykuta (2009:849)	Pre-planting hedging decisions were not significantly affected by education, but producers with higher levels of education hedged more prior to harvest.
	Franken, *et al*. (2012:334)	Education had an increased positive effect on a producer's willingness to make use of hedging strategies.
Formal education,	Welch, *et al*.	Producers who received some form of training on the use of options and futures

Factor	Source	Result
training courses and sources of information	(2013:7)	continued to use them as price risk management method.
Perception to income stability	Shapiro & Brorsen (1988:149)	Perceived hedging as an income stabiliser, but not necessarily as risk reduction mechanism, which influenced the amount of hedging to a greater extent.
	Collins (1997:498)	Producers always aim to maximise profit, whereas hedging might reduce this potential. The probability of hedging was increased by the need to avoid financial failure rather than the need to minimise income variability.
	Sartwelle, *et al.* (2000:109)	As the risk preference of producers increased with a consequent increase in income variability, there was no real change in their adoption of derivative instruments to hedge.
	Dorfman & Karali (2008:9)	Producers who were breaking even or losing money tended to hedge significantly more than financially sound producers.
Amount of debt	Shapiro & Brorsen (1988:149)	Highly leveraged producers are more likely to hedge. Usually required to hedge before financing will be granted.
	Goodwin & Schroeder (1994:943)	The amount of debt significantly increased the probability that a producer would make use of hedging instruments.
	Musser, *et al.* (1996:75)	An increased debt-to-assets ratio had a direct positive influence on the amount of produce hedged.
	Collins (1997:489)	Confirmed that producers with higher debt levels were more likely to hedge.
	Woolverton & Sykuta (2009:847)	Producers with higher debt levels were more likely to hedge more produce, especially prior to planting.
	Franken, *et al.* (2012:335)	Found that producers with larger farms tended to carry more debt, but that older producers carried less debt. Amount of debt increased willingness to hedge by means of options and futures to ensure stable cash flows to repay debt.
Basis risk	Miller & Kahl (1987:34)	Basis certainty did not necessarily imply that producers were more willing to increase forward contracting in relation to derivative hedging.
	Lapan, Moschini & Hanson (1991:68)	A producer's level of risk aversion increased as their uncertainty regarding the basis increased. An increase in basis risk influenced the decision to hedge by means of futures or options. An increased basis risk led to an increase in the use of options. However, they were not necessarily used as hedging instruments but rather in a speculative manner.
	Lapan & Moschini (1994:466)	Producers face both price and production risks. Basis risk, which arises due to location, timing and quality differences, had a considerable effect on a producer's hedging decision, especially when production was uncertain.
	Moschini & Lapan (1995:1025)	Hedging decisions should always account for the price risk associated with the price difference between the futures price used to hedge and the cash price when the futures contract is settled.
	Collins (1997:498)	If a producer were confronted with the potential of higher future cash prices and a low probability of financial failure, they usually chose not to hedge.

Factor	Source	Result
Basis risk	Frechette (2000:897)	Producers who were further away from a central marketplace are more at risk if futures and cash prices diverge from local cash prices which significantly reduce their hedging demand.
	Tomek & Peterson (2001:962)	Basis risk remained an important consideration for producers who aimed to use derivative instruments to manage price risk.
Alternative means to reduce risk	Shapiro & Brorsen (1988:152)	Producers who participated in government farm programmes, had crop insurance, or earned some form of off-farm income were less likely to hedge.
	Makus, *et al*. (1990:627)	Producers who participated in government commodity programmes were positively influenced to make use of derivatives. Those who already made use of forward contracts were even more likely to make use of options and futures.
	Goodwin & Schroeder (1994:944)	Government programmes of federally subsidised insurance programmes were seen as substitutes for forward pricing as an instrument to reduce risks. Producers who actually purchased multiple-peril crop insurance were, however, significantly more likely to make use of hedging instruments.
	Sartwelle, *et al*. (2000:109)	Producers who made use of multi-peril crop insurance and/or crop revenue protection reduced their use of forward contracts and rather hedged by means of futures and options.
	Katchova & Miranda (2004:95)	Producers who received crop insurance payments were less likely to hedge by means of derivative contracts.
	Woolverton & Sykuta (2009:845,849)	Producers who formed part of government income support programmes hedged a significantly smaller percentage of expected production. Contrary to the finding by Shapiro and Brorsen (1988:152), the study found that producers with off-farm income tended to hedge, especially prior to harvest as yields became more certain.

Source: Compiled by author

The international literature presented in Table 4.1 illustrates that the factors which influence a producer's willingness to make use of derivative or forward marketing may be combined into two broad categories. The first category includes the characteristics of the producer and the farm. These comprise of the producers' age, experience, and education level, the financial position of the producer, as well as the farm size and location in terms of basis. The second category involves the influence of alternative risk management techniques, such as diversification, government insurance, or income support programmes, as well as alternative means of income.

This categorisation does, however, not mean that the influential factors should be viewed in isolation. The way in which these factors interact and influence a producer's decision-making process is clearly displayed in Table 4.1. Also, a producer's willingness to accept more risk will be greatly influenced by their financial situation (Collins, 1997:498), and a greater risk appetite will not necessarily have an effect on the producers' willingness to make use of alternative hedging methods (Sartwelle *et al*., 2000:110). Throughout the majority of these studies one aspect became evident. Producers have long become used to traditional cash or forward marketing versus derivatives contracting by means of futures and options. The reality is that older (more experienced) producers are at the helm of their respected farms and have built successful enterprises over time through specific marketing methods. They have no reason to suddenly change marketing methods to something they are unfamiliar with.

Shapiro and Brorsen (1988:152) stated that the only way to increase producer hedging is to change their perception of hedging from its ability to increase income to its ability to reduce income variability. Makus *et al*. (1990:630), as well as Goodwin and Schroeder (1994:946), already proposed that educational programmes on hedging should be directed at younger and educated producers who manage larger specialised farms, as well as those who are more financially leveraged in order to increase the general use of derivatives as hedging instruments. Arguably, the factors that influenced producer decisions remained fairly constant throughout the literature summarised in Table 4.1. These observations lead to the conclusion that more should be done to ensure successful education; more time will be required to bridge the age gap between older and younger producers to encourage hedging by means of derivative contracts.

One of the first studies of this nature for the South African context was done by Bown, Ortmann and Darroch (1999:292-298). The aim was to determine which factors influenced producers' choice of marketing method. In terms of producer characteristics, results showed that larger farms in terms of size and financial turnover were usually not owned by an individual, and were more likely to make use of forward pricing contracts. Older producers with more farming experience were less likely to make use of any form of price risk management. The study further showed that users who made use of higher level risk management tools (such as futures and options) had undergone more years of formal education, were younger, had less experience in terms of farming years, and had access to storage facilities. It was argued that older producers were still accustomed to the traditional, fixed-price controlled marketing environment and younger producers were quicker to adopt free market methods (Bown *et al*., 1999:292-298).

A follow-up study on the characteristics that influenced grain producers' preferences was done by Ueckerman *et al.* (2008:231-233). Results showed that grain producers were not homogenous, and factors such as regional geographic characteristics, farm size, meaningful price predictions, and industry trends influenced their willingness to make use of derivative instruments. Woolverton and Sykuta (2009:845) also compared general findings from the market contexts in the United States of America (US) and that of South Africa and focussed on the impact of government support programmes on producers' hedging practices. Similarities were that commodity-specific specialisation increased pre-planting hedging, whereas experience in terms of farming years decreased hedging prior to planting. A difference was, however, that SA producers earning off-farm income were more likely to hedge due the tax-reducing effect of hedging. In terms of government support programmes, the study found that SA producers who did not receive government support in general acquired more insurance and hedged a larger percentage of their crop than US producers. Another interesting observation was that price risk management decisions affected SA production decisions, and these decisions were made simultaneously. US producers, on the other hand, tended to plant first and then decide on a price risk management strategy as the season progressed (Woolverton & Sykuta, 2009:849).

The literature presented above and the comparison between SA and US producers in particular definitely show clear similarities, but also clarify the unique situation SA producers are faced with each season. Mofokeng and Vink (2013:10) confirmed that only 35 per cent of South African producers in their sample made use of available price risk management instruments. They attributed this low percentage to a continuous learning curve after deregulation. Another important reason for the willingness of SA producers to employ pre-harvest price risk management strategies specifically is production uncertainty. Adverse weather conditions significantly influence production expectations and lead to costly buyouts of hedging contracts if the physical product cannot be delivered against the contract. SA producers have to deal with this reality and, in addition, acquire crop insurance to account for adverse weather events since they are not subsidised in any manner. These factors reiterate the importance of a versatile but purposeful hedging strategy that is able to incorporate meaningful price predictions and geographical characteristics. Most importantly, such a strategy should enable a producer to share in upward market price potential to ensure effective price risk management and limit potential costly contract buyouts.

4.2.2 Price risk management strategies

Effective price risk management with the main aim to reduce income variability and to lock in profit remains a cornerstone in any sustainable farming business. Patrick, Musser and Eckman (1998:49) found that, although producer marketing strategies included goals to sell produce at a margin above input cost at an above average price, and to reduce the probability of getting a low price, they seldom hedged at price levels appropriate to achieving these goals. The main reasons for sub-optimal hedging were attributed to producers' perceptions and experiences of different hedging strategies. A producer's perception of a hedging strategy may arguably be linked to the success of a strategy within a specific production season. The reality, however, remains that not all strategies will be optimal for each season and producers are to a great extent forced to absorb and interpret an array of information in an attempt to make an informed marketing decision (Gronum & van Schalkwyk, 2000:505).

Nevertheless, producers are fully aware of the impact that a meaningful, flexible, and risk-orientated marketing strategy may have on the profitability of a farming business (King & Lybecker, 1983:124).

This does, however, not mean that there is consensus with regard to an optimal price risk management strategy, or even a price risk management strategy. Producers view a hedging strategy as a means to reduce risk and often base the success of different strategies on their personal experiences with such strategies (Patrick, Musser & Eckman, 1998:49). Hedging strategy research by extension economists affiliated with companies actively engaging in the agricultural sector and academic economists, however, rarely focus on the risk-reducing aspects of hedging strategies (Schroeder, Parcell, Kastens & Dhuyvetter, 1998:292). Instead, research in this regard tends to focus on the profitability of hedging strategies, and extension economists and academic economists disagree on this point as there is no consensus regarding the effectiveness and applicability of hedging strategies *per se* (Parcell, Schroeder, Kastens & Dhuyvetter, 1998:403). On the other hand, producers and extension economists believe that it is possible to improve producer income by deploying specific hedging strategies, while academic economists tend to contest these findings (Schroeder *et al*., 1998:289).

In order to address these contradictory findings published by extension and academic economists, the following two subsections will focus on the effectiveness of international (Section 4.2.2.1) and South African (Section 4.2.2.2) price risk management strategies. The findings from these subsections may also form an important foundation for identifying hedging strategies to evaluate as viable price risk management strategies. The reader is furthermore reminded that the application of each of the derivative instruments which may be referred to in the price risk management strategy literature review was explained in Chapter 2 (Section 2.3.3.2 & Section 2.3.3.3).

4.2.2.1 International price risk management strategies

International price risk management strategy research, as a result, includes fairly controversial findings with regard to marketing strategies and specifically pre-harvest marketing strategies[24]. The first general finding states that pre-harvest marketing strategies will not increase producer income, whereas the counter argument states that certain pre-harvest marketing strategies will on average provide producers with a better income compared to merely selling at harvest (Brorsen, 1998:286-287). The one side of the argument usually follows a more theoretical approach with the pillars of the argument resting on the foundations of the efficient market hypothesis (EMH). However, research along the line of price

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24 Pre-harvest strategies are associated with forward contracting by means of future or option contracts as well as physical delivery forward contracting to local processors or buyers. An alternative to pre-harvest strategies are post-harvest strategies, which involve decisions to store and sell produce at a later stage or to sell the produce in the cash market at harvest and remain in the market with derivative instruments in an attempt to gain from potential upward price ovements (King & Lybecker, 1983:124).

forecasting and marketing strategies based on historical data backtesting became subject to severe critique. Critics wrote off the validity of the research to such an extent that research funding became a challenge (Brorsen & Irwin, 1996:69). However, relevant research from both sides of the argument prevailed.

One of the more recent studies which argued in favour of the implications of the EMH was conducted by Zulauf and Irwin (1998:314). The methodology followed a fairly theoretical approach in their evaluation, which they defended by stating that it eliminated pretesting bias such as a potential drought-risk premium on which strategies were sometimes based. In order to objectively evaluate general strategies commonly applied in the marketing of commodities, they organised the strategies into four categories. These categories[25] were routine strategies, systematic strategies, strategies based on individual-generated forecasts, and – lastly – strategies based on market-generated forecasts of expected production profits (Zulauf & Irwin, 1998:311). Several strategies in each category were compared and results showed that pre-harvest routine strategies yielded a higher return than selling at harvest, but that the difference was not statistically significant. Systematic strategies also tended to vary by crop and the timing of economic indicators was not so easy to judge consistently, given the influence of systematic risk factors (Zulauf & Irwin, 1998:322). Strategies based on individual forecasting showed mixed results to which it was argued that no forecasting model had ever been able to generate consistent results in a single market (Zulauf & Irwin, 1998:324). In general, the study found that neither of the individual strategies or groupings showed consistent or statistically significant results proving that a producer's income could be increased by deploying them as hedging alternatives. Nevertheless, the study of Zulauf and Irwin (1998:328) suggested that producers should first and foremost manage production costs and base their production and marketing decisions on profitability, which may be evaluated by means of the futures market as a source of market expectations.

The other side of the argument, represented by research contrasting EMH fundamentals, however, continued to test marketing strategies in an attempt to justify the relevance, importance and applicability

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[25] Routine strategies involve buying or selling during the same period within each individual production cycle (Zulauf & Irwin, 1998:311). Systematic strategy buying or selling decisions are based on a specific variable indicator value. This indicator value may be based on the state of the economy or economic indicators such a bond yield (Zulauf & Irwin, 1998:319). Strategies based on individual-generated forecasts are based on forecasting models such as econometric or multivariate models or even technical trading models which aim to predict price movements or trends from past data (Zulauf & Irwin, 1998:322).Market-generated forecast based strategies are based on the expected profit a producer will realise by deploying different or specific hedging strategies based on current futures and option prices (Zulauf & Irwin, 1998:324).

of their research. A relevant study of note was done by Hauser and Eales (1987:123), who evaluated nine different pre-harvest option-based hedging strategies in an attempt to distinguish between the different risk/return relationships in terms of the expected realised price of these strategies. An important result was that the hedging effectiveness in terms of expected return variance of either of the strategies was at least 70 per cent better than not hedging. Another relevant result showed that option hedging remained costly and risky, regardless of the strategy, since the level of risk increased linearly with the level of return. In terms of risk behaviour, the study also found risk-seeking below the level of expected return and risk-aversion above the level of expected return, especially when a hedger deployed a minimum price or put-option strategy (Hauser & Eales, 1987:134). This finding conforms to the behavioural finance (Chapter 3, Section 3.2.4.3) state of mind called loss aversion where investors seem to be risk-averse when faced with decisions regarding the potential of definite gains, but become risk-seeking when these decisions are substituted with the prospect of losses.

When production, price and the expected basis remains uncertain under different levels of risk aversion, the study of Lapan, Moschini and Hanson (1991:68) argued that production may be hedged by the use of futures only and that only non-diversifiable basis risk remains a factor that may influence a production decision depending on the risk appetite of the producer. The use of options were linked to speculative trading in an attempt to benefit from potential price bias arising from the influence of private information on price formation. Moschini and Lapan (1992:618), however, found that the use of options as hedging instruments reduces income variability when the cost of production is certain prior to planting, but that the cost of hedging through options may also influence production decisions. Lapan and Moschini (1994:476) added to these results by stating that the optimal hedge should always be time-varying or adapted to accommodate changing market conditions and yield risk in particular, which inevitably influences basis risk. Moschini and Lapan (1995:1047) confirmed that options remain a meaningful hedging tool when production and basis risk are considered. Their results showed that, even when the market is assumed to be efficient, options strategies will be preferred by a risk-averse producer.

The study by Musser, Patrick and Eckman (1996:76) also emphasised that producers who make use of option hedging strategies hedged a greater percentage of their expected crop. They reiterated that an option hedging strategy may not always be the optimal strategy in a specific year, but that it remains the only marketing strategy able to consistently reduce price risk over time. Wisner, Blue and Baldwin (1998:305) also concluded that producers should consider options in their marketing strategies, since they are able to accommodate production risk and stabilise variable seasonal returns. Their results showed that a naïve marketing strategy could create cash-flow problems due to the large income variability, but that alternative strategies that made use of futures and options would realise a larger mean net return. However, only some of the option-based strategy net returns were significantly better than that of the naïve strategy (Wisner *et al*., 1998:303). As a result, options were regarded an important hedging alternative to reduce the risk of non-delivery and to be able to maintain upward price potential in years when prices rise sharply.

Despite all of the relevant research relating to the performance and applicability of basic hedging strategies, most producers still sold two thirds of their crop in the bottom third of the price range over a given season (Hagedorn, Irwin, Good, Martines-Filho, Sherrich & Schnitkey, 2003:3). This result was re-evaluated by Hagedorn, Irwin, Good and Colino (2005:1279) and they found an improvement in the hedging level of producers closer to the middle third of the seasonal average price. The study, however, reiterated the fact that producers should avoid selling towards the end of the marketing year. This tendency of producers to hedge late in the season was attributed to the fact that they view yield variability as a far greater risk than price-risk variability. The residual risk of hedging in the form of potential cash-flow implications may consequently be amplified by hedging when yield is still uncertain (Harwood, Heifner, Coble, Perry & Somwaru, 1999:76). In addition, hedging decisions from a risk management perspective only remain an attractive proposition if producers are able to cover hedging costs. Covering hedging costs may not be possible even if yield is uncertain, which inevitably leads to producers trying to manage their price risk when yields become certain and prices are lower (Varangis, Larson & Anderson, 2002:7).

An attempt to increase producer hedging participation prompted the development of a set of “new generation” hedging strategies. These strategies were developed in an effort to take the emotion out of producers’ discretionary price risk management decisions and improve the price that producers receive by providing a set of specific rules to base a hedging decision on (Hagedorn *et al.*, 2003:3). These contracts consist of three main types. The first category is called automated contracts. These contracts aim to realise a price above or at least in line with the average seasonal price. Automated contracts follow a specific set of rules to gradually hedge produce linked to the specific contract for the duration of a season. Managed hedging contracts are the second category, and this contract bases hedging decisions on the recommendations of marketing advisory services. The last general category is called combination contracts, which is a combination of automated and managed hedging contracts. In this instance, producers share in the hedging profits made by the advisory service. The study of Hagedorn *et al.* (2003:7) argued that these contracts definitely have an important role to play as a diversifying marketing alternative for producers, but added that these contracts should form part of a producer’s marketing plan as a whole and not become their only marketing plan or hedging alternative.

The international hedging strategy literature included provides a general overview of the different types of hedging strategies developed and evaluated over time. Arguably, no strategy was identified that was able to provide consistent superior hedging performance, but characteristics and specific derivative instruments emerged that should form part of an effective strategy. Hedging strategies as part of the South African market context developed mostly from international literature as well as the basic derivative instrument combinations that became available to producers when the derivatives market was introduced after deregulation.

4.2.2.2 South African price risk management strategies

The first general study worth mentioning was conducted by Grönum and Van Schalkwyk (2000:510) in the early years after deregulation, and already confirmed that producers should always consider flexible hedging strategies. They reiterated that such a strategy should be able to account for unforeseen price reactions due to changing fundamental factors such as possible drought and associated yield risk. Several basic hedging strategies were evaluated and results showed that they were able to reduce price and income risk, especially when hedging decisions accounted for input cost and changing fundamental factors. These findings coincided with those of an international study by Zulauf and Irwin (1998:328), which suggested that producers should first and foremost manage the cost of production and base their production and marketing decisions on profitability.

A second study of note that may also be linked to international literature was done by Scheepers (2005:40), who evaluated price risk management from a portfolio theory based approach. In this instance, the portfolio theory based approach involved comparing four hedging strategies based on the mean price received and the variability of the strategy price achieved over time as a measure of risk. As part of the hedging strategy comparison, the study included a base strategy with no hedging and produce was sold in the cash market at harvest. The base strategy realised a better mean return than the second strategy, which involved the selling of all expected produce during the planting period by means of futures contracts. The base strategy, however, showed a much larger variance in the mean price achieved. The third strategy built on the second by including the purchase of a call option to enable participation in upward price movements. The last strategy was similar to the third, but differed in the sense that the call option was not bought in the same main futures hedging month as the short futures contract. The call option was specifically bought in an earlier main hedging month to reduce option cost, and to test the theory that prices tend to gradually decline closer to the main hedging month as yield and supply become more certain. This strategy outperformed the other three in terms of average mean price achieved, but selling all produce at planting time remained the strategy that achieved the smallest price variance (Scheepers, 2005:48).

The study of Rossouw (2007:62) also evaluated hedging strategies that individually followed a portfolio-based trading rule approach aimed at obtaining a below average purchase price for a buyer or processor of maize. In this instance, the portfolio-based approach included the comparison of hedging strategies based on average return and standard deviation but the type of strategies may also be linked to the "new generation" collective or volume hedging type contracts described by Hagedorn *et al.* (2003). The first main hedging strategy was a momentum strategy, where the hedger buys into the market when the price increases (or remains unchanged) but when the market price retracts or trades down, no hedging is implemented. The strategy was able to outperform the average market price for five of the six years evaluated, but the outperformance value varied significantly (Rossouw, 2007:81). The second strategy was a maximum price strategy established through call options. Call options were bought to cover all procurement needs and to establish a maximum price level. The call options were actively managed to reduce total option cost and optimise the average buy-in or maximum price level. This was done by selling back call options when the market price fell below the average hedge level and replacing these call options with long futures. The strategy outperformed the average price benchmark for each year reviewed, but the variation in outperformance was much higher than the momentum strategy (Rossouw, 2007:94). The third strategy was called an indexed strangle strategy, which entailed that futures contracts were bought on each trading day until the delivery month to ensure a contract average buying price. In an attempt to reduce the purchase price below the average contract price, out-of-the-money put and call options were sold for all of the tonnages hedged by long futures contracts. These options were sold during the time of the year when, historically, option volatility was historically at a peak. Out-of-the-money put options were sold at a specific percentage below the market price and out-of-the-money call options were sold at a specific percentage above the market price. The strategy, however, included the risk that the tonnages may become unhedged if the market price increased above the short-call strike levels but also that the tonnages hedged may double if the price decreased below the short-put strike levels. Strategy results showed that the average market price was outperformed in each of the seasons included in the analysis (Rossouw, 2007:104). The study concluded that, based on average return over time, the maximum price strategy was the first choice, followed by the indexed strangle strategy, and – lastly – the momentum strategy (Rossouw, 2007:116).

A study by Cass (2009:27) moved away from the portfolio type or volume strategy hedge approach to an all-inclusive grain marketing approach when he compared an array of pre-harvest, post-harvest, and alternative marketing alternatives. These alternatives ranged from options and futures hedging, storing the physical underlying commodity after harvest and selling at a later stage, using maize as animal feed to add value before selling the animals and even included bio-ethanol production from maize plants. The advantages and disadvantages of all of these strategies were considered and they were compared based on the extent to which each strategy outperformed the average July contract (traditional main delivery month) price. Results showed that storing maize in a registered silo operator facility and selling in three equal portions in July after harvest, December, and February of the following year was the strategy with the highest probability of success and the lowest risk. From a derivative hedging perspective, buying a put option in February also showed a very high success rate, but also more variability than some of the storage options. The put option was, however, much more successful than merely selling by means of futures contracts in February (Cass, 2009:104).

More recent research conducted by Strydom, Grové, Kruger and Willemse (2010:4), as well as by Venter, Strydom and Grové (2012:4), evaluated routine hedging strategies. Between the two studies, two general strategies were backtested and compared to a benchmark strategy. The benchmark strategy was merely to sell the produce at the cash price after harvest. The first strategy was to purchase a plain put option strategy after planting. The second strategy was implemented by selling futures for the total produce in three equal segments at planting, pollination and harvest. The study of Strydom *et al*. (2010:6) also included a strategy that aimed to sell the total produce by means of futures in twelve equal segments or three-week intervals from planting to harvest. Venter *et al*. (2012:6) also included a variation where the total produce was sold by means of futures contracts in the critical pollination month of February. The general results for both studies were that the minimum price (put) strategy achieved the highest mean return over time. In terms of standard deviation, the strategies that included more selling intervals showed a smaller deviation. Furthermore, the benchmark strategy performed the worst in terms of average return and standard deviation for both studies.

Both studies, however, found that a comparison of the results by means of average return and standard deviation could not conclusively identify the most effective strategy. The simplest reason for this finding was that, although a specific strategy may have the largest standard deviation in expected return, the strategy outperformed all the other strategies when the strategy results of each individual year were compared. The same result was evident from the results by Rossouw (2007), where the strategy with the highest expected return also had the greatest standard deviation. As a result, the risk of variability in return may be disregarded by merely evaluating a strategy based on expected return, and selecting a strategy with the smallest return variability may result in no return at all. In order to address this issue, Strydom *et al*. (2010) and Venter *et al*. (2012) compiled a cumulative distribution function (CDF) of the prices resulting from each strategy in an attempt to identify the optimal strategy on a probability of success scale. However, the CDF ranking was unable to conclusively rank the strategies, since the strategies outperformed each other in several different probability ranges. The choice of optimal hedging strategy would therefore depend on the risk appetite of the individual producer (Strydom *et al*., 2010:12; Venter *et al*., 2012:11). The optimal strategy in terms of a specific level of risk aversion was further analysed by means of utility weighted risk premiums. Strydom *et al*. (2010:13) found that a risk-averse producer should always deploy the put strategy and that the twelve equal segments, as well as the three equal segments strategies, did not differ significantly in terms of their risk preference. Venter *et al*. (2012:14) confirmed that the put strategy will be optimal for a risk-averse producer and found that the February strategy would be the least beneficial for a risk-averse producer.

From the hedging strategy research presented above, it becomes evident that a hedging strategy should always be designed and implemented to ensure that the intended produce remains hedged and that the derivative instruments used in the strategy are able to capture any potential upward market movement. Selling at harvest, or even selling the complete expected produce at one specific point in time prior to harvest also do not seem to be optimal over the longer term. An optimal strategy was mainly determined according to the relative performance of each strategy against a specific market benchmark – usually the average market price or the standard deviation of expected returns over time. The only studies that included a measure of risk-weighted return was Strydom *et al*. (2010) and Venter *et al*. (2012), when they ranked strategies according to the CDF. Nevertheless, this measure could not conclusively rank the strategies and the choice of optimal strategy was linked to the producer's risk appetite.

In order to find a less subjective solution to more conclusive rank hedging strategies in terms of both risk and return, this study aimed to address this shortcoming by applying risk-adjusted performance measures (from hereon "performance measures") to the hedging strategy return data. The development of performance measures stems from the Markowitz (1952) mean-variance portfolio construction approach, whereby an efficient portfolio may be weighted or optimised according to either expected return prerequisites or risk in terms of variance (σ). A combination of investments, which could include hedging strategy returns and standard deviation ($\sqrt{\sigma}$) may thereby be combined to determine the optimal combination in terms of maximum return or minimum risk. As a result, several risk and return combinations can be structured for the same set of investments, but the combination with the maximum return will most likely not be the combination with the smallest risk or portfolio standard deviation (Markowitz, 1952:79).

The Markowitz mean-variance approach, which only included or considered the first (mean) and second (variance) order moments, has however been subject to critique. Shortly after Markowitz (1952) proposed his mean-variance optimisation approach, Roy (1952:434) considered the implications of minimising the upper bound of the chance of losses if information is confined to only the first and second-order moments. The study implied that investors tend to be more protective of portfolio wealth against the possibility of making losses, and are not necessarily interested in how prices deviate around a profitable mean. From this argument Markowitz (1959) was inspired to introduce the downside risk measure, named semi-variance, thus replacing the ordinary variance to, for the first time, include downside risk in portfolio selections.

Nonetheless, the theory of portfolio analysis was still assumed to be essentially normative by many, which led some studies to continue measuring risk on the basis of variance through the application of the standard deviation as the denominator of the Sharpe ratio (Sharpe, 1966). Over time, many criticised this denominator, as it measures only the dispersion of returns around its historical average and penalises positive and negative deviations from the historical average in a similar manner, thus leading to a misperception of actual risk (e.g. Harlow, 1991; Lhabitant, 2004). This implies that the standard deviation does not differentiate between downside and upside risk (Harding, 2002:2; De Wet, Krige & Smit, 2008:71), especially if the divergence from normality becomes more apparent when the higher moments (skewness and kurtosis) of the return distributions are taken into account (Kat, 2003:9). This can pose a problem when trading in the South African white maize market, as it is known for significant price fluctuations with consequent high return volatility (Geyser & Cutts, 2007:303).

These findings suggest that the traditional ratios would find it difficult to rank volatile returns (Lo, 2002:36) due to its risk denominator, and will thus fail to capture downside surprises (Lamm, 2003:20). With this outcome rendering the creditability of the traditional performance ratios inconsequential, it opens the field of performance measurement to establish solutions for overcoming the limitations imposed by the standard deviation. The following section focuses on performance measure development, which includes the advantages, potential shortcomings and applicability of the different measures available. The goal of this section is to identify performance ratios which may be able to more conclusively rank hedging strategies, a function presented as a shortcoming in the literature consulted.

4.3 Performance measures

Performance measures are generally applied to rank investment performance. Investment choices often stem from these rankings and investments with higher rankings are preferred. These rankings may, however, differ depending on the specific risk measure deployed or the risk threshold chosen.

Investors may therefore choose to maximise return rather than account for risk or *vice versa.* The main aim of performance measures will be to manage risk and to provide a risk-averse investor with the means to measure the degree to which an investment compensates him or her for the risk exposure taken (Platinga & De Groot, 2001:1). The importance of performance measures also gained momentum with the emergence of a vast range of different investment fund alternatives, which must be evaluated for effective capital allocation (Weisman, 2002:80).

Over time, performance measure analysis became synonymous with initial performance measure development such as the well-known Sharpe ratio (1966) and the Treynor ratio (1965). The Sharpe ratio measures the relationship between the net return achieved (strategy or investment return minus a risk-free return) and the standard deviation of the strategy or investment returns (Sharpe, 1966:122). The Treynor ratio (1965:69-70), however, makes use of a different risk measure in the form of beta (β). This risk measure represents the systematic risk or the non-diversifiable risk component known as the assets beta (β), which may in turn also be linked to the capital asset pricing model (CAPM) through the security market line (SML) as valuation measure (Reilly & Brown, 2012:205).

The application of the CAPM model resides in the linear relationship it derives between the expected return of an asset or portfolio and covariance with a representative market portfolio. This co-movement between the assets return variance and the market portfolios return variance provides a measure for the assets market risk or beta (β) of the asset. This linear relationship may then be used to determine if an asset or portfolio of assets is mispriced when the expected return of the asset or portfolio does not correspond with the linear relationship presented by the CAPM model (Reilly & Brown, 2012:18; Marx, *et al.*, 2013:40). Consequently, the CAPM model provides a benchmark for performance evaluation.

The first and original developments in the CAPM model may also be attributed to work by Treynor (1962) on capital asset pricing and subsequent work by Sharpe (1964) on the pricing of capital assets (French, 2003:62-63). After the development of the CAPM, one of its first applications was in studies on performance of mutual funds by Treynor (1965) and Sharpe (1966), with both authors compiling a predictor of mutual fund performance. These studies concluded that the differences in fund performance may be attributed to the risk reward profile of a specific fund. Sharpe (1966:138) specifically stated that the main aim of fund managers was not to search for mispriced assets to invest in, but to diversify the portfolios in line with their specific risk reward mandates. As a result, both these ratios rank as optimal the portfolio with the highest ratio or excess return per unit of risk.

The main difference between these two ratios remains the specific risk measure deployed by each ratio. Over time it became evident that the Sharpe ratio was more appropriate when an investor placed all of his risk capital in a single investment or investment type, whereas measures such as the Treynor ratio proved more appropriate when risk capital was divided between different investments or investment types (Eling & Schumacher, 2007:2633). Also, the return distribution of an investment or strategy should be normally distributed for measures that only account for expected return and standard deviation, such as that of Sharpe.

Brooks and Kat (2002:37), for instance, found that investment returns with high kurtosis and negative skewness resulted in high Sharpe ratios, which overstated performance. Mahdavi (2004:47) stated that specific option strategies (especially when writing or selling options applicable to the agricultural market) may result in returns with a low standard deviation but with large skewness. The Sharpe ratio of such a strategy would be biased in the sense that it usually outranks the Sharp ratio of the options underlying asset returns. These specific shortcomings inherent to performance measures which only accounted for the first two moments provided the necessary justification for the development of several other performance measurements. Table 4.2 below aims to summarise some of the relevant performance measures within specific approach categories.

Table 4.2: Performance measures

Measurement approach	Equation	Variables
Traditional performance measures	Sharpe ratio = $\frac{R_{p-}r_f}{\sigma_p}$ (4.1) (Sharpe, 1966:122).	R_p is the portfolio return, r_f the risk-free rate, and σ_p the portfolio standard deviation.
	Treynor ratio = $\frac{R_{p-}r_f}{\beta_p}$ (4.2) (Treynor, 1965:69-70).	R_p is the portfolio return, r_f the risk-free rate, and β_p the risk measure.
	Jensen's α = $(R_p - r_f) - \beta(R_m - r_f)$ (4.3) (Jensen, 1968:393).	R_p is the portfolio return, r_f the risk-free rate, R_m the return on a market benchmark, and β_p the risk measure.
Measuring performance based on lower partial moments (LPMs)	Lower partial moment: $LPM_{ni}(\tau) = \frac{1}{T}\sum_{t=1}^{T}\max[\tau - r_{it}, 0]^n$ (4.4) Only negative returns or returns lower than a benchmark or acceptable return is used to measure risk. A minimum acceptable return may be a risk-free rate, average return, or even zero (Sortino & Van der Meer, 1991:29).	The minimum acceptable return *r* for security *i* is represented by τ with the order *n* of the LPM, which may differ between ratios. A higher order would be more applicable as investor risk aversion increases.
	Omega = $\frac{\int_\tau^b (1-F(x))dx}{\int_a^\tau F(x)dx}$ (4.5.1) (Keating & Shadwick, 2002a:3) applied by Eling & Schumacher (2007:2635) as: Omega = $\frac{r_i^d - \tau}{LPM_{ni}(\tau)} + 1$ (4.5.2)	Omega deploys a LPM of order 1 which relates to expected shortfall from τ.

<table>
<tr><th>Measurement approach</th><th>Equation</th><th>Variables</th></tr>
<tr><td rowspan="3"></td><td>Sortino = $\frac{r_i^d - \tau}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.6)
(Sortino & Van der Meer, 1991:29).</td><td>Sortino deploys a LPM of order 2 which relates to the semi-variance from τ, therefore only including the negative returns as a risk measure.</td></tr>
<tr><td>Kappa 3 = $\frac{r_i^d - \tau}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.7)
(Kaplan & Knowles, 2004:3).</td><td>Kappa 3 may be seen as a generalised measure, usually deploying a LPM of order 3. Kappa of order 1 may be seen as omega and kappa of order 2 as the Sortino ratio.</td></tr>
<tr><td>Upside potential ratio = $\frac{\sum_{t=1}^{T} t^{+} \frac{1}{T}(R_t - R_{mar})}{\sum_{t=1}^{T} t^{-} \frac{1}{T}(R_t - R_{mar})^2}$ (4.8.1)
(Sortino, Van der Meer & Platinga, 1999:52), applied by Eling & Schumacher (2007:2635) as:
UPR = $\frac{HPM_{1i}(\tau)}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.8.2), whereby the ratio combines the higher partial moment (HPM) of order 1 with the LPM of order 2.</td><td>Where T is the number of periods in the sample, R_t is the return of an investment in period t, and t^{+}=1 if $R_t > R_{mar}$, t^{+}=0 if $R_t \leq R_{mar}$, t^{-}=1 if $R_t \leq R_{mar}$ and t^{-}=0 if $R_t > R_{mar}$.</td></tr>
<tr><td rowspan="3">Performance measurement based on drawdown.</td><td>Calmar ratio = $\frac{r_i^d - r_f}{-MD_{i1}}$ (4.9)
(Young, 1991:40).</td><td>Where r_i^d represents the average return, r_f the risk-free rate, and MD_{i1} the lowest return or maximum possible loss incurred in the time period considered.</td></tr>
<tr><td>Sterling ratio = $\frac{r_i^d - r_f}{\frac{1}{N}\sum_{j=1}^{N}(-MD_{i1})}$ (4.10)
(Kestner, 1996:44-46).</td><td rowspan="2"></td></tr>
<tr><td>Burke ratio = $\frac{r_i^d - r_f}{\sqrt[2]{\sum_{j=1}^{N}(-MD_{i1})^2}}$ (4.11)
(Burke, 1994:56).</td></tr>
<tr><td rowspan="4">Performance measurement on the basis of value at risk (VaR)</td><td>VaR is the loss value with a known probability an investor is willing to accept over a specific time period. Standard value at risk may be written as:
$VaR_i = -(r_i^d + z_\alpha * \sigma_i)$ (4.12),
and under the condition that the VaR is exceeded:
$CVaR_i = E[-r_{it} \mid r_{it} \leq -VaR_i]$ (4.13),
and when the return distribution is non-normal:
$MVaR_i = -(r_i^d + \sigma_i * (z_\alpha + (z_\alpha^2 - 1) * \frac{S_i}{6} + (z_\alpha^3 - 3 * z_\alpha) * \frac{E_i}{24} - (2 * z_\alpha^3 - 5 * z_\alpha) * (\frac{S_i^2}{36})$
(4.14).</td><td rowspan="4">Where z_α is the α-quintile of the standard normal distribution. S_i is the skewness and E_i the kurtosis of the return distribution.</td></tr>
<tr><td>Excess return on VaR = $\frac{r_i^d - r^f}{VaR_i}$ (4.15)
(Dowd, 2000:216).</td></tr>
<tr><td>Conditional Sharpe ratio = $\frac{r_i^d - r^f}{CVaR_i}$ (4.16)
(Agarwal & Naik, 2004:85).</td></tr>
<tr><td>Modified Sharpe ratio = $\frac{r_i^d - r^f}{MVaR_i}$ (4.17)
(Gregoriou & Gueyie, 2003:81).</td></tr>
</table>

Source: Compiled by author

Expanding on Table 4.2 would not be a difficult task. Cogneau and Hubner (2009a, 2009b) compiled an extensive literature review and listed more than 100 performance measures. These measures were categorised and compared based on asset selection and market timing as well as the way they are computed in terms of standardised or individual measures, absolute or relative measures, and also excess return or gain measures. The studies included an array of measures that built on previous measures or developed as an adaption of existing measures. The Sharpe ratio may for example be seen as the building block for several alterations of the original ratio due to its simplicity and ease of calculation (Cogneau & Hubner (2009a:4). The value at risk categorisation in Table 4.2 already included some of these alterations, which may be expanded by the Sharpe ratio adapted to accommodate autocorrelation (Lo, 2002), the adjusted Sharpe ratio by Mahdavi (2004) to account for non-normality, and the adaption by Watanabe (2006), and Zakamouline and Koekebakker (2008), to include skewness and kurtosis. Cogneua and Hubner (2009a:7), however, stated that not even these alterations could eliminate the shortcomings of the original ratio. These original ratios, nevertheless, are still widely used by investment managers to portray or compare the performance results of investments funds (Grau-Carles, Sainz, Otamendi & Doncel, 2009:1).

It will therefore be meaningful to expand on the benefits and shortcomings of the main ratios presented in Table 4.2 in four different subsections (4.3.1 – 4.3.4) and thereby include the main critique and benefits of performance measures in general. Subsection 4.3.5 includes the findings from studies that included the results from various measures in an attempt to reach consensus regarding performance rankings.

4.3.1 Traditional performance measures

Traditional performance measures remain an important cornerstone in the development of performance measures to compare investment results and make informed investment decisions on a risk-adjusted basis. The Sharpe ratio, for instance, captures both risk and return in a single measure, ultimately yielding the excess return per unit of risk. From formula 4.1, an increase in expected return or a decrease in return variability will increase the value of the Sharpe ratio. The ratio also only uses the investment's own return variability as a unit of risk and does not compare the return volatility against a set benchmark (Dowd, 2000:212). This characteristic of the Sharpe ratio enables the ratio to compare or assess different investment types.

Beck and Nagy (2003:96), however, criticised the Sharpe ratio in this regard by stating that a single measure with no general reference value provides no meaningful comparison value. They argued that similar funds or investments should be compared in terms of their Sharpe ratio value to make an informed decision. Amenc, Martellini and Sfeir (2004:2) reiterated the fact that the Sharpe ratio does not account for any form of excess performance since the ratio does not distinguish between the return realised by the market portfolio, and the return achieved by the investment which is vested in the same market. However, they admitted that it would not be easy to combine investment alternatives into peer groups to compare Sharpe ratios since the groupings may be chosen too broadly or too narrowly, due to the differences in investment management approaches or to account for different levels of diversification (Amenc *et al.*, 2004:3).

Apart from these challenges, that merely relate to the difficulty in compiling peer group investment types, another prerequisite would be to avoid correlation between investment alternatives and the market. This must to be done to adhere to the inherent Sharpe ratio assumption that the return of an investment is uncorrelated with the market portfolio return to avoid biased rankings (Sharpe, 1994: 54-56). In addition, the Sharpe ratio only includes total risk and does not account for the correlation in return variability which may be induced by the market portfolio. Lo (2002:45) found that the ratio may be overstated by as much as 70 per cent when serial correlation is not considered. Kat (2003:9) stated that autocorrelation would cause an overestimation of the mean and an underestimation of the standard deviation. Other econometric measures or statistical moments usually at the heart of critique against the Sharpe ratio are volatility, skewness, and kurtosis.

Harding (2002:1) went so far as to state that risk or volatility in returns may be hidden or become unobservable through the Sharpe ratio if the returns are not stationary. If the moments of a return series do not remain constant over the time period considered, the value of the Sharpe ratio may become biased. Volatility is usually measured by the standard deviation and although volatility may be induced by positive returns, the standard deviation only mirrors upside and downside risk and therefore smoothes extreme values which intuitively ignores higher moments. The standard deviation as a risk measure in these instances may therefore not reflect true downside risk if a sequence of significant losses occurred and also fails to indicate if the fund manager was able to reduce risk by avoiding or managing sudden market downturns (Martin, 2004:2). Skewness and/or high kurtosis that may be evident in the return distribution therefore fails to adhere to the assumption of the Sharpe ratio that the returns should be normally distributed (Hubner, 2004:2).

Another aspect linked to the higher moments of the return distribution which is not considered by the Sharpe ratio through the standard deviation as risk measure, is the parametricity of the return distribution. The reality that two very different distributions may realise the same Sharpe ratio confirms that the measure may not provide an accurate representation of the investments return per unit of risk (Harding, 2004:5). Differences in return distributions for similar investment types are easily caused by option-based strategies, especially when out-of-the-money short option strategies are implemented, which tend to produce lots of small profits with occasional large losses. Goetzmann, Ingersoll and Ross (2002:8) as well as Bailey, Li and Zhang (2004:3) stated that the risk-return relationship of derivative instrument trading strategies result in biased traditional performance measure results, since they tend to lower the observed return volatility without influencing the annualised return. However, Sharpe (1994:54) already acknowledged these findings and other critique against or limitations to the traditional Sharpe ratio when he stated that the Sharpe ratio "*will not by itself provide sufficient information to determine a set of decisions that will produce an optimal combination of asset risk and return, given an investor's tolerance for risk*".

As a ranking criterion, the Treynor ratio is similar to the Sharpe ratio. The Treynor ratio differs in risk measure since it includes the systematic risk (market beta) of the portfolio as a risk measure. The portfolio with the greater mean return over the market representative portfolio will have the highest ranking, according to Treynor. Rankings by means of the Treynor ratio would, however, only be meaningful if the investments or strategies compared are well diversified to reduce total risk to systematic risk only. An investment that is not well-diversified will not rank the same in terms of Sharpe and Treynor (Kanellakos, 2005:50).

Another aspect influencing the applicability of the Treynor ratio is the fact that the ratio stems from CAPM and applies to mean-variance analysis (Hubner, 2004:3). In terms of CAPM, investors only evaluate return mean and variance and assume that returns are normally distributed, which means that upside and downside risk are viewed the same (Leland, 1998:3). Higher moments will accordingly lead to biased rankings, especially when dynamic, option-based strategies are deployed (Leland, 1998:5-6). CAPM, and consequently Treynor, will therefore have difficulty explaining or ranking past performance when returns are not normally distributed. Ronaldo and Favre (2003:2) confirmed that neither beta nor any form of excess return in terms of alpha are suitable to measure performance of returns not normally distributed.

As a result, Jensen's alpha, which also uses beta as a risk measure, may produce biased results when higher moments are not considered. The excess return or alpha measure is only the amount of risk-adjusted return generated through active management (Schneeweis & Spurgin, 1999:84). Jensen's alpha is therefore not a ranking mechanism, only a measure that shows to what extent a manager was able to outperform the market representative index. One of the main concerns is that portfolio managers may be able to alter alpha by chance or specific timing, and thereby generate superior performance (Grinblatt & Titman, 1989:394). Also, managers would have to continuously outperform the market index on a risk-adjusted basis, which means that they may include additional unsystematic risk compared to a passive buy-and-hold strategy and thereby directly contradict several efficient-market hypothesis findings in this regard (Chapter 3, Section 2).

The findings above clearly show that ranking measures such as Sharpe and Treynor, as well as excess return measures such as Jensen's alpha, may produce misleading results when the return distribution and higher moments are not considered. A superior performance measure result should therefore not be regarded as the identification of an optimal portfolio or superior fund manager skill, but rather as an indication to critically evaluate the influential underlying risk and return factors (Kat, 2003:10). As a result, development in performance measurement moved from return per unit of risk to the risk of not achieving an expected return.

4.3.2 Performance measurement based on lower partial moments (LPMs)

Traditional measures such as Sharpe intuitively view positive and negative deviations from expected return in the same manner, and thereby effectively penalise positive return deviations. Positive deviations from the mean may also reduce the actual risk involved by equalizing the influence of negative returns below the mean through the standard deviation or variance as risk measures (Mao, 1970:353). Investors, however, are only concerned with loss or returns lower than the expected or threshold return. Markowitz (1959:194) stated that semi-variance or returns lower than the expected return should be viewed as a more pure form of risk measure. Downside risk measures also provide investors with a more concise view of the real risk involved in an investment (Nawrocki, 1999:1).

The meaningfulness of mean-variance risk measures, which included downside risk or semi-variance, was questioned by researchers such as Friend and Blume (1970), Gaumnitz (1970), Stone (1973), Jean (1975) well as Ang and Chau (1979). In general, they found that the preferred risk measure would depend on the distribution of returns and that higher moments should be considered to avoid biased measurement and comparisons. Thereafter, new developments in performance measurements all but ceased until Sortino and Price (1994) incorporated the concept of downside risk or lower partial moments (LPMs), which stem from Sortino and Van der Meer (1991), into performance measures. The Omega ratio was developed by Keating and Shadwick (2002a, 2002b) shortly after, and the search for an all-inclusive risk-adjusted performance measure continued with the Kappa 3 measure by Kaplan and Knowles (2004). The Kappa 3 measure is unique in the sense that it incorporates both Sortino (Kappa of order 2) and Omega (Kappa of order 1), which are special cases of Kappa. The choice of Kappa (K1, K2, etc.) is an important consideration when evaluating different investment alternatives (Kaplan & Knowles, 2004:8). Research regarding higher Kappa values appear to be scarce or yet to be developed. As a result, the advantages and shortcomings of the Sortino and Omega ratios are also applicable to the Kappa 3 ratio.

The Sortino ratio is basically a modified Sharpe ratio that uses semi-variance rather than standard deviation as a risk measure. But the downside risk measure (semi-variance) is not just the negative returns below the mean, but the return below a minimum acceptable return and may be seen as the second partial moment from the LPM framework (Plantinga, Van der Meer & Sortino, 2001:4). The aim of Sortino and Price (1994) was also to establish a ratio not sensitive to higher moments or differences in return distributions. Platinga, *et al*. (2001:2) argued that this feat had been successfully achieved, since the downside risk measure was able to overcome the bias that may be introduced by skew distributions. There is, however, no consensus in this regard.

Lien (2002:492) showed that, when a return distribution exhibits skewness and high kurtosis, the Sortino ratio tended to rank investment performance in the same order as the Sharpe ratio. Harding (2002:2) stated that the conditions of stationarity and parametricity should be met and the distribution known in order to draw any relevant conclusions from a Sortino ranking. Nevertheless, not all findings were against the relevance of the Sortino ratio, with Amenc, Noël, Martellini and Vaissie (2004a:15) stating that the Sortino ratio was more relevant than the Sharpe ratio, especially if the distribution was negatively skewed. Bacmann and Gawron (2004:4) cautioned that the ratio did not provide a full representation of the negative risk when extreme negative returns were present in the distribution.

These findings reiterate the notion that the return distribution should still be considered, especially when different types of investments are being compared. Pedersen and Satchell (2002:6) argued that, if several investment types or groupings are compared by means of the Sortino ratio and the same risk-free rate and return threshold is used, the Sortino ratio would probably be optimised by a low-risk bond type portfolio, which may not necessarily be a true representation of a diversified portfolio. As a result, a comparison of different investment portfolio types by means of Sortino may lead to biased results. Amenc, *et al*. (2004a:21) also pointed out that the threshold level is an important consideration. If the threshold is estimated too low, the downside risk may be underestimated and *vice versa*. A relevant example of where the Sortino ratio may not be relevant, is when option strategies are deployed to provide cover against downside price movements. A threshold level at the option strike level would cause no negative returns in the return distribution. In these instances where “riskless strategies” are implemented, Platinga, *et al*. (2001:6) recommended that the upside potential ratio (UPR) be used. However, Lien (2002:492) illustrated that, when distributions are normally distributed, the Sortino ratio, upside potential ratio, and Sharpe ratio give the same ranking. It therefore seems that the issue with non-normal distributions are not resolved by these ratios. Researchers consequently needed to devise a method to measure performance and compare investments even when returns were not normally distributed.

The search for a performance measure that addressed the shortcomings of the traditional mean-variance approach measures progressed significantly when Keating and Shadwick (2002b:2) introduced their "universal" performance measure, Omega. The measure incorporates or captures the influence of higher moments completely since all the available information from the return distribution is included in the cumulative distribution function used to calculate Omega (Keating & Shadwick, 2002b:8-9). Omega, as a result, makes no assumption of the return distribution and captures both lower partial moments (LPMs) and higher partial moments (HPMs). The Omega may therefore be seen as the ratio between returns above and returns below the set return threshold as shown in Figure 4.1 (Farinelli & Tibiletti, 2002:7). A higher Omega value will, as a result, be preferred to a lower value. The return threshold may differ significantly and range from a minimum acceptable return to a risk-free rate which may consequently be linked to an investor's risk preference or tolerance level (Favre-Bulle & Pache, 2003:12). The threshold should however be kept constant when comparing different investment return distributions (Keating & Shadwick, 2002b:11-12). An Omega value can nevertheless be calculated at any relevant return distribution threshold value to rank investments, whereas is becomes difficult to rank negative Sharpe ratios (Bachman & Scholtz, 2003:3).

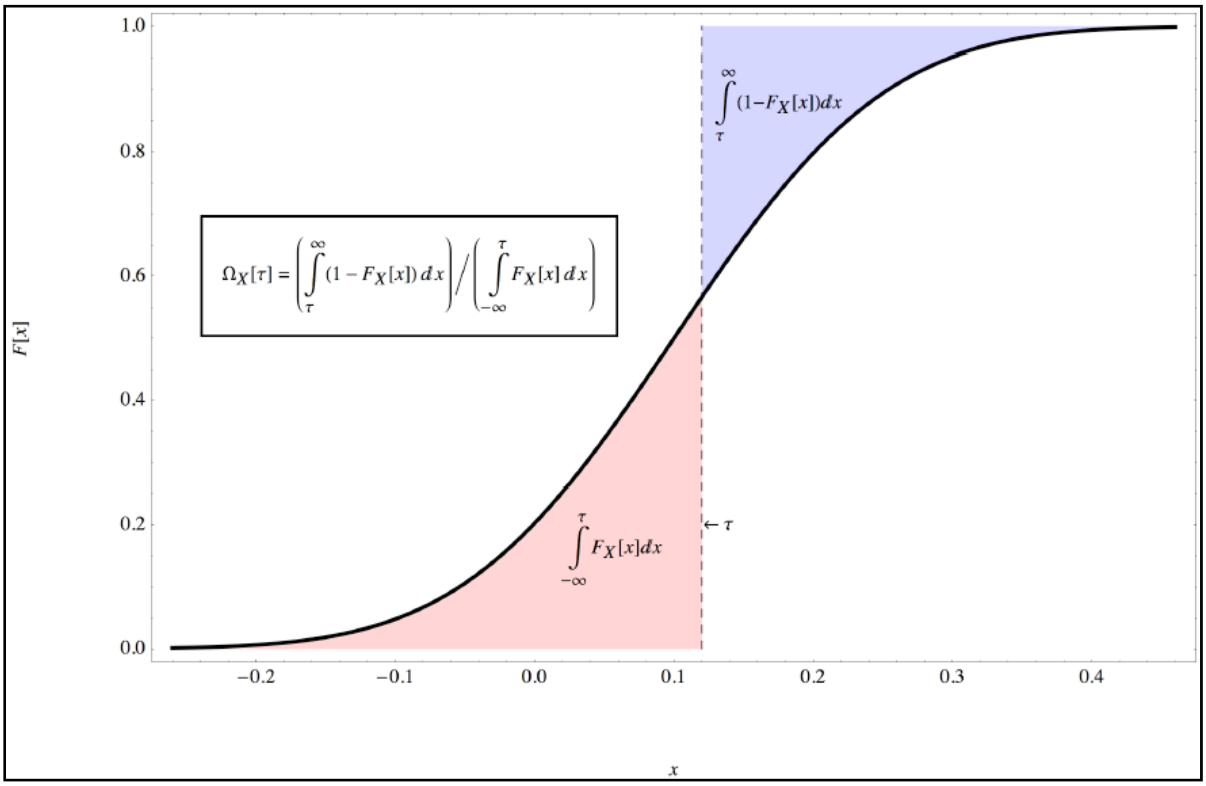

Figure 4.1: Graphic representation of the Omega Ratio
Source: Frey (2009:6)

The Omega measure is, however, more than a specific value measured at the set threshold. The Omega function provides a value for all the values in the distribution that may be plotted on a graph. Plotting several Omega functions on the same graph (e.g. Figure 4.2) visually displays other key evaluation or ranking criteria that may be linked to the risk characteristics of investors (Du Toit, 2005:5). Omega functions to the left side of a threshold value (e.g. 0% in Figure 4.2) show how big or limited negative returns will be. A function that approaches infinity faster will rank higher with more limited negative returns. In Figure 4.2, the fixed income investment approaches infinity the fastest, which confirms the intuitively less risky investment type. The same function to the right side of the threshold value shows the probability of achieving greater positive returns and would be preferred if it approached zero at a much slower pace. In Figure 4.2, the trading investment approaches zero at the slowest pace, which means that this investment has the highest potential for positive returns. A higher ranking on both sides of the graph will therefore be preferred by the rational investor since it shows a higher probability of positive returns (Du Toit, 2005:6).

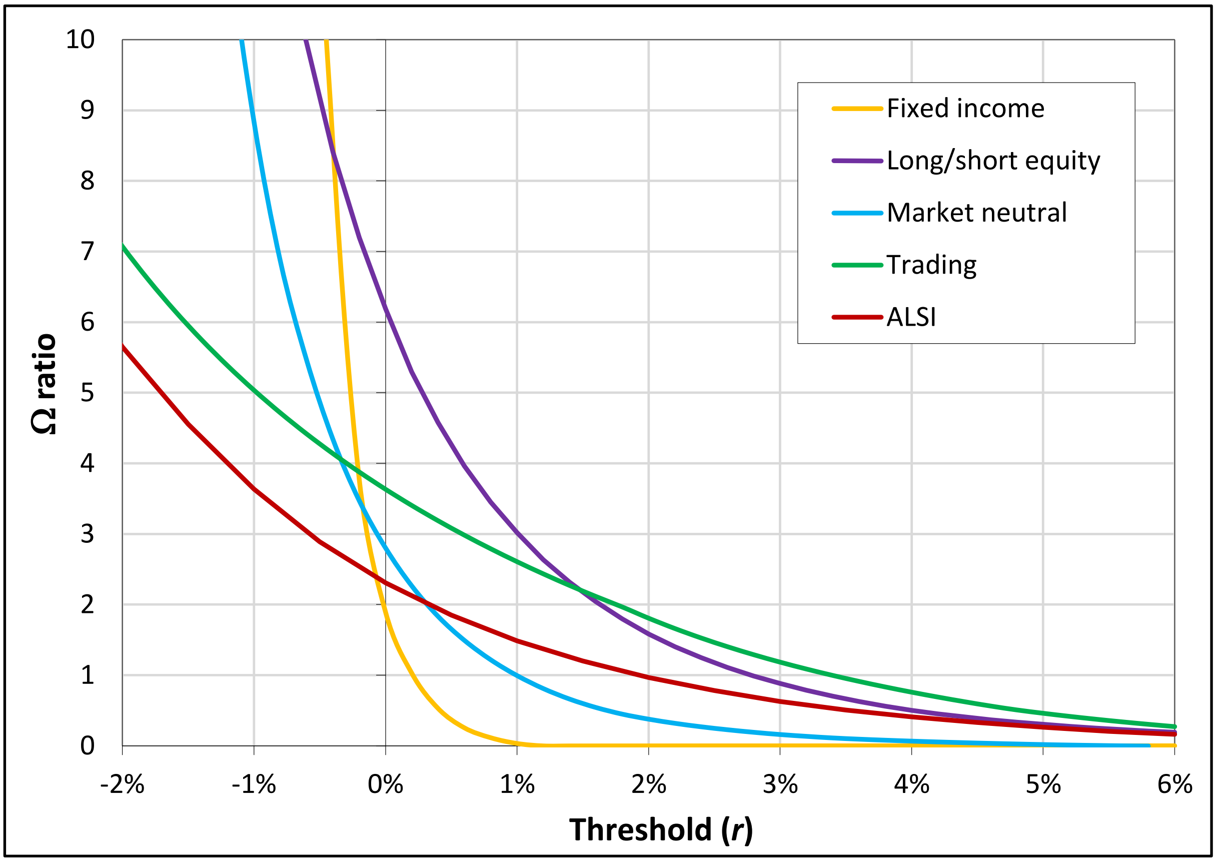

Figure 4.2: Omega ratios compared
Source: Botha (2007:467)

Ranking investments based on their Omega value at different thresholds, however, also presents a negative aspect. Different investors naturally prefer different threshold levels. Figure 4.2 clearly shows that, if the threshold is moved from 0% to 2%, the trading investment would be preferred whereas the long/short equity would have been preferred at the 0% threshold. Du Toit (2005:6) cautions against evaluating only a single Omega ranking at a specific threshold value since it disregards the information contained in the full distribution function. It is therefore important to also consider the investments for which the Omega function moves to infinity faster below the threshold, as well as the investment with the higher probability of a positive return.

There are also other concerns regarding the Omega function's sensitivity to sample size. Favre-Bulle & Pache (2003:18) stated that the number of observations should be at least a 100 and that accurate results could only be expected from 200 observations. However, Amenc, *et al.* (2004a:20) reduced the required sample size when they found that only 40-50 observations were necessary to ensure stable results. Another concern with Omega was that fund managers would be able to improve the Omega ratio of investments by leveraging investments. Frey (2009:12) called this feature the Omega leverage bias, which lead the Omega function to rank highly leveraged, though undesirable investment distributions as optimal distributions. Investors with moderate risk thresholds may as a result unknowingly select investments with a substantial downside risk. Frey (2009:17) did conclude that a fixed chosen threshold may obscure downside risk and that varying the threshold could provide a more conclusive ranking and reduce potentially obscured downside risk bias. Also, the study proposed that other measures such as the Sharpe ratio, which is not influenced by leverage, be applied to confirm rankings.

4.3.3 Performance measurement based on drawdown

A third category of risk-adjusted measures is the result of performance measure development in practice instead of from a theoretical point of view. These measures also focus on negative returns as a measure of risk captured by the drawdown or loss incurred over a specific time period (Eling & Schumacher, 2006:432). When applying either a maximum drawdown, an average of drawdowns, or the variance of drawdowns over a specified period, the Calmar, Sterling and Burke ratios transpire (Wiesinger, 2010:23).

The Calmar ratio was initially developed by Young (1991:40) to measure commodity fund performance. The ratio measures the excess return over a risk-free rate divided by the maximum loss (maximum drawdown) over the period. A smaller maximum loss would therefore result in a greater Calmar ratio value. The aim of the measure was to improve on the shortcomings of the Sharpe ratio, and accommodate the reality that the risk-free rate value changes over time. Young (1991:40) claimed that the Calmar ratio was an improvement on the Sharpe ratio and a slight modification of the Stirling ratio, since it was able to provide an up-to-date measure of a commodity fund's performance whereas the Stirling ratio was calculated on a yearly basis.

The Stirling ratio differs from the Calmar ratio in terms of the drawdown calculation. Instead of a maximum drawdown, it uses the average of a certain number of the smallest drawdowns within the specified period. Consequently, the Stirling ratio is less sensitive to aggressive drawdowns or outliers than the Calmar ratio. The original Stirling ratio nevertheless added an arbitrary 10 per cent to the average of the smallest drawdowns to ensure that the risk measure did not differ significantly from a potential maximum drawdown (Bacon, 2009:11). The original Stirling, however, had no academic or scientific foundation, as it was developed to be applied in practice. The original measure has been altered over time and generally applied in literature to calculate return as excess return over the risk-free rate, and to ignore the 10 per cent adjustment of the average drawdown risk measure (Lhabitant, 2004:84). The Burke ratio is another ratio that developed from practical application and gained recognition in literature. The ratio differs in terms of the risk measure, which is the square root of the sum of a specific number of the smallest drawdowns within the specified time period. As a result, the ratio is less sensitive to outliers than the Calmar ratio, but ensures that the larger drawdowns in the dataset are not merely averaged but more meaningfully weighted (Bacon, 2008:91)

Schumacher and Eling (2010:2) evaluated the Calmar, Striling and Burke ratios and specifically addressed the gap between theory and practice when it came to performance measures based on drawdown. The research aim was to link ranking results of the drawdown measure to the Sharpe ratio in an attempt to draw some conclusions based on their theoretical foundations. The study built on the results of Eling and Schumacher (2007:2639), which found high-ranking correlations between drawdown-based measures and the Sharpe ratio. The comparison required that the simulated return distributions conform to specific location and scale parameters such as the normal, student's t, or logistic distribution. Secondly, drawdown was defined as cumulated excess returns rather than compounded cumulative returns. Schumacher and Eling (2010:5) stated that by using compounded cumulative returns, the value of drawdown measures can be increased through different combinations of risk-free asset and risky portfolios along the capital market line. Results showed that rankings based on these conditions would be similar for the Sharpe ratio and drawdown-based ratios. They concluded that the same theoretical foundation applied to the Sharpe ratio may be applied to drawdown measures. Based on this result, they argued against the usefulness and popularity of drawdown measures, since it is much simpler to calculate a Sharpe value. Nevertheless, some thoughts on their applicability were that drawdown measures presented a worst-case scenario or that it was more difficult to manipulate drawdown measures. The popularity of the concept of measuring risk by means of drawdown measures are however not restricted to these measures since value at risk (VaR) measures also make use of maximum drawdown or expected maximum loss as a risk denominator.

4.3.4 Performance measurement based on value at risk (VaR)

Value at risk (VaR) has gained popularity and is regarded as an essential tool for risk managers, since it provides a single figure probable estimate of downside risk or potential loss in a given time period. The time period evaluated may differ depending on the type of risk measured or investment evaluated. A bank may, for instance, measure VaR on daily or weekly return intervals whereas other investments may measure monthly exposure intervals. As a result, VaR is not a measure of maximum loss, but indicates how great the loss may be for a given probability (Simons, 1998:36). One of the general assumptions of the original VaR calculation was that return distributions follow a standard normal distribution. From this assumption, the VaR is usually calculated at the 95 per cent and 99 per cent confidence intervals. From the mean, these confidence interval levels correspond to 1,645 and 2,326 standard deviations respectively. This means that the VaR is that value at the confidence interval for which there is either a five per cent or one per cent chance of realising a greater loss over the time horizon (Jorion, 2006:110).

The normality assumption and the fact that the standard deviation as risk measure is included in the VaR calculation, however, immediately encompasses the general problems attributed to Sharpe or other standard deviation-based measures. The failure of Long-Term Capital Management (LTCM) in 1998 emphasised the need to deploy the correct type of risk-adjusted performance measure to investments or distributions which included undesirable higher moment characteristics (Liang & Park, 2007:334). The need for normality is highlighted by the fact that the VaR measure lacks subadditivity[26] when the distribution is non-normal, which shows a potential lack of diversification (Embrechts, 2000:453; Mcneil, Embrechts & Frey, 2005:114; Zakamouline, 2010:8). This does not necessarily mean that VaR succumbs completely to higher moments, since Gupta and Liang (2005:248) confirmed that VaR is superior to other mean-variance approach measures in this regard. It does, however, mean that the VaR variables and inputs need to be correctly defined.

Beder (1995:12), for instance, showed that the VaR is sensitive to the method deployed for calculating the value as well as changes to the underlying parameters. Lo (2001:19-20) warned that VaR does not

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26 Subadditivity means that the total risk as a portfolio should be smaller than or equal to the sum of the individual risk of the assets included in the investment. If this is not the case, it reflects badly on the level of portfolio diversification (Kremer, 2008:24).

provide any indication of how big a loss may be incurred if the threshold level is breached. He noted that the amount of data required to construct a meaningful distribution of returns remained unclear, but that enough data could enable VaR to incorporate higher moments, time-varying risk factors and event-dependent correlations. Gupta and Liang (2005:223) stated that the confidence level should always be chosen high enough to reduce any potential capital loss to the smallest probability and amount possible. The time horizon should always consider the liquidity of the assets in the portfolio and be chosen according to the time it would take to correct or reduce a loss by liquidating assets or the time needed to acquire the necessary funds to make up potential losses. Wiesinger (2010:35) varied parameters such as the confidence level, the risk-free rate and the number of drawdowns considered. Results showed that VaR is fairly resistant to changes in the underlying parameters, but that changes in the computation method of VaR caused significant changes in its value. These changes in the value of VaR may also be attributed to changes in the VaR model to account for shortcomings in the original model.

One of the alterations of the original VaR model, to overcome the fact that VaR does not consider losses outside of the confidence interval, is the Conditional VaR (CVaR) which provides an expected loss if the VaR, at the set confidence interval, is exceeded (Albrecht & Koryciorz, 2003:2). The CvaR, however, still assumes normality in the return distribution which was addressed by the development of the Modified VaR (MVaR), which adjusts VaR to account for skewness and kurtosis by means of the Cornish-Fisher expansion of the standard normal distribution (Favre & Galeano, 2002:8). The Cornish-Fisher expansion ensures that the estimated VaR at the threshold is calculated as a more negative value when the distribution is negatively skewed. This ensures that the risk of negative skewness and excess kurtosis is largely addressed. In the case where the distribution shows positive skewness or kurtosis in line with the normal parameters, the Cornish-Fisher expansion results in a reduced VaR estimate (Grau-Carles, Sainz, Otamendi & Doncel, 2009:9). Since VaR may be seen as a risk measure, both altered VaR measures were used as risk measures in die Sharpe formula to assess risk-adjusted performance.

The Conditional Sharpe ratio, which uses CVaR as a risk denominator, was first used by Argawal and Naik (2004:66) to compare the results to the traditional mean-variance framework. Results showed that optimal portfolios identified by the CVaR measure reduced the risk of low probability but high value tail losses by as much as 54 per cent compared to the mean-variance framework. The normality requirement, however, remains relevant for CVaR as risk measure, which leads to the logic application of MVaR as a risk measure in the Sharpe ratio formula. Gregoriou and Gueyie (2003:77) compared the traditional Sharpe and the Modified Sharpe ratios in their evaluation of hedge fund returns known for non-normality in the return distributions, and found that the Modified Sharpe ratio evaluated non-normal returns more accurately.

From the discussion based on the ratios grouped in Table 4.2 above, none of the ratios is a clear-cut optimal measure without any shortcomings or aspects to consider. The main research which led to the development of many of these ratios also focussed primarily on the rectification of a shortcoming of one of the other measures without necessarily comparing the results or rankings of several types of performance measures. There are, however, several performance measure evaluation studies that included various measures to reach consensus in terms of asset return performance rankings.

4.3.5 Evaluating various performance measures to rank asset returns

Throughout the development of performance measure literature, researchers focussed on the factors that may influence or limit the effectiveness of risk-adjusted performance measures' accurate ranking of different investments or asset returns. There have, however, been several studies that evaluated different performance measures to compare the rankings of the same set of asset returns. The main aim of this endeavour may be viewed as a way to assess whether factors such as normality, skewness, kurtosis, threshold levels, or confidence intervals have a significant influence on performance rankings as literature findings state (Wiesinger, 2010:1).

One of the first comparative studies of this nature, which included traditional performance measures (Sharpe, Treynor, Jensen), lower partial moments (Sortino), and drawdown measures (Calmar, Sterling) was done by Pedersen and Rudholm-Alfvin (2003). The study evaluated global financial services as well as the alternative investment market, with the aim of determining whether more complex measures than the Sharpe ratio would be able to provide meaningful additional information with regard to asset performance. In terms of global financial services, the rank correlation across the whole spectrum of measures included was above 80 per cent. The study found that the application of traditional Sharpe-based approaches remained appropriate measures, which were backed by practice and literature. The study reiterated that the cost of acquiring the necessary data as well as the effort and time to calculate or model more complex measures, should always be considered before including them as decision criteria (Pedersen & Rudholm-Alfvin, 2003:166). The evaluation of alternative investment returns, however, clearly showed that measures may differ considerably in their rankings, especially when extreme losses lead to considerable negative skewness in the return distribution. Based on this finding, the study concluded that it is important to consider the underlying assumptions of mean-variance-based measures and determine if the assumptions are accounted for to ensure that rankings are not biased (Pedersen & Rudholm-Alfvin, 2003:168). Building on the alternative investment performance measure analysis literature, Eling and Schuhmacher (2006:3) compared the performance ranking of hedge fund, bond, and equity indices. These indices were compared by means of 11 different performance measures, which included measures of all the different categories of measures included in Table 4.2. The study found that there was a remarkably high correlation in the rankings of the different measures, and that any difference that might occur by using the Sharpe ratio would be insignificantly small when comparing funds constructed in the form of indices (Eling & Schuhmacher, 2006:5).

Shortly after, Eling and Schuhmacher (2007:2634) expanded on this study by evaluating hedge fund data instead of hedge fund indices for 2763 funds. This was done since hedge funds are notorious for having negative skewness and/or high kurtosis that deviates from normal distribution criteria. The analysis included 13 performance measures from all of the main types of measures and mainly aimed to compare the Sharpe ranking to the ranking of other measures. Results showed that the first two moments (mean and variance) were sufficient in describing the return distribution, even if the return data were not distributed normally. The study confirmed that the Sharpe ratio would be adequate to rank hedge fund performance (Eling & Schuhmacher, 2007:2645). A similar study by Liang and Park (2007:359) also focussed on hedge fund performance, but only included alternative measures such as semi-deviation and VaR. The study concluded that higher moments should not be ignored when analysing hedge fund risk, since cross-sectional variation in hedge fund returns could be explained more conclusively if skewness and kurtosis were considered when performance measures were evaluated.

The study by Eling (2008:54), however, moved away from mainly hedge fund type data and included 38 954 different investment or mutual funds including equities, bonds, real estate, hedge funds, funds of hedge funds, commodity trading advisor funds, and commodity pool operators. The analysis also included 11 different measures from the types of measures included in Table 4.2. The results by Eling and Schuhmacher (2006, 2007) were confirmed, since the Sharpe rankings did not differ significantly from the other and newer measures (Eling, 2008:59). The study concluded by stating that the Sharpe ratio remained relevant since it was based on a sound theoretical framework, was consistent with expected utility theory, included a range of statistical tests to confirm possible weakness or bias in the measure, and was preferred in practice due to its simplicity (Eling, 2008:63). The study did, however, not write off the use of other measures but confirmed that the Sharpe ratio should also not merely be written off based on literature findings, which tend to focus on the possible weaknesses the measure might have. Despite these findings by Eling and Schuhmacher (2006, 2007) and Eling (2008), which largely confirmed the relevance of the Sharpe ratio as well as the high level of correlation between the different types of ratios, later studies delved deeper into the confirmatory methods applied and the factors influencing the results of other measures.

Zakamouline (2010:3) criticised Eling and Schuhmacher (2007), as well as Eling (2008) for the small sample of performance measures included in their studies and referred to the more than 100 different measures included in Cogneau and Hubner (2009a, 2009b). He noted that the Spearman's rank correlation coefficient applied to confirm performance measure ranking correlation can be misleading, since there is no set threshold value for the correlation measure which may lead to biased interpretations. Results from the inclusion of other measures and correlation comparison showed that rankings between alternative measures and the Sharpe ratio definitely differ despite a statistically high correlation between rankings. An analysis of the data distributions found that the fund return data included by Eling and Schuhmacher (2007) and Eling (2008) were generally distributed normally. He pointed out that, even if distributions were non-normal, they belonged to the same class of elliptical distributions, and therefore showed the same kind of deviation from normality which may render the main reason for applying alternative measures insignificant (Zakamouline, 2010:4). The study concluded that higher moments definitely have an influence in performance measure rankings, but that the influence, especially of skewness, is more significant than kurtosis.

Wiesinger (2010:25) also included the main performance measures from Eling and Schuhmacher (2006, 2007) and Eling (2008) in an analysis of Swiss bank investment products. The study included the specific additional alternative measures from Zakamouline (2010), which confirmed different rankings compared to Sharpe. An analysis of the data showed that the annualised monthly returns were mostly normally distributed, which could be attributed to the high rank correlation between the different measures revealed by the Sharpe ratio (Wiesinger, 2010:31). The results did, however, show a large variation in correlation between alternative measures. The subsequent study aimed to determine if changes in the underlying parameters of the alternative measures, such as confidence levels, minimum return thresholds, risk-free interest rates, or the number of drawdowns would change the variability in the ranking correlation (Wiesinger, 2010:35). These results showed that alternative performance measure rankings and correlations did not differ much when confidence levels or the number of drawdowns were changed. Changes in the calculation method for VaR and CVaR, however, showed significant rank changes. Variation in the interest rate as a threshold for Omega also brought about ranking changes. In general, the conclusion was that, despite certain ranking changes when parameter changes were included, the ranking correlation between risk-adjusted performance measures remained high. Also, the study recommended that the information contained in the higher moments in terms of investment risk, which is highlighted by specific measures, should always be taken into account to make an informed decision (Wiesinger, 2010:41). This finding was confirmed by Van Heerden (2015:12), who compared daily, weekly and monthly closing prices over three periods - prior, during and after the 2007-2009 financial crisis - in terms of return distribution normality. Based on the presence of normality or the lack thereof, the study set out to prove that Sharpe rankings may differ if the data is not normally distributed. Results showed that the presence of higher moments and non-normality influenced the Sharpe rankings. Also, that for the specific data set, monthly data was found to be more normally distributed. The study recommended that different data frequencies always be considered and tested for normality to determine the best data frequency fit in an attempt to eliminate possible performance measure ranking discrepancies (Van Heerden, 2015:12).

From the discussion presented in this section, it becomes clear that findings may differ in terms of performance measure evaluation gauged by means of different measures. It is also evident that one should evaluate the presence of higher moments in the return data. If higher moments point to non-normality, it is necessary to consider the impact thereof on investors' preferences as well as on performance measure rankings. Investors would always prefer positive skewness and negative excess kurtosis (Wiesinger, 2010:26). Hence, it is possible that there is no general optimal measure applicable to all data sets with optimal results, but there will always be a measure or specific combination of ratios for each unique circumstance which is able to adhere to an investor's risk preference and account for any possible discrepancy in the return distribution (Bacon, 2009:12).

4.4 Chapter summary

Managing price risk by means of derivative contracts in the futures market remains a controversial concept. In theory, it provides the best possible means for a producer to ensure that the value of the crop he or she is planning to produce is hedged to secure a minimum income level. However, it does not necessarily mean, before or during the production season, that the futures price would be at a price level that would provide a producer with the opportunity to hedge at a profitable level. Hedging may also lead to costly futures contract buy-outs due to factors such as adverse weather events preventing a producer from producing a crop to be delivered against the contract price. Producers are, as a result, confronted with variables generally out of their control in terms of price formation. The harsh reality, therefore, is that a producer would still receive the market price based on the general market consensus of the impact that these variables should have on current and future price changes. But this does not mean that the general market consensus price would be of fair value for a specific producer.

Producers should, as a result, never separate production decisions from marketing decisions in any given season. This implies that a profitable or sustainable production decision should be based on the futures price a producer is able to hedge at before or during the planting window. Local and international studies have confirmed that established futures market platforms provide for efficient price formation. The futures price at that point in time would, therefore, already have accounted for the influence that several factors may have on the price. Thus producers would be able to use the derivative market as an efficient price risk transfer mechanism. The reality, however, remains that producers are reluctant to make use of this market mechanism due to several reasons ranging from their specific physical location to the market (which relates to basis risk), the size of their farm and whether they are the owner or not, their farming experience and level of specialisation, as well as their level of education in terms of tertiary qualifications or courses in the application of derivative instruments. The independent influence of each of these factors are difficult to distinguish, and would probably be a combination of several factors inevitably influencing a producer's hedging decision.

The general underlying decisive factors would, however, probably be the producer's financial situation in terms of liquidity, as well as the producer's risk profile. Arguably, a producer's risk profile would also be influenced by financial liquidity. A producer who has adequate liquidity would for instance be able to absorb market downturns and not be forced to sell at potential market lows to settle outstanding production debt. The counter argument might be that producers who have adequate liquidity would be able to finance the required cash flow or cost of hedging. Literature confirms that producers in a financially sound position would rather accept more risk than mitigate the risk through derivative instruments. As a result, the most likely way to influence a producer's willingness to adopt derivative instruments is to change their perception that price risk management only mitigates downward price risk. This perception may likely be changed if a hedging strategy is able to reduce income variability and provide the opportunity to share in upward price movements whilst reducing the cost of hedging. Including all of the characteristics in a specific hedging strategy however remains a challenging endeavour which would require an adaptable strategy. This highlights the need to deploy a dynamic hedging strategy which is able to accommodate changing market conditions.

Several hedging strategies have been evaluated over time from an international and South African market point of view. All of these strategies included advantages and disadvantages, but the general consensus remained that a producer would be able to reduce income variability by deploying some form of hedging strategy as opposed to remaining unhedged and selling in the cash market after harvest. Also, including more selling intervals reduced income variability even more, but was still not able to realise the highest mean return. Hedging strategies were however mainly measured or ranked based on mean return and standard deviation of return. Later studies applied cumulative distribution functions, which only added a probability of realising a minimum return by deploying a specific strategy.

As a result, it became evident that the choice of hedging strategy would depend on the producer's risk profile, since none of the measures was able to conclusively rank hedging strategy performance.

This shortcoming of hedging strategy rankings is one of the aspects this study aims to address by applying risk-adjusted performance measures as ranking criteria. An array of different measures exists but the measures from mainstream literature will remain the focus of this study. These measures were mainly categorised based on specific calculation methods. They include mean-variance type measures such as traditional performance measures, which provide a measure of excess return per unit of risk and lower partial moments that include only negative returns or returns below a threshold as a risk measure. Measures which developed based on the shortcomings of mean-variance type measures include drawdown measures, which calculate a ranking measure based on the lowest return or maximum possible loss in the time period considered and value-at-risk measures that are based on the probability of realising a greater loss than a specific value over a specified time period.

All of these measures remain subject to specific critique, which in general includes the ability of a performance measure to account for higher moments in the return distribution. Measures that should conform to the assumption of normality, such as mean-variance type measures, are subject to ranking bias when higher moments such as negative skewness and high kurtosis are present in the return distribution. Several studies reiterated this shortcoming of traditional and other mean-variance based performance measures, whereas other studies that included several different types of measures, showed a significantly high ranking correlation between the different measures despite the presence of non-normality in some of the asset return distributions.

Literature, nevertheless, has showed that it remains meaningful to determine whether the return distribution falls within the set parameters for a normal distribution. In the instance where all distributions are found to be distributed normally, all performance measures would probably yield identical rankings that may act as conformation of hedging strategy performance. If some distributions were however found to be non-normal, and especially when distributions show significant negative skewness, it would be meaningful to apply specific applicable measures that are able to account for higher moments. Even then, conformation by several measures would add to the significance of the rankings found.

In terms of the objectives of this study, which was to identify 10 applicable derivative hedging strategies, several applicable hedging strategies were identified to evaluate and compare over time. The applicability of the derivative-based hedging strategies may, furthermore, be based on the factors that influence a producer's willingness to adopt these strategies. As a result, the insight gained in the characteristics an optimal hedging strategy should have in order to improve and increase producer hedging will aid in the decision-making process of which strategies to include as part of the empirical study. Furthermore, in order to form the foundation of one of the envisaged contributions of this study, the performance measure review included the necessary background on applicable measures and an alternative approach to conclusively ranking the hedging strategies evaluated. The following chapter specifies the specific hedging strategies as well as the performance measures included in this study. A thorough methodological approach to comparing or linking optimal strategies to specific seasonal outcomes by means of influential seasonal factors is also discussed.

CHAPTER 5

Methodology

"Research is the process of going up alleys to see if they are blind." - Barstow Bates (1967)

5.1 Introduction

The aim of all the literature included up to this point in the study was to address several of the objectives as set out in Chapter 1 and to lay the foundation for the methodological approach to be followed in Chapter 5. The South African agricultural market development from a regulated market to a free market system, Chapter 2 (Sections 2.2 and 2.3) provided the necessary background to the changes in the marketing mechanism, which forced producers to adopt the use of derivative instruments in an attempt to manage their price risk. Producers' lack of understanding of these instruments led to several bad experiences, as well as a general mistrust in the price formation mechanism, which to a great extent increased their unwillingness to make use of the available price risk management instruments (Jordaan & Grové, 2007:548).

Chapter 4 (Section 4.2.1) added to the factors that influence a producer's hedging decision, but also identified several requirements a hedging strategy should have in order to increase producers' willingness to adopt such a strategy. These requirements included the incorporation of meaningful expected market trends based on geographical characteristics (such as climate variables), yield expectations, and production patterns (Ueckermann, Blignaut, Gupta & Raubenheimer, 2008:234). The importance of a hedging strategy's ability to accommodate changing market conditions (Lapan & Moschini, 1994:476) also became evident from the hedging strategy literature, as discussed in Chapter 4 (Section 4.2.2). However, in order to evaluate hedging strategies, a thorough understanding of the relevant derivative instruments applied when implementing these strategies, was required. Thorough explanations of each of these instruments were addressed in Chapter 2 (Section 2.3.3). Also, in order to address the requirement that a hedging strategy should be linked to meaningful expectations of price formation, several influential market factors were also identified in Chapter 2 (Section 2.4). From this background, the aim or main objective of the study is to link different production seasons by means of similarities between these influential market factors or market drivers, and characterise the market accordingly. By doing so, this aim will unlock the ability to identify an optimal hedging strategy for a specific type of season in advance as certain market characteristics emerge. To accomplish this goal, this chapter is methodologically broken down as follows.

Section 5.2 discusses the different influential market price driving factors to be included in the study. The factor description will provide the required background to the description of the different types of data that will be included as part of the influential factor and hedging strategy analysis. Following the data description, Section 5.3 focuses on clustering and percentile rank groupings as methods, which may be applied in an attempt to link different production seasons, based on influential factor similarities (characterising the market). Section 5.4 discusses and explains the implementation of the 10 different hedging strategies, which are evaluated as part of the analysis. In order to more conclusively rank these hedging strategies, the applicable performance measures (which were identified in Chapter 4, Section 4.3), are included in Section 5.5. Finally, Section 5.6 summarises the empirical review which was contectualised in the form of Table A1, included in the Appendix, in onder to provide a meaningful road map of the process to follow.

5.2 Influential market price drivers

Price formation in each market is primarily based on role players' interpretation of and reaction to new information. The swift rate of adjustment of market prices based on a logical or general expectation of the impact of changes in influential market price drivers will, as a result, ensure effective price discovery (Zapata, Fortenbery & Armstrong, 2005:4). It is therefore meaningful to consider the influential factors or drivers of the SAFEX white maize price as discussed and described in Chapter 2 (Section 2.4) for inclusion in the clustering and percentile ranking groupings methods discussed in Section 5.3. The discussion of these factors will facilitate an understanding of each factor, with specific reference to the changes that may be expected in the market price due to changes in the influential factor values. This subsection is structured as follows. Section 5.2.1 and Section 5.2.2 provide a thorough description of each of the factors included in the study. It is, however, important to distinguish between the factors included in each subsection to clarify the reason for the subdivision.

The factors included and discussed as part of Subsection 5.2.1 include factors that can take on a monthly value. Several of these factors, specifically price factors, may take on daily values, whereas supply and demand figures only take on monthly values due to the formal publication intervals determined by government councils or institutions. In order to derive a meaningful comparison of the factors over time, the analysis of these factors is based on monthly values that are described in the statistical description in Section 5.2.3 below. The descriptive data includes a review of normality tests with their interpretation and relevance to the implementation of cluster analysis, percentile grouping, and ranking analysis. Furthermore, these factors specifically form the foundation of the data analysis in terms of percentile rankings and clustering, which is discussed in Section 5.3 below. This means that these factors take on a specific value at a specific point in time, and the ranking or the clustering of these values may enable the linkage of different production seasons based on the similarities between the factor values of different production seasons at a specific point in time. Also, these factors – with the exception of the Southern Oscillation Index (SOI) (Section 5.2.1.5) – do not constitute reasons for expectation of development in the factor value or the expected influence of the factor value on the development of the July white futures price.

In order to include a more forward-looking or expectation approach to July white maize futures price development, four additional factors are included in Subsection 5.2.2. These factors do not form part of the clustering or percentile ranking and grouping analysis, but the derived value of each of these factors will facilitate an additional linkage between similar seasons on a more holistic expectation level, which will be included in the final filter model. As a result, these four factors do not take on monthly values, but are single values or descriptions at a specific point in time (hedging decision window from August to October). The discussion of each of these factors provide additional clarity in this regard.

5.2.1 Influential market price drivers of the SAFEX white maize price

Each of the factors included as part of the empirical review are based on specific factors identified in literature (Chapter 2, Section 2.4). The inclusion of each factor also considers not only the factor values themselves, but their possible relation to the relevant white maize continuous or futures price at a specific point in time. Also, the influence each factor may have on the other factors at a specific point in time is considered and discussed as part of the factor inclusion decision-making process. As a result, the raw factor data is not necessarily the only data evaluated in the statistical description of the data (Section 5.2.3). Where relevant, specific ratios based on the raw factor data are included to include more insight into the relative factor values. The source and calculation method of these relations are, however, clearly specified as part of the background and data source discussion of each relevant factor.

5.2.1.1 White maize continuous price

The inclusion of the white maize continuous price as important factor in July white maize futures contract price formation cannot be overstated. The fact that price formation occurs in the cash market and spills over to the futures market confirms this premise (McCullough, 2010:120). Nevertheless, it is important to link the continuous white maize futures contract to the cash price available to producers, since SAFEX discontinued their publication of a representative cash price in 1999. Scheepers (2005:28) argued that the continuous white maize contract price may be seen as the best available proxy for the cash price available to producers, since all cash price basis calculations are based on this price. The continuous white maize futures contract is compiled by adding the MTM (mark-to-market) prices of each current month in a time series. The continuous white maize price in July will be the July price from the first trading day in July up to and including the last trading day in July. Thereafter, the continuous white maize price becomes the August contract MTM price from the day after the last trading day in July up to and including the last trading day in August. This process repeats itself to form a continuous white maize contract price. Figure 2.3 provides a representation of the continuous white maize price.

Figure 5.1: White maize (WM) continuous price
Source: Compiled by the author from Thomson Reuters Eikon for commodities data

Apart from the fact that the continuous white maize price will be the SAFEX price used to derive the cash price for producers, it also provides a comparison price level against which to evaluate export competitiveness and import calculations. A white maize price that is closer to export parity represents an ample supply scenario, whereas white maize prices closer to import parity represent a potential white maize shortage scenario (Auret & Schmitt, 2008:109). It is therefore meaningful to include both import and export parity as factors to provide information regarding the relative level of the current white maize price.

5.2.1.2 Import and export parity ratio

The relative value of import and export parity as price levels, which incorporate several other important price determinant factors, were emphasised by Auret and Schmitt (2008:108). Research by Meyer, Westhoff, Binfield and Kirsten (2006:370-374) even proposed that expectations for price formation in a specific season should be linked to three different and specific trade and policy regimes in the form of (1) an import parity regime when stock availability is expected to be low; (2) an export parity regime when stock availability is expected to be high; and (3) a neutral regime when no surplus or shortage is expected. In order to show all the relevant inputs that influence import and export parity calculations, the following breakdown is provided in Table 5.1.

Table 5.1: Calculating import and export parity prices

Import parity calculation inputs (VAT Excl.)	USA Gulf (no.3Y)
International FOB prices ($/mt)	163.00
Freight Rates ($/mt)	39.00
Insurance (0.3% of FOB) ($/mt)	0.49
COST, INSURANCE AND FREIGHT (CIF) ($/mt)	202.49
Converted to R/t	
R/$ Exchange rate	15.05
COST, INSURANCE AND FREIGHT (CIF) (R/mt)	3047.68
Financing cost	25.05
COST, INSURANCE, FREIGHT AND FINANCING (R/mt)	3072.73
Discharging cost:	
Cape Town	205.87
Durban	199.28
Import Tariff	0.00
FREE ON RAIL (FOR) (R/mt)	
Cape Town	3278.60
Durban	3272.01
Railage cost (R/mt)	
Durban to Randfontein	320.00
DELIVERED:	
Durban to Randfontein (R/mt)	**3592.01**

Export Parity Calculation Inputs	USA Gulf (no.3Y)
FOB Gulf value ($/mt)	163.00
Difference in quality and locality of SA	10.00
SA FOB price ($/mt)	173.00
Converted to R/t	
R/$ Exchange rate	15.05
FOB Gulf value (R/mt)	2603.65
Marketing costs:	
Financing (Prime rate 10% - 30 days) (R/mt)	21.40
Railage:	
Randfontein – Durban harbour	320.00
Loading costs: (R/mt)	
Durban Harbour (Mainly spout method)	192.50
EXPORT REALISATION (R/mt):	
Randfontein	**2069.75**

Source: SAGIS (2018b)

Based on the generalised calculation of import and export parity provided in Table 5.1, Grain SA (2018a) calculates and publishes daily estimates. Figure 5.2 below provides a visual comparison between the Grain SA (2018a) import and export parity and the white maize continuous price. From Figure 5.2 it becomes evident that prices tend to move within the range of import or export parity. The specific price value of import and export parity is included to evaluate whether the values are high or low compared to their historical value. Arguably, prices will adjust according to current or expected stock availability, whereas changes in other factors, such as the CBOT (Chicago Board Of Trade) maize price and the USD/ZAR exchange rate, may influence the import or export parity price level (Auret & Schmitt, 2008:108).

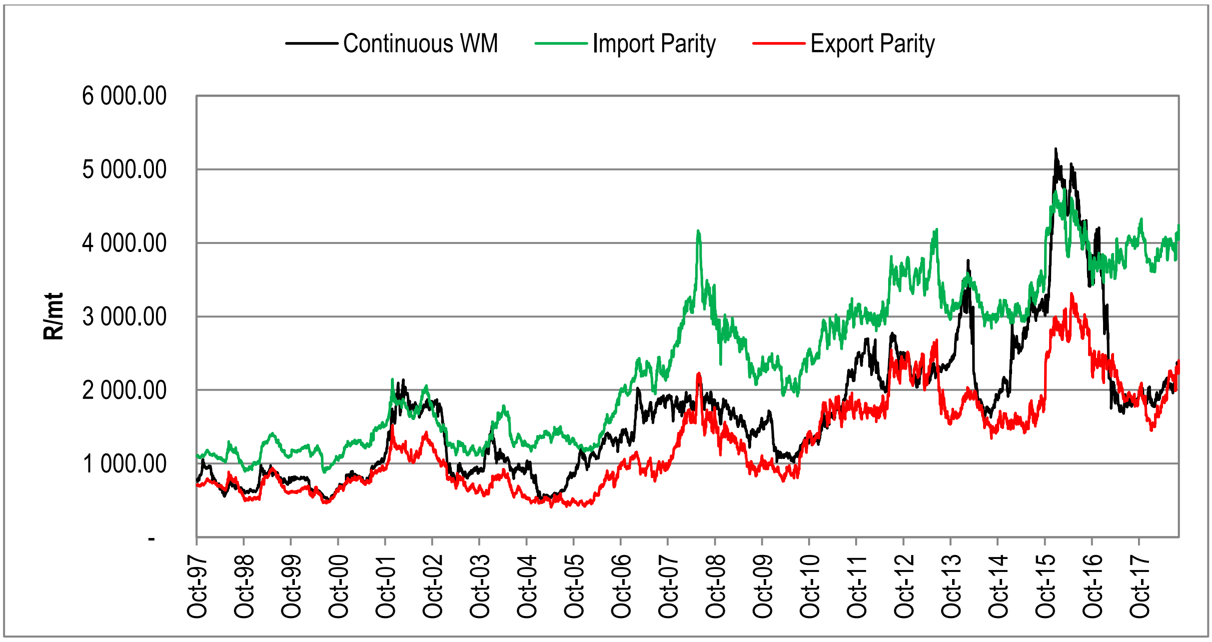

Figure 5.2: Calculated import and export parity compared to the white maize (WM) continuous price

Source: Compiled by the author from Grain SA (2018a) parity price data

It is therefore be meaningful to include measures of the ratio of the white maize price to import and export parity to determine if the current white maize price is relatively close to or far from either parity price levels. The relative measure of import and export parity is calculated as follows:

$$IPR = \frac{White\ maize\ continuous\ price}{Import\ parity}, \tag{5.1}$$

where IPR is the import parity ratio and a high ratio of closer to one or even greater than one means that white maize prices are close to import parity, whereas a low ratio value that is closer to zero means that white maize prices are far from import parity.

If market prices are relatively closer to import parity, one may expect limited upward market price potential and from a price risk management perspective, opt to make use of the current relatively high market price levels to sell physical stock or to implement an applicable futures month hedging strategy.

Suitable strategies for when prices are closer to import parity are identified in Section 5.4 and Section 5.5 below. Consequently, it would also be meaningful to consider an applicable hedging strategy when market prices are closer to export parity, since market prices may remain stable at these price levels for prolonged periods if all other factors remain stable. Price levels closer to export parity may be determined by EPR below.

$$EPR = \frac{White\ maize\ continuous\ price}{Export\ parity}, \tag{5.2}$$

where EPR is the export parity ratio and a ratio closer to one, or even smaller than one, means that white maize prices are close to export parity; whereas a high ratio in value, greater than one, means that white maize prices are far from export parity.

As a result, the combined analysis of all of these values may provide the means to reach a more pertinent conclusion, especially if the market price is closer to import or export parity. It is important to include the CBOT maize price and the USD/ZAR exchange rate as independent factors, since a change in these values will lead to a shift in the import and export parity price levels (calculation in Table 5.1). For instance, prices may remain close to export parity, but due to an appreciation of the rand against the US dollar, the price level of white maize may decrease in value in line with export parity.

5.2.1.3 The continuous CBOT maize price and USD/ZAR exchange rate

The US continuous (cash) maize price, which is traded on the CBOT, may be seen as the main price discovery mechanism in the world (Auret & Schmitt, 2008:108). The continuous or cash CBOT maize price may also be applied as a representative price for futures price expectations, since Armstrong, Zapata and Fortenbery (2003:4) found that price formation occurs in the futures market and spills over to the cash or continuous price. As a result, future production expectations and other fundamental supply and demand factors will already be included in the continuous CBOT maize price. Also, Van Wyk (2012:67-68) confirmed that the spill-over from the CBOT maize futures contract to the South African white maize futures contract was significant, and showed a greater effect when the CBOT price traded down and realised negative returns.

Apart from the continuous CBOT maize price, which directly influences the South African white maize parity price, the effect of the USD/ZAR exchange rate also has a significant effect on price formation. The significant effect was confirmed by the explanatory model developed by Auret and Schmitt (2008:108), who found that the USD/ZAR was an important input in the forecasting model they developed, as it not only influenced parity price levels, but correlated significantly with the US corn contract traded in rand per metric tonne on SAFEX.

Consequently, both the US continuous maize price traded on CBOT and the USD/ZAR exchange rate value are included as important influential price formation factors in this study. To accentuate this notion, Figure 5.3 below shows a visual representation of the SAFEX white maize (WM) continuous price in relation to the CBOT price converted from US dollar per bushel to rand per metric tonne, with the USD/ZAR spot value on a secondary axis.

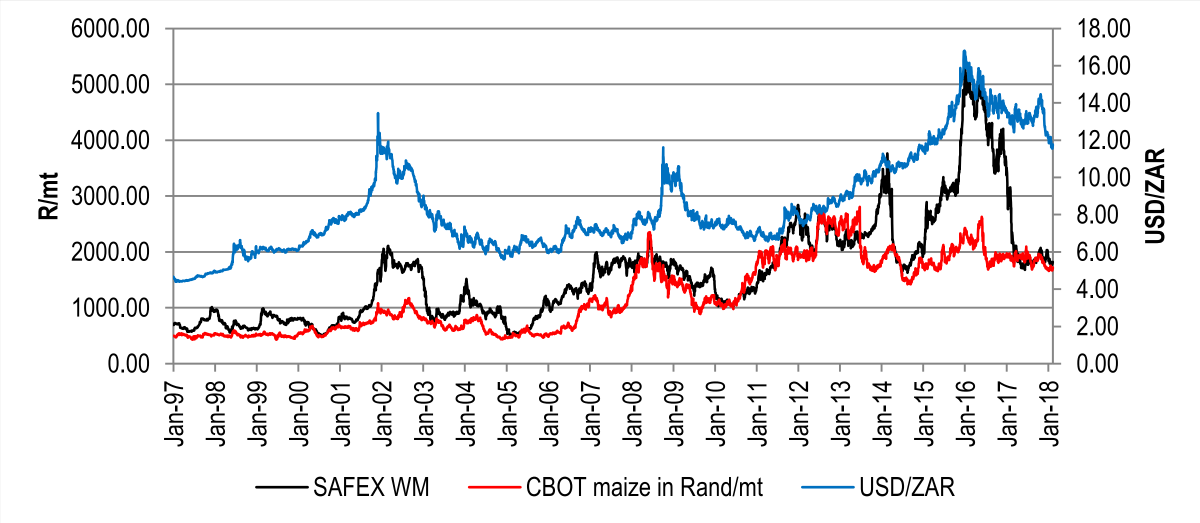

Figure 5.3: ***SAFEX continuous WM compared to the continuous CBOT maize price in R/mt***
Source: Compiled by the author from Thomson Reuters Eikon for commodities data

Figure 5.3 above clearly illustrates that the continuous CBOT maize price converted from dollar per bushel to rand per metric tonne may be seen as a type of export parity price level, since the SAFEX continuous white maize price rarely falls below this comparative price level. The influence of the rand on the SAFEX continuous white maize price can be clearly seen, especially when considering the influence of a depreciating rand on the white maize price. Also, the influence of the continuous CBOT maize price and the USD/ZAR increases when the SAFEX price trades closer to import or export parity (Auret & Schmitt, 2008:108). However, these movements of the SAFEX WM price from export parity to import parity is largely determined by current and expected stock availability (Meyer, Westhoff, Binfield & Kirsten, 2006:370-374). During times of supply surplus, the market mechanism pushes prices closer to export parity to enable the competitive export of available surplus. Conversely, prices increase to import parity when a shortage occurs, which enables the market mechanism to address the shortage by importing maize.

5.2.1.4 Maize stock availability (Days' stock)

The amount of available stock is published on a monthly basis by the South African Grain Information Service (SAGIS). The progressive monthly balance sheet only shows available stock based on carry-over stock from the previous month and actual supply and demand figures established for the specific month. Table 5.2 below shows the progressive white maize balance sheet for the 2017-2018 marketing year, from 1 May 2017 to 30 April 2018. Apart from the progressive balance sheet, which provides an indication of the rate of stock acquisition, utilisation and imports or exports, market role-players attempt to forecast expected ending stocks for the marketing year based on the progressive figures.

These forecasts or scenario analyses depend greatly on the current Crop Estimate Committee (CEC) report (which enables the forecaster to include expected production), as well as linear projections of current utilisation to estimate carry-over, or unutilised stock. These estimates may nevertheless be fairly accurate within a specific marketing year, but will most likely become less accurate once the following production year overlaps with the current marketing year. As a result, scenario analyses of the following production year are based on the expected ending stock for the current marketing year, as well as estimates for the following marketing year. Estimates for the following year are based on several specific assumptions, which may include CEC intentions to plant hectares, average yield figures, expected utilisation, as well as export or import expectations. The formalisation of such an estimate was introduced by the National Agricultural Marketing Council (NAMC) on 31 July 2013 in the form of a South African Supply and Demand Estimates (SASDE) report that is compiled on a monthly basis (NAMC, 2013). The estimates included in each SASDE report are based on a specific set of assumptions and inputs reported in Table 5.3 below.

However, the SASDE data is only available from 2013, which means that a similar estimate of unutilised stock or stock availability for earlier seasons could not be obtained. As a result, this study focused on the stock availability at a specific point in time to compare seasons based on the existing SAGIS progressive monthly figures. A stock utilisation figure may be calculated as follows:

$$Utilisation\ per\ day = \frac{(Utilisation + Sundries)}{30}, \tag{5.3}$$

upon which stock availability days may be calculated as follows:

$$Days'\ stock = \frac{Unutilised\ stock}{Utilisation\ per\ day}, \tag{5.4}$$

This measure provides an indication of the number of days that stock is available based on the current rate of supply and demand. A low days' stock value indicates low stock availability which may be followed by an increase in market prices to curb demand and to simulate additional supply to re-establish sufficient stock availability. However, the stock utilisation measure in the form of days' stock is not the only measure evaluated as part of the methods applied in Section 5.3 in an attempt to link seasons based on similar factor values. The specific values for supply (acquisition) and demand (utilisation), as well as ending stock for each month, as indicated by Table 5.2 above, are included to evaluate and confirm consensus between the different fundamental factors. A low days' stock measure value should, as a result, be confirmed by a low ending stock value due to a decrease in supply or increase in demand. The reaction of market prices may for instance not always be confirmed by a single fundamental factor in isolation. Market prices may increase, even at high supply or days' stock levels. This increase in prices may however be justified when evaluating the increase in demand despite factors that could potentially eradicate current high-ending stock levels. All of these measures depend on or are influenced by production expectations. In order to include a measure of expected production, the study includes a proxy measure for expected weather in the form of the Southern Oscillation Index (SOI) (Meinke & Hammer, 1997).

Table 5.2: Progressive white maize balance sheet

	May 2017	Jun 2017	Jul 2017	Aug 2017	Sep 2017	Oct 2017	Nov 2017	Dec 2017	Jan 2018	Feb 2018	Mar 2018	Apr 2018	Progressive May 2017 - Apr 2018
(a) Opening Stock	597 837	1 264 335	4 066 841	6 319 825	6 733 786	6 294 931	5 802 475	5 247 231	4 733 269	4 205 238	3 659 675	3 070 458	597 837
(b) Acquisition	1 184 939	3 439 775	2 923 251	1 082 929	177 031	115 509	87 427	38 475	60 198	41 690	49 811	67 558	9 268 593
Deliveries directly from farms (i)	1 184 939	3 439 775	2 923 251	1 082 929	177 031	115 509	87 427	38 475	60 198	41 690	49 811	67 558	9 268 593
Imports destined for RSA	0	0	0	0	0	0	0	0	0	0	0	0	0
(c) Utilisation	461 315	495 959	529 700	593 009	548 328	579 121	598 040	537 351	552 913	538 486	587 594	578 160	6 599 976
Processed for the local market:	459 162	493 936	526 260	587 418	541 852	572 204	588 846	532 275	546 855	532 094	581 663	571 401	6 533 966
Human consumption (iii)	386 804	347 363	367 615	402 341	367 544	389 546	411 349	344 121	353 956	346 978	370 424	371 463	4 459 504
Animal feed/Industrial	71 356	145 616	157 512	183 867	173 000	181 372	176 259	187 280	191 842	184 142	210 447	198 956	2 061 649
Gristing	1 002	957	1 133	1 210	1 308	1 286	1 238	874	1 057	974	792	982	12 813
Bio-fuel	0	0	0	0	0	0	0	0	0	0	0	0	0
Withdrawn by producers	1 114	802	2 835	3 632	2 507	3 677	5 932	3 157	2 500	3 067	3 183	3 479	35 885
Released to end-consumer(s)	1 039	1 221	605	1 959	3 969	3 240	3 262	1 919	3 558	3 325	2 748	3 280	30 125
(d) RSA Exports	49 754	142 341	138 281	64 551	74 680	36 717	36 852	28 983	32 541	37 121	77 102	133 046	851 969
Products (ii)	4 873	2 397	2 559	1 953	3 204	5 115	5 625	2 512	3 415	2 755	3 341	4 289	42 038
Whole maize	44 881	139 944	135 722	62 598	71 476	31 602	31 227	26 471	29 126	34 366	73 761	128 757	809 931
(e) Sundries*	7 372	-1 031	2 286	11 408	-7 122	-7 873	7 779	-13 897	2 775	11 646	-25 668	-1 843	-14 168
(f) Unutilised stock (a+b-c-d-e)	1 264 335	4 066 841	6 319 825	6 733 786	6 294 931	5 802 475	5 247 231	4 733 269	4 205 238	3 659 675	3 070 458	2 428 653	2 428 653

Source: SAGIS (2018a)

Note: Sundries* refer to maize stock surplus/shortage which may occur due to the handling process of grain. The figure is largely a balancing figure between acquisition and utilisation since both of these figures are statutory reporting requirements for all role-players in the food value chain. For instance, a transporter loads a full load of maize at an elevator. When delivering to a mill, the grain are sampled and graded. Due to transport losses, potential foreign material, or a percentage of the grain which was damaged in the handling process, the net weight of the load received is adjusted to account for the loss in stock which can be processed effectively.

Table 5.3: SASDE report sources and assumptions

Information	Source of information
Opening stocks	SAGIS information
Production and retentions by producers	Crop Estimates Committee (CEC) (only crop estimates and not intentions to plant or hectares planted will be used)
Imports	Individual traders (not only SACOTA members) and millers to supply information directly to NAMC
Supply	
Consumption Human Animal Gristing	BFAP projections, NAMC projections, statistical data and trends. S&DC can use white maize and yellow maize ratios to determine consumption.
Retentions Seed etc.	The same consumption items should be used as SAGIS for the different grain products.
Exports Products Whole grain	Individual Traders (not only SACOTA members) and millers to supply information directly to NAMC.
Demand	
Carry out/closing stocks	Balancing number at the end

Source: NAMC (2013)

5.2.1.5 Southern Oscillation Index (SOI)

The SOI is the main weather-based measure this study included as part of the analysis. The SOI is a measure of the difference in air pressure between Tahiti and Darwin. The difference in atmospheric pressure results in trade winds that normally blow from the east to the west across the Pacific Ocean, to deviate from the pattern. During an El Niño event, the atmospheric pressure changes to the extent that trade winds weaken or even change direction, which results in warmer than normal sea surface temperatures over the central and eastern tropical Pacific Ocean. This phenomenon results in an increased chance of below-normal rainfall, especially over the western white maize producing areas of South Africa. The opposite La Niña event is characterised by above average strong trade winds that cause warmer than normal sea surface temperatures over the northern areas of Australia (Darwin), with an increased chance of above normal rainfall over South Africa (NOAA, 2005). As a result, SOI is applied as a pre-determinant or proxy for seasonal climate forecasting (The Long Paddock, 2018).

The application of SOI as a proxy has also been refined to predict the probability of an El Niño or La Niña event. The probability of an El Niño event increases when the SOI value decreases and maintains a value below -7, whereas the probability of a La Niña event increases when SOI values increase above and maintain a value higher than +7. The SOI values obtained from The Long Paddock (2018) were applied in this study and a visual representation of the change in SOI values are provided in Figure 5.4 below. These values were calculated on a monthly basis since 1876 by means of Troup's (1965) formula, which results in an index scale of between -35 to +35 and may be calculated as follows:

$$SOI = \frac{PA(Tahiti) - PA(Darwin)}{Std\ Dev.\ Diff} \times 10, \tag{5.5}$$

where $PA()$ is the pressure anomaly which is the monthly mean minus the long-term mean, which is derived from the 1887-1989 base period; and the $Std\ Dev.\ Diff$ is the standard deviation of the difference in air pressure derived from the 1887-1989 base period. A Troup SOI value of -10 means the SOI is 1 standard deviation on the negative side of the long-term mean for that month. Troup's monthly SOI value is derived from the normalised Tahiti minus Darwin mean sea level pressure (mslp) (The Long Paddock, 2018).

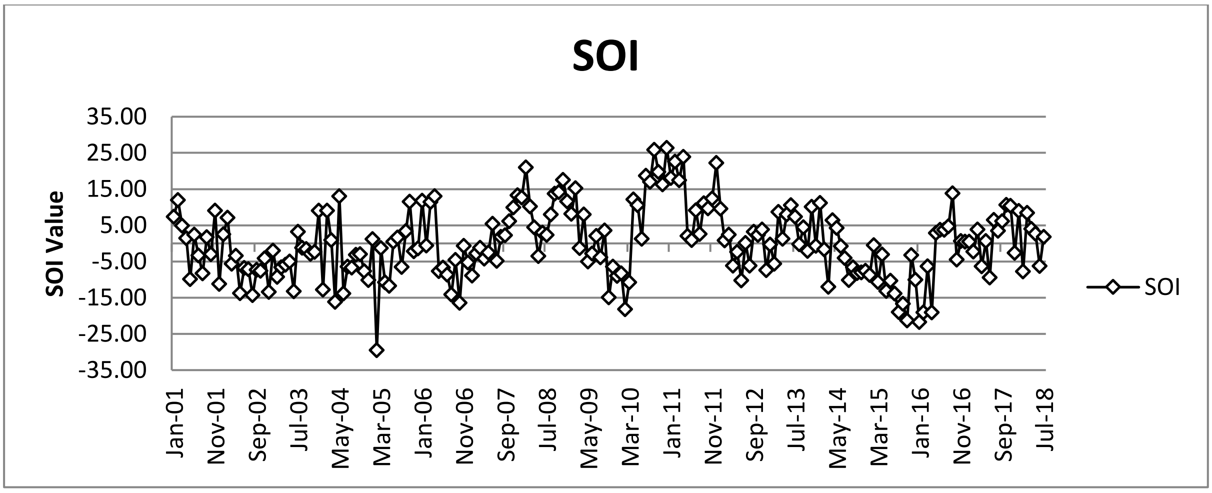

Figure 5.4: SOI values and phases of SOI from 2000 to 2018
Source: Compiled by the author from The Long Paddock (2018) SOI data

Over time, the influence of El Niño and La Niña on South African production became evident, since an El Niño event has the potential of above normal temperatures and below normal rainfall for especially the Western part of the maize production region. The direct correlation between water stress (due to dry conditions) and the SOI with corresponding ENSO (El Niño Southern Oscillation) events have been proven by Martin, Washington and Downing (2000:1473). This is relevant because water stress remains one of the primary determinants of yield and therefore expected production.

5.2.2 Additional important price determinant factors

All of the influential factors discussed in subsection 5.2.1 were included with the main aim of providing measurements that may be grouped or ranked in order to compare the specific values based on historical figures at a certain point in time. The specific methods that may enable such groupings or rankings are discussed in Section 5.3. **It is however important to realise that none of these values are used to create a forecast of the July white maize price at a certain point in time, but to link the level of the most recent values to prior seasons when these values were on similar value levels or intervals. From this analysis, it may be possible to create scenarios for the expected price progression of the following season based on the price progression in seasons where several factor values were on similar levels.**

The process may furthermore be seen as dynamic, since the scenario analysis may change as the season progresses, based on the influence of new data points obtained. A season may therefore start out with characteristics similar to a specific prior season, but as the influential factor values change, the progression of the season may portray the dominant influential factors from another season. This assertion corresponds to the Adaptive Market Hypothesis (AMH) (Chapter 3, Section 3.2.6), since the market price development would most likely be similar for seasons that portray similar influential factor values at a specific point in time, but would also seek to adapt to portray changes in the influential price determinant factors. The changes in the price determinant factors throughout a season may, as a result, have a short term influence on price formation, since the market will continuously aim to adapt as new price implications based on changes in influential factor values enter the market information realm.

As a result, it may also be beneficial to include actual realisations or a more holistic view of specific seasons in terms of the general price trend; historical and expected marketing year-end stock levels; input cost in relation to the price level at the point a production decision has to be made; as well as realised and expected El Niño and La Niña events that occurred. These values provide a longer term overview expectation for the season and may influence the production decision of producers as well as the longer term price formation expectation of market participants. All of these measures provide a single value at a specific point in time for each past season, but it is also possible to obtain an expected value from existing data for the following season. Due to the single value nature of the factors that provide an overview of market conditions or factor circumstances for a given season, they are not included as part of the ranking or grouping analysis. However, the single values at the beginning of the production season, when production and hedging decisions have to be made, do form part of the total seasonal comparison analysis done by means of the filter model described in Section 5.3.2 below.

5.2.2.1 General price trend

The inclusion of a general price trend stems from several findings included in the study up to this point. The first argument comes from two of the assumptions of technical analysis, which assumes that prices move in trends and that history tends to repeat itself (Reilly & Brown, 2012:543-544). A study based on the July corn and soybeans contracts on CBOT found that trading against the market trend resulted in very poor results as opposed to trading or going with the market trend (Stevenson & Bear, 1970:75-79). More recently, and this from a South African perspective, Roberts (2009:25) showed that trend-following, indicator-based systems were able to outperform a buy-and-hold strategy.

The challenge with the shorter July white maize contract remains the relatively short time period that the contract is active until expiry, which makes it difficult to establish meaningful longer term trends by means of trend-following indicators, such as moving averages or the moving average convergence divergence (both indicators are discussed in Section 5.4.2.10 below). However, McCullough's (2010:120) finding that price formation occurs in the cash market and spills over to the futures market, provides the alternative to evaluate the current trend in the continuous white maize contract in an attempt to establish an expected price formation direction in the July white maize futures contract.

Figure 5.5 below shows the continuous white maize futures contract since the beginning of 2000 up to the end of the July white maize futures contract in 2018. The simple interpretation of the main trend is done by means of the 100-day (blue line) and 200-day (red line) simple moving averages of the continuous white maize price (black line). The price may be deemed in an up-trend when the 100-day moving average is above the 200-day moving average, and in a down-trend when the 100-day moving average is below the 200-day moving average. As a result, the price trend of the continuous white maize contract may be used as a proxy for the expected price trend in the July white maize futures contract.

The single value or factor identification measure, which is included in the filter model, is the stance of the trend in the continuous white maize price in the fourth quarter (Q4) of each calendar year, which also corresponds to the planting window when hedging decisions are made. If the 100-day moving average is above the 200-day moving average at that point in time, the single specification for trend is "upward" and if the 100-day moving average is below the 200-day moving average trend at that point in time, the single specification for trend is "downward". There are also specific seasons when the trend changes in the evaluation time-frame, which is indicated as such in the filter model.

In addition to the price expectation based on the trend in the continuous white maize contract, it would be meaningful to include a more forward-looking measure in terms of expected stock levels. An upward market price expectation based on the continuous trend may be confirmed by a relatively low carry-over stock level expectation (Auret & Schmitt, 2008:109; Geyser, 2013:17). The day's stock measure included in Section 5.2.1.4 is, however, purely a measure of the current stock levels included and does not include any expectation of available stock at the end of the marketing year. As a result, a stock-to-usage figure that provides a measure of expected stock availability in the form of a ratio or comparison to expected demand or total usage would also provide a meaningful comparison between production seasons at a specific point in time.

Figure 5.5: The long term continuous price trend
Source: Thomson Reuters Eikon for Commodities (2018)

5.2.2.2 Stock-to-usage

A measure of expected stock-to-usage may be seen as an annual realisation of the monthly days' stock measure. Table 5.2 (Section 5.2.1.4) above shows the progression from the beginning of the marketing year in May up to the end of the marketing year in April. The progressive measure as a result provides a measure of the utilisation and stock availability at the end of the applicable marketing year. Stock availability may furthermore be expressed as a simple unutilised stock figure in metric tonnes or as a ratio of stock-to-usage, which may be calculated as follows:

$$Stock - to - Usage = \frac{Unutilised\ stock}{Total\ utilisation\ for\ the\ marketing\ year}. \quad (5.6)$$

The influence of realised stock levels on price formation becomes evident in Figure 5.6 below. A low marketing year-end stock-to-usage ratio may be associated with an increase in continuous WM prices, whereas more than sufficient marketing year-end stock-to-usage (relatively higher) may be associated with initial price decreases and a sideways trading market.

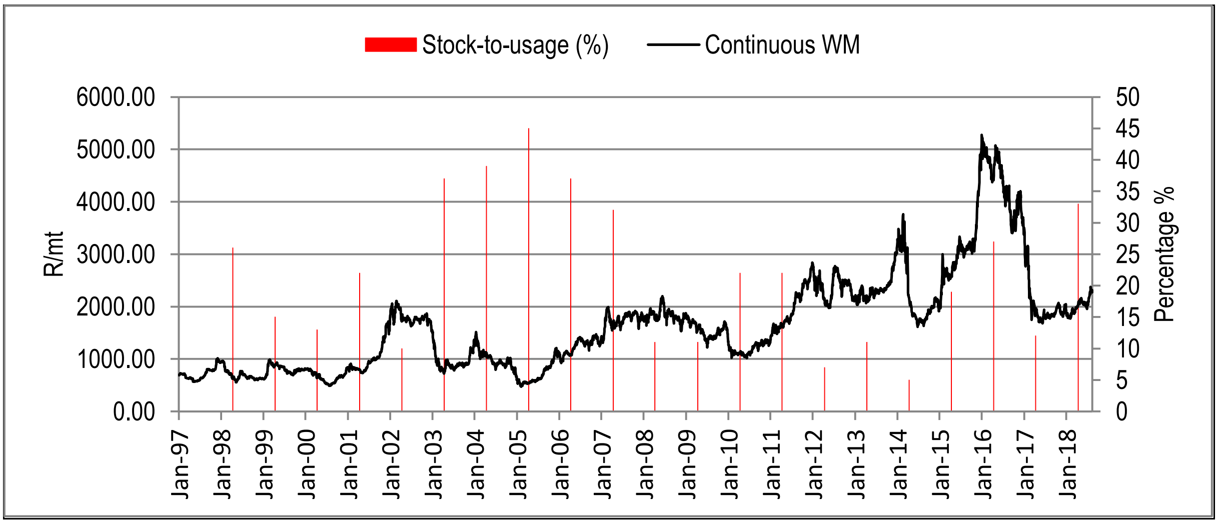

Figure 5.6: Stock-to-usage and the continuous white maize (WM) price trend
Source: Continuous WM price from Thomson Reuters Eikon for Commodities (2018) and stock-to-usage compiled from SAGIS (2018a)

The forward-looking nature of the relationship between price formation and realised stock-to-usage is also clear from Figure 5.6. The continuous WM price and especially the futures price react to the expected ending stock level before the final figure materialises at the end of a marketing year. The fact that a production year overlaps with two different marketing years should also be taken into consideration. An example of the implication that overlapping marketing and production years have on price formation is visible over the 2015-2016, 2016-2017, and, finally, the 2017-2018 marketing years.

The 2015-2016 production year was characterised by the expectation of a very strong El Niño event, only matched by two previous seasons in 1982-1983 and 1997-1998 (GGWeather, 2018). Prices reacted accordingly, but the actual low stock realisation due to the impact of the El Niño event only materialised at the end of the 2016-2017 marketing year. During the time period of actual low stock levels for white maize from July 2016 to April 2017, the market was confronted with the forecast that the 2016-2017 production year is expected to be a normal to weak La Niña, which could restore current low stock levels. Prices reacted accordingly, and already came down during the 2016-2017 production year despite the fact that stock levels were only restored in the period from May 2017 up to the end of the 2017-2018 marketing year harvest period.

In order to capture this market expectation, the study linked each production year from August to the following July with the realised stock-to-usage at the end of April for the following marketing year. The realised stock-to-usage level could then be used to link different production seasons based on expected ending stock at the beginning of the season. When evaluating a new production season against the historical data, a forward-looking stock-to-usage measure could then be calculated from the supply and demand estimates done by the NAMC, as explained in Section 5.2.1.4 above. An example of the ending stock expectation for the 2018-2019 marketing year based on the 2017-2018 production year was already included in Chapter 2, Section 2.4.1 as Table 2.11. Apart from expected ending stock, another forward-looking measure that is based on the expected seasonal weather and may influence expected production is provided by means of several prediction models of sea surface temperatures.

5.2.2.3 Sea Surface Temperatures (SST) and predictions

From the SOI proxy for expected weather phenomena (discussed in Chapter 2, Section 2.4.2.1 as well as in Section 5.2.1.5 above), the actual realisation of Sea Surface Temperatures in the tropical Pacific, which confirms El Niño or La Niña circumstances, is measured by means of the Oceanic Niño Index (ONI) (GGWeather, 2018). The ONI measure is a 3-month moving average of the SST for the Niño 3.4 region. Over time it became possible to identify trends in the ONI measure, which could be linked to specific weather phenomena and their relative intensity. If the ONI value remains above +0.5 for five consecutive 3-month moving-average index values, a warm or El Niño event may be confirmed. The opposite event in the form of the cold or La Niña event occurs when the ONI value remains below -0.5 for five consecutive 3-month moving-average index values.

The intensity of the event based on consecutive ONI values was grouped even further based on the breach of a specific threshold for at least three consecutive 3-month moving-average periods (GGWeather, 2018, NOAA, 2018). Figure 5.7 below provides a breakdown of the intensity of measure of ONI values since 1950, which provides a visual comparison of different intensities of actual El Niño or La Niña occurrences.

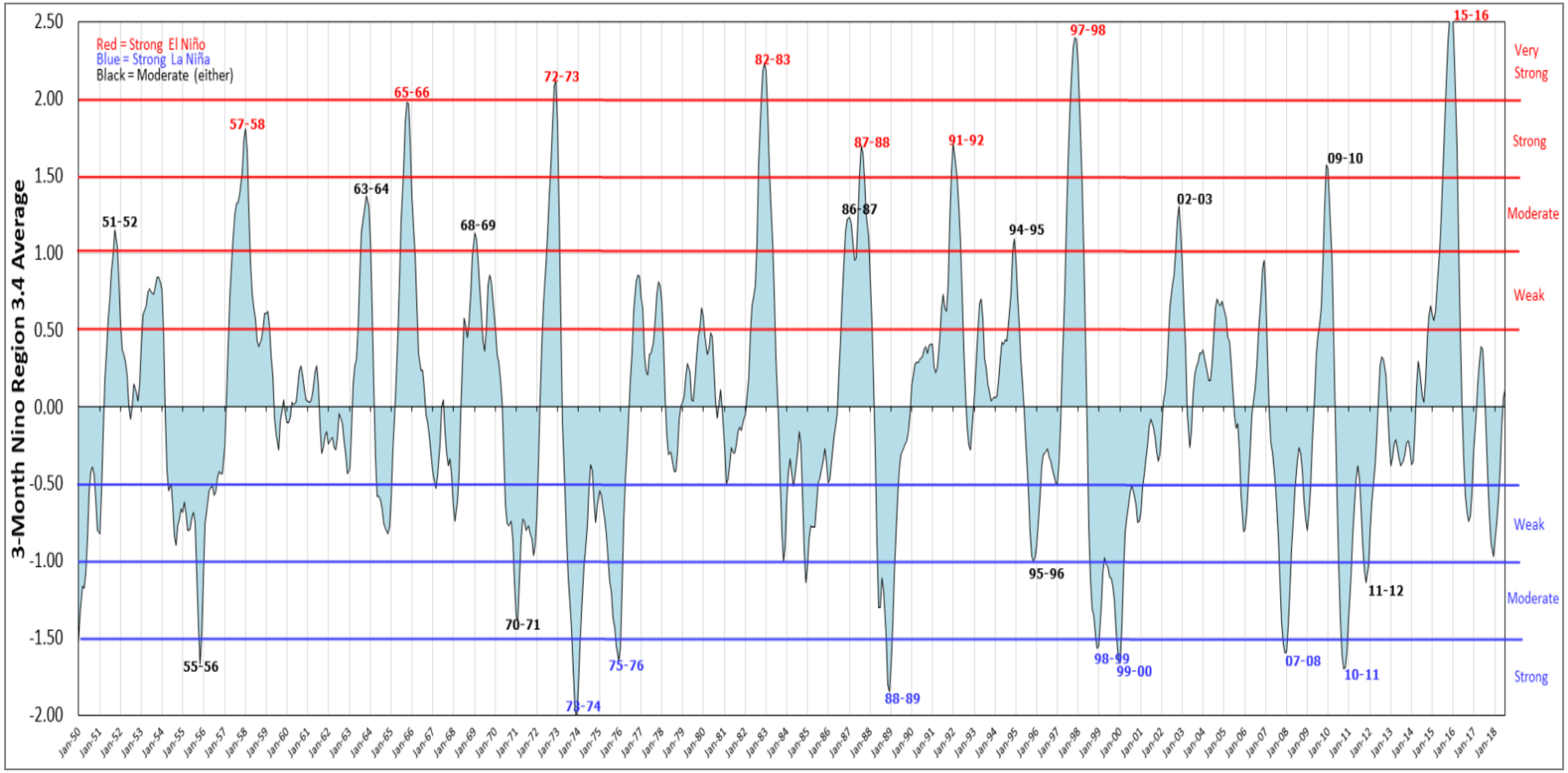

Figure 5.7: ***The 3-month moving-average Niño 3.4 region value***
Source: GGWeather (2018), data available from GGWeather (2018) and NOAA (2018)

The ONI data classification of the different intensities of actual El Niño or La Niña occurrences makes it possible to link expectations in this regard for the following season. The International Institute for Climate and Society (IRI, 2018) maintains and publishes monthly reports that provide the official ENSO (El Niño Southern Oscillation) probability forecast. The forecast values are based on several statistical and dynamic models, which may be used to determine an average forecast from all models. Figure 5.8 below shows the forecast published on 19 September 2018.

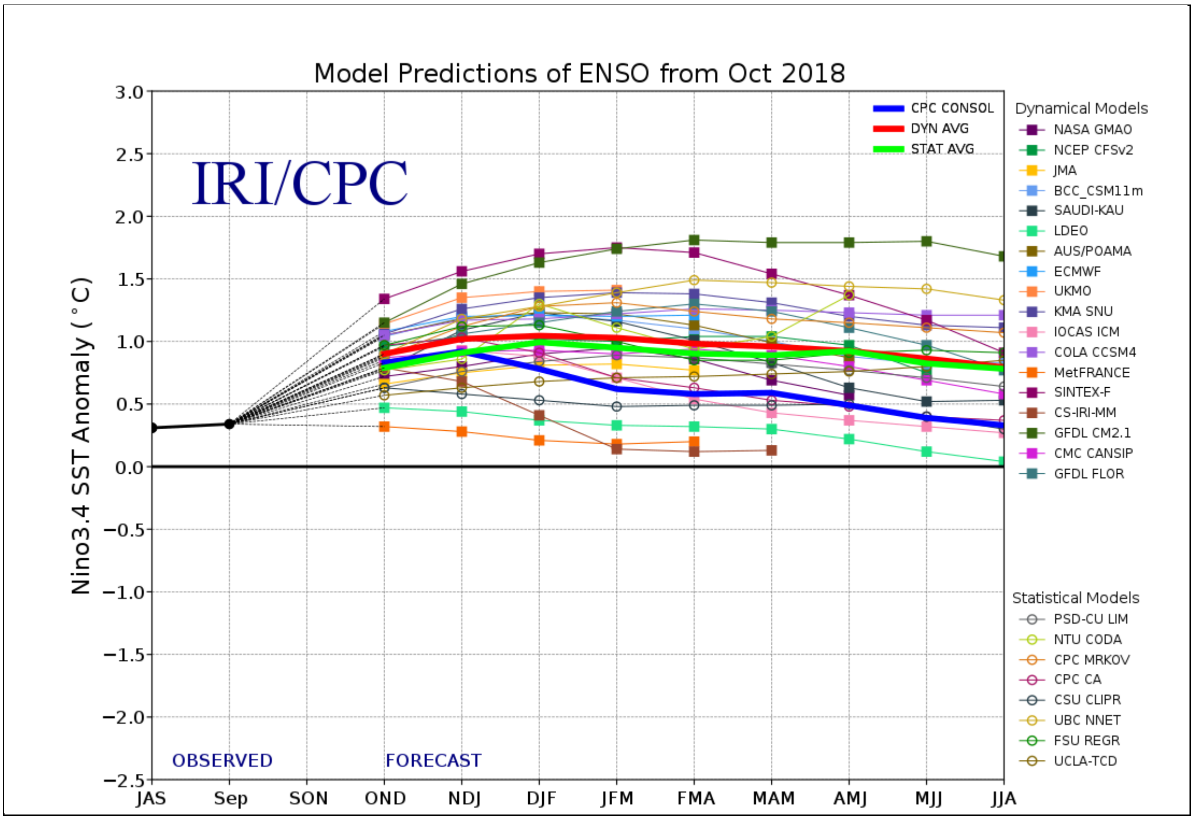

Figure 5.8: ENSO model predictions
Source: IRI (2018)

From the forecast data averages, the research institute also provides a probability forecast of the expected El Niño or La Niña event. The intensity of these events are not necessarily specified, but a combination of the historical data in Figure 5.7 above and the predictions made in Figure 5.8 provides the necessary information to make an informed observation of the seasonal outlook and the intensity thereof. For instance: based on the statistical and dynamic forecast models (Figure 5.8), an average Sea Surface Temperature (SST) value of around 0.8 degrees Celsius above zero can be expected from November 2018 up to February 2019. Since the three-month average of SST is used to calculate ONI values, the average expected SST value (Figure 5.8) may be used to estimate ONI values that can be linked to the intensity scale in Figure 5.7. Based on the expected ONI value, the expected El Niño occurrence may be classified as a weak El Niño occurrence, since the ONI value falls between the +0.5 to +1 ONI value range. In addition, the IRI (2018) also calculate and publish probabilistic and model-based forecasts of ENSO (Figure 5.9 below). These forecasts provide a probability of the occurrence of the ENSO, which may be linked to its intensity evaluation based on expected ONI values. As a result, the probability of the weak El Niño event occurring during the planting and pollination time period in the production cycle (identified from the +0.8 expected ONI value) remains fairly strong above 60% in both forecasts (Figure 5.9 below) and should not merely be disregarded due to its probable weak nature.

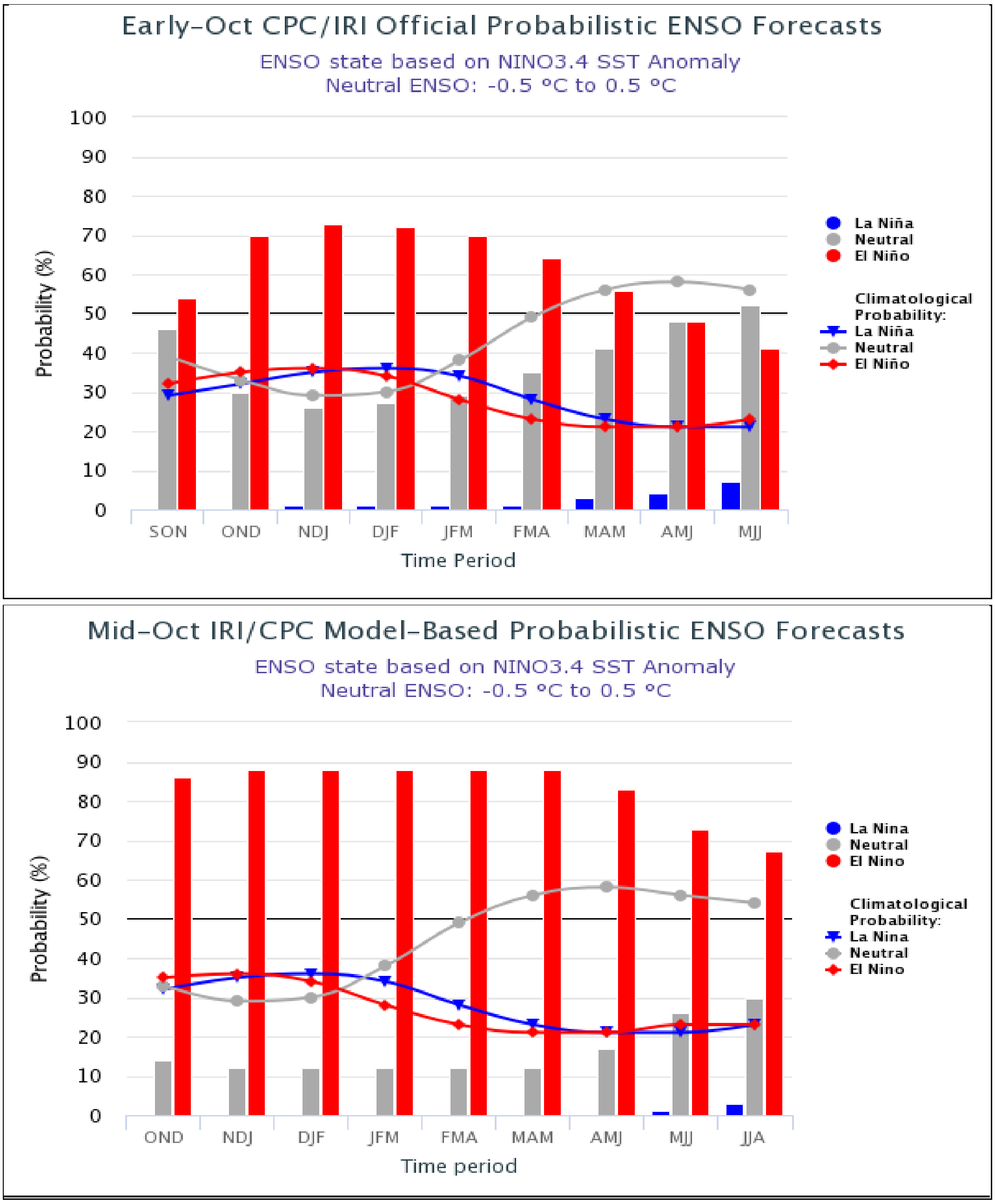

Figure 5.9: IRI/CPC Official Probabilistic and Model-Based Probabilistic ENSO Forecast
Source: IRI (2018) (October 2018 forecasts)

All three of the additional annual measures in the form of the general market price trend (Section 5.2.2.1), stock-to-usage expectations (Section 5.2.2.2), as well as expectations regarding the potential seasonal weather phenomena (Section 5.2.2.3) provide possible scenarios for the upcoming season, which may be linked to similar scenarios that occurred in previous seasons. However, none of the measures consider the profitability of a production decision. The importance of this consideration in terms of production decisions and consequent hedging decisions was emphasised by Zulauf and Irwin (1998:328), as well as King and Lybecker (1983:124), when they suggested that producers should base their production and marketing decisions on profitability, which may be evaluated by means of the futures market as a source of market expectations. In order to address this potential shortcoming, the study included a measure that is based on input cost calculations during the production decision phase of the season.

5.2.2.4 Profitability measure: Futures price versus input cost

The question of what to produce in a particular production season is arguably influenced by as many factors as a producer's hedging decision (Chapter 4, Section 4.2.1). Chavas, Kim, Lauer, Klemme and Bland (2001:231) identified production decision factors such as weather conditions during the planting window and the rest of the production season, as well as seed technology that may be linked directly to yield expectations. Chamberlin, Jayne and Headey (2014:56) also identified crop-specific land suitability and yield potential as important considerations. Ultimately, producers aim to maximise profits that may be constrained by environmental and economic factors, as well as the physical location that influences transportation cost and the demand for a specific product (Benke, Wyatt & Sposito, 2011:90).

As a result, producers consider the profitability of each of the different crops that will not be constrained by other influential factors. Meyer, Westhoff, Binfield and Kirsten (2006:374) confirmed that the determinants for production area projections are commodity prices, yield potential or projections, rainfall expectations during the planting window, and particularly the relative cost of inputs for a specific commodity. Therefore, if producers in general are able to produce white maize, yellow maize or sunflowers and the general profitability of maize compared to sunflowers is lower, more producers may opt to produce sunflowers that may lead to an increase in maize prices due to the expected reduction in production. Consequently, it makes sense to determine the threshold or price-to-input cost ratio from where futures prices tend to increase to ensure sufficient production to meet expected demand. Such a threshold may be determined by calculating a ratio of the average price during the planting decision window from the beginning of September to the end of October and the relative direct input cost calculation as shown in Equation 5.7 below.

$$Price\text{–}\ to\text{–}\ input\ cost = \frac{Average\ July\ futures\ price}{Direct\ input\ cost}, \quad (5.7)$$

where the average July futures price is the average of the July white maize futures contract from the beginning of September to the end of October during the previous calendar year. The direct input cost, on the other hand, is the actual realised direct or variable input-cost-per-hectare figure obtained from Grain SA (2018b), with the general calculation provided in Table 5.6 in Section 5.4.3 below. The direct input cost per hectare is used instead of input cost per metric tonne, since the result per metric tonne realised per season may differ significantly from one producer to the next. Also, the actual realised yield may differ from the yield expectation at the beginning of the production season. Actual realised input costs per hectare may be linked to yield expectation at the beginning of a production season, since producers may be very particular about utilising fertiliser and other inputs such as seed according to these yield goals. Unfortunately there is always the possibility that the yield goal may not be achieved, which means that dividing actual input costs by the actual yield achieved at the end of a production season may significantly skew input cost per tonne.

To summarise – all of the factors that influence price formation for the South African white maize market was identified from applicable literature in Chapter 2 (Section 2.4) and discussed in Section 5.2.1 above. Several of these factors, such as import parity, export parity, and available white maize stock are adapted to not only represent the specific factor value, but applicable ratio measures in the form of the IPR, EPR and days' stock measures. These ratio measures are aimed at combining factors such as utilisation and available stock levels into a single measure of available stock days, or to provide a relative measure of import and export parity to the white maize price to determine if the price is closer to import or export parity instead of evaluating these values in isolation. All of the factors that take on price values are available from the relevant sources in daily, as well as monthly frequencies. However, factors such as the days' stock available and the SOI are only available in monthly intervals. In order to align the frequency of all the factors, this study standardised the evaluation interval to monthly factor values and applied the proposed clustering and percentile ranking and grouping methods in Section 5.3 to the monthly interval values for all the factors identified in Section 5.2.1. The main aim was to group or match the relative values of the factors at a specific point in time in order to compare or identify similarities in factor values for different production seasons.

The additional factors that were included in the form of the general price trend (Section 5.2.2.1), the annual stock-to-usage (Section 5.2.2.2), sea surface temperature (SST) values (Section 5.2.2.3), and the input cost profitability measure (Section 5.2.2.4), were included to provide single independent characteristics or identification measures of past seasons. All of these measures, however, have forward-looking estimations for the following production year, which may be used to link the single independent characteristics of previous seasons with the upcoming season's forward-looking estimation of the same measures. As a result, the single-value forward-looking measure characteristics that may be identified during the planting window of a new production season may be used as additional confirmatory factor values to link a new season to appropriate similar previous season(s), based on the same independent characteristic or identification measure for each factor during the planting window.

The analysis of the comparison of different seasons based on factor value similarities therefore include the ranking or grouping of the factor values identified in Section 5.2.1 by means of the clustering and percentile ranking analysis described in Section 5.3 below, as well as the single value or descriptions of the additional factors described above. The additional factor single value or description is included in the filter model described in Table 5.8, Table 5.9 and Table 5.10 below. The monthly factor values as described above will require a thorough statistical description, since they form part of the clustering and percentile rank and grouping analysis. Section 5.2.3 below provides the necessary information in tabular form and includes the statistical characteristics of the monthly factor data, as well as the different July white maize futures contracts included in the hedging strategy evaluation.

5.2.3 Statistical description of data

The inclusion of descriptive statistics provides a relevant overview of the data characteristics associated with the different types of data included in this study. It is, however, important to clarify that Section 5.2.3 only includes the statistical description of the factor and price data discussed up to this point in Chapter 5. The statistical description of the hedging strategy returns, which were evaluated by means of performance measures, is discussed in Section 5.5.1 below. The importance of normality in the evaluation of specific performance measure results was discussed in Chapter 4, Section 4.3. It is therefore relevant to include an evaluation of the data descriptives as part of the methodological chapter since the results thereof may influence or rather determine the specific performance measures included in the methodological approach. These aspects will nevertheless be revisited in the discussion of the statistical description of the hedging strategy return data. Section 5.2.3 already includes the calculation and interpretation of descriptive statistical measures, such as skewness (S) and kurtosis

(K), as well as four relevant normality tests. These interpretations are relevant when evaluating the statistical characteristics of the return data in Section 5.5.1.

In order to ensure that Section 5.2.3 follows a structured approach, an important first step in this section is to provide a summary of the different types of data, their sources, available time spans, as well as the data frequency in Table 5.4 below. This is followed by basic descriptive statistics (Table 5.5) and a thorough evaluation of the data distributions in terms of normality (Table 5.6).

Table 5.4: Data source, available time span, and frequency

Type of data	Abbreviation	Data source	Data available since	Available frequency
White maize continuous contract closing (Rand/metric tonne)	WM-C	Thomson Reuters	20 January 1997	Daily
Import Parity (Rand/metric tonne)	IP	Grain SA	27 October 1997	Daily
Import parity ratio (Rand/metric tonne)	IPR	From Grain SA data	27 October 1997	Daily
Export parity (Rand/metric tonne)	EP	Grain SA	27 October 1997	Daily
Export parity ratio	EPR	From Grain SA data	27 October 1997	Daily
CBOT continuous contract closing price (USD cent/bushel)	CBOT-C	Thomson Reuters	02 January 1973	Daily
USD/ZAR	USD/ZAR	Thomson Reuters	04 January 1971	Daily
Acquisition (Supply) (metric tonne)	SUPPLY	SAGIS	01 May 2000	Monthly
Utilisation (Demand) (metric tonne)	DEMAND	SAGIS	01 May 2000	Monthly
Unutilised Stock (metric tonne)	ENDING STOCK	SAGIS	01 May 2000	Monthly
Stock availability ratio	DAYS' STOCK	From SAGIS data	01 May 2000	Monthly
Southern Oscillation Index	SOI	The Long Paddock	31 January 1876	Monthly
White maize July contract closing price (Rand/metric tonne)	WM Jul""	Thomson Reuters	01 August 1997	Daily
White maize July contract price option volatility (%)	WM Jul"" Vols	JSE	02 January 2002	Daily
White maize March contract closing price (Rand/metric tonne)	WM Mar""	Thomson Reuters	01 August 1997	Daily
White maize March contract price option volatility (%)	WM Mar"" Vols	JSE	02 January 2002	Daily

Source: Compiled by the author

Note: The "" after Jul"" and Mar"" refers to the individual contract years, since several are included. E.g., the 2018 July and March white maize futures contracts are abbreviated as Jul18 and Mar18.

From the data availability column in Table 5.4 above, the evaluation period for the influential factor analysis (Section 5.3 and the white maize hedging strategy comparison (Section 5.4) is established. Influential factor data consists of monthly intervals from January 2001 up to and including July 2018 due to the constraint of option volatility availability as input for evaluating hedging strategies. All of the factor values available in daily format were transformed into monthly format by taking the last value for each month as the representative monthly value. Taking the last value for each month as a representative monthly value corresponds with the data value provided by the Thomson Reuters (2018) database if the price data are extracted in monthly intervals.

However, for the evaluation of hedging strategies applied to the different March and July white maize futures contract prices, daily contract closing prices were used. The only limiting factor in this regard was that white maize option volatility for the March and July contracts were only available from January 2002. As a result, the hedging strategies applied to the data were based on the July white maize futures contract from the July 2003 contract up to and including the July 2018 contract. The corresponding March futures contracts were also included where applicable. In terms of the descriptive statistics, each individual March and July white maize contract were evaluated from the first trading day in October of the previous year up to and including the last trading day of the March and July contracts, respectively.

The demarcation in the data above provides the necessary foundation for the inclusion of relevant descriptive statistics in Table 5.5 below. Two of the important basic descriptive measures are skewness (S) and kurtosis (K), which provide an immediate glance at the shape of the probability density function (PDF) of the data. These two values are also known as the third and fourth moments applied in the calculation of the distribution normality. Skewness is a measure that assigns a value to the asymmetry of the PDF, whereas kurtosis is a measure of the shape (peakedness/flatness) of the PDF (QMS, 2009:317). The two respective values may be calculated as follows:

$$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\bar{x}}{\hat{\sigma}}\right)^3, \tag{5.8}$$

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\bar{x}}{\hat{\sigma}}\right)^4, \tag{5.9}$$

where $\hat{\sigma}$ is an estimator for the standard deviation based on the biased estimator for the variance, which may be denoted as $\hat{\sigma} = s\sqrt{\frac{N-1}{N}}$. The skew value of a standard normal (Gaussian) distribution is zero, which implies a pure symmetric distribution.

As a result, a positive skew value indicates that the right tail of the distribution is longer than the left, but that the bulk of the distribution lies to the left of the mean. In contrast, a negative skew value implies that the left tail of the distribution is longer than the right, but also that the bulk of the distribution lies to the right of the mean (QMS, 2009:318). Therefore, when a distribution is either positively or negatively skewed, more observations are located to the left or the right of the mean, which leads to an increase in tail risk. An increase in tail risk may cause potential surprise results, since the standard deviation as a risk measure does not differentiate between downside and upside risk, leading to a misperception of actual risk (Harding, 2002:2; De Wet, Krige & Smit, 2008:71).

When interpreting the kurtosis (K) measure value, however, a value exceeding three indicates a peaked distribution (leptokurtic) relative to a normal distribution and a kurtosis smaller than three to a flat (platykurtic) distribution compared to a standard normal distribution (QMS, 2009:317-318). Kurtosis can also take on positive or negative values. Positive values point to peakedness with heavier tails than a standard normal distribution, whereas negative kurtosis can be associated with lighter tails and flatter distribution than a standard normal distribution (DeCarlo, 1997:292). Consequently, leptokurtic distributions can be associated with a distribution where the tails denote more probability than normal. The peakedness of these distributions can be associated with long periods during which the market price trends are followed by periods of significant price volatility, shown by the fat tails in the distribution. Conversely, platykurtic distributions point to significantly smaller return volatility (tail risk) with the bulk of the return probability around the mean (Culp, 2001:44).

Applying these general descriptive statistic interpretation principles to the values included in Table 5.5 below show that the factor data and July white maize price data are predominantly positively skewed and platykurtic. These characteristics imply a smaller risk for downside surprises over time due to a smaller tail risk. The July white maize volatility data as well as the March white maize price differ in the sense that the data tend to be more negatively skewed but show similar platykurtic characteristics. The March contract volatility, however, includes years where the kurtosis becomes significantly greater than three and the distributions are as a result leptokurtic. All of the March contract volatility years that show high kurtosis may also be described by positive skewness, which means that these contracts have a greater probability of a positive change in option volatility. None of the distributions for any of the factor data, contracts price data, or contract price volatility data show a combination of high kurtosis and negative skewness. Such a combination would have been a definite reason for caution, since it would mean that there was a higher probability (heavier tails due to high kurtosis) of a negative return surprise (negative skewness).

Table 5.5: Basic descriptive statistics

Factor data Statistics	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	SUPPLY	DEMAND	ENDING STOCK	DAYS' STOCK	SOI
No. of observations	211.00	211.00	211.00	211.00	211.00	211.00	211.00	211.00	211.00	211.00	211.00	211.00
Minimum	498.00	1111.42	0.36	434.95	0.81	187.50	5.64	13000.00	279000.00	274318.00	26.13	-29.50
Maximum	5035.00	4551.38	1.20	3260.12	2.44	806.50	15.87	3439775.00	598040.00	6733786.00	465.86	26.40
1st Quartile	1169.50	1630.53	0.58	883.05	1.11	242.25	7.11	43942.00	358201.00	1831756.00	136.13	-6.65
Median	1763.00	2748.73	0.68	1361.75	1.29	359.75	8.07	101984.00	394000.00	2811104.00	211.16	-0.60
3rd Quartile	2169.00	3384.89	0.83	1807.26	1.58	431.13	10.73	720560.00	457500.00	3941500.00	292.75	6.81
Mean	1837.65	2598.99	0.71	1398.69	1.36	385.65	9.15	506199.98	413937.55	2944824.92	217.05	0.01
Standard deviation	904.71	981.03	0.18	648.44	0.33	159.36	2.61	766081.88	73057.31	1429293.75	105.35	9.82
Skewness	1.36	0.03	0.57	0.52	0.69	0.89	0.81	1.80	0.73	0.36	0.27	0.17
Kurtosis	2.26	-1.22	-0.34	-0.40	0.01	-0.06	-0.49	2.37	-0.24	-0.56	-0.74	0.01

July WM Statistics	WM Jul 03	WM Jul 04	WM Jul 05	WM Jul 06	WM Jul 07	WM Jul 08	WM Jul 09	WM Jul 10	WM Jul 11	WM Jul 12	WM Jul 13	WM Jul 14	WM Jul 15	WM Jul 16	WM Jul 17	WM Jul 18
No. of observations	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00	204.00
Minimum	743.00	795.00	522.00	839.00	1087.00	1377.00	1220.00	1019.00	1282.00	1682.00	1824.00	1611.00	1875.00	2784.00	1678.00	1876.00
Maximum	1989.00	1578.00	1100.00	1419.00	2021.00	2200.00	2078.00	1680.00	1866.00	2738.00	2459.00	2479.00	3338.00	5142.00	2950.00	2224.00
1st Quartile	871.50	992.00	576.00	986.00	1305.75	1513.25	1555.00	1107.00	1404.75	1960.00	2105.00	1920.50	2024.50	3873.50	1839.00	1999.00
Median	1038.00	1081.00	598.00	1105.00	1609.00	1645.00	1599.00	1158.00	1594.50	2031.00	2205.00	2099.00	2592.00	4667.00	2021.00	2052.00
3rd Quartile	1736.25	1209.00	902.00	1171.00	1729.00	1839.25	1830.00	1516.75	1696.50	2130.50	2288.25	2165.50	2781.25	4864.00	2580.00	2105.00
Mean	1271.53	1116.02	716.94	1100.68	1536.13	1695.75	1669.84	1283.29	1560.78	2059.00	2191.48	2063.54	2465.24	4312.84	2169.29	2050.13
Standard deviation	418.91	164.70	187.27	148.11	254.65	212.60	197.10	213.70	157.40	184.75	128.05	180.73	423.33	752.56	380.68	77.91
Skewness	0.29	0.76	0.79	0.26	0.09	0.50	0.29	0.52	-0.04	1.26	-0.53	-0.36	0.14	-1.00	0.50	-0.17
Kurtosis	-1.64	0.04	-1.03	-0.51	-1.29	-0.85	-0.82	-1.43	-1.45	2.91	-0.15	-0.07	-1.32	-0.63	-1.23	-0.63

July WM Volatility Statistics	WM Jul 03 Vols	WM Jul 04 Vols	WM Jul 05 Vols	WM Jul 06 Vols	WM Jul 07 Vols	WM Jul 08 Vols	WM Jul 09 Vols	WM Jul 10 Vols	WM Jul 11 Vols	WM Jul 12 Vols	WM Jul 13 Vols	WM Jul 14 Vols	WM Jul 15 Vols	WM Jul 16 Vols	WM Jul 17 Vols	WM Jul 18 Vols
No. of observations	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00	183.00
Minimum	26.00	25.00	33.00	20.50	23.50	23.50	26.00	24.00	26.50	23.50	25.50	17.00	21.00	18.00	22.00	21.25
Maximum	51.00	60.00	55.00	56.00	50.00	38.00	45.00	41.50	36.00	33.00	37.50	28.50	43.50	34.50	39.00	33.75
1st Quartile	31.00	37.00	39.00	26.38	31.25	31.00	29.50	29.00	31.13	27.50	26.50	23.00	24.00	23.50	30.50	23.50
Median	35.00	41.00	42.00	37.50	37.50	32.50	33.00	34.00	33.00	29.50	27.50	26.00	25.00	28.25	34.00	26.00
3rd Quartile	42.00	45.00	48.38	47.00	43.00	33.50	35.00	38.00	35.50	32.50	29.50	27.50	28.00	32.00	36.50	31.75
Mean	36.04	40.90	43.20	37.47	37.09	32.43	32.71	33.48	32.76	29.55	28.27	24.82	26.73	27.60	32.93	27.63
Standard deviation	6.82	6.60	5.75	10.36	6.87	2.97	4.07	4.96	2.49	2.72	2.41	2.89	4.59	4.71	4.26	4.32
Skewness	0.47	-0.05	0.19	-0.09	-0.27	-0.23	0.47	-0.24	-0.34	-0.40	1.65	-0.89	1.61	-0.21	-0.82	0.03
Kurtosis	-1.01	-0.04	-1.10	-1.48	-1.08	0.26	-0.28	-1.29	-0.91	-1.10	2.75	0.08	1.99	-1.05	0.03	-1.73

March WM Statistics	WM Mar 03	WM Mar 04	WM Mar 05	WM Mar 06	WM Mar 07	WM Mar 08	WM Mar 09	WM Mar 10	WM Mar 11	WM Mar 12	WM Mar 13	WM Mar 14	WM Mar 15	WM Mar 16	WM Mar 17	WM Mar 18
No. of observations	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00	121.00
Minimum	877.00	898.00	471.00	834.00	1185.00	1608.00	1551.00	1023.00	1230.00	2129.00	2044.00	2322.00	1830.00	3033.00	1750.00	1772.00
Maximum	1944.00	1514.00	1071.00	1227.00	1994.00	1971.00	1956.00	1726.00	1685.00	2696.00	2560.00	3765.00	2908.00	5296.00	3966.00	2140.00
1st Quartile	1275.00	955.50	561.25	903.25	1339.00	1775.50	1710.50	1192.00	1329.00	2337.25	2175.00	2411.75	1979.00	3249.50	2895.00	1870.00
Median	1752.00	1094.00	815.00	994.50	1427.00	1829.00	1789.00	1535.00	1372.00	2429.00	2330.00	2762.50	2045.00	4301.00	3439.00	1941.50
3rd Quartile	1864.00	1255.50	952.00	1100.50	1481.00	1904.00	1856.50	1597.00	1494.75	2529.00	2481.50	3105.25	2424.00	4938.00	3626.75	2004.00
Mean	1566.44	1122.75	774.41	1009.08	1474.35	1831.86	1780.80	1430.97	1414.15	2435.16	2325.05	2804.19	2193.60	4158.81	3242.35	1941.37
Standard deviation	361.55	175.47	196.64	105.80	201.29	82.48	100.29	215.28	111.56	148.12	166.34	387.90	295.58	811.76	528.50	94.14
Skewness	-0.79	0.48	-0.13	0.01	1.35	-0.31	-0.35	-0.48	0.75	0.01	-0.10	0.39	0.91	-0.14	-0.96	0.09
Kurtosis	-0.97	-1.03	-1.52	-1.23	0.86	-0.56	-0.61	-1.43	-0.68	-0.54	-1.53	-0.89	-0.63	-1.74	-0.05	-0.92

March WM Volatility Statistics	WM Mar 03 Vols	WM Mar 04 Vols	WM Mar 05 Vols	WM Mar 06 Vols	WM Mar 07 Vols	WM Mar 08 Vols	WM Mar 09 Vols	WM Mar 10 Vols	WM Mar 11 Vols	WM Mar 12 Vols	WM Mar 13 Vols	WM Mar 14 Vols	WM Mar 15 Vols	WM Mar 16 Vols	WM Mar 17 Vols	WM Mar 18 Vols
No. of observations	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00	101.00
Minimum	22.00	35.00	40.00	36.50	33.00	27.00	28.00	35.00	29.00	26.50	22.50	21.50	26.00	28.75	34.00	25.50
Maximum	45.00	60.00	78.00	64.00	70.00	34.00	38.00	45.50	40.00	46.00	38.50	37.50	62.00	44.00	51.00	38.00
1st Quartile	27.00	40.00	49.88	45.38	40.50	32.00	33.00	39.00	33.50	28.00	26.00	25.00	26.50	34.00	39.00	33.50
Median	29.50	42.50	58.00	53.75	43.00	32.50	36.00	40.00	35.00	29.50	28.00	25.50	27.00	39.50	40.50	34.50
3rd Quartile	32.00	48.63	64.50	57.63	45.50	33.50	37.00	41.50	37.00	31.13	29.00	32.50	30.00	42.00	41.00	36.00
Mean	30.43	44.89	58.11	51.94	43.85	32.18	35.21	40.04	35.14	30.19	27.55	27.86	30.85	38.39	40.95	33.73
Standard deviation	5.58	6.18	10.09	7.01	5.36	1.70	2.56	2.14	2.56	3.66	2.47	4.14	8.95	4.37	4.15	3.42
Skewness	1.06	0.86	0.09	-0.54	1.51	-1.44	-1.16	-0.63	-0.16	2.22	1.43	0.70	2.62	-0.44	1.32	-1.26
Kurtosis	0.62	-0.25	-0.87	-0.84	4.80	1.58	0.63	0.96	-0.72	6.31	6.04	-0.73	6.18	-0.99	1.39	0.84

Source: Compiled by the author

Despite all of the different ways to interpret skewness and kurtosis in an attempt to evaluate normality, there appears to be no definite combination of skewness and kurtosis that resembles the characteristics of a normal distribution. In order to confirm if the distributions of the different data conform to the normal distribution with a mean (skewness) of zero and kurtosis of three (QMS, 2009:317), four tests for normality are included. A thorough description of these evaluations and their results are, however, required and are included to conclude the rest of the statistical description of the factor data.

The first normality test will be the Jarque-Bera (JB) test, which was developed by Jarque and Bera (1980, 1987) and is an asymptotic test based on Ordinary Least Square (OLS) residuals (Thadewald & Buning, 2007:88). The calculation includes skewness (S) and kurtosis (K) to estimate the JB-statistic as follows:

$$Jarque - Bera\ (JB) = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right), \tag{5.10}$$

where S is the skewness and K the kurtosis of the distribution. Interpreting the JB-statistic under the null hypothesis of a normal distribution requires the interpretation of a χ^2-distribution with two degrees of freedom. The probability that is estimated may be seen as the probability that the JB-statistic exceeds (in absolute value) the observed value under the null hypothesis (QMS, 2009:318; Toringa & Camps, 2010b:194).

The second normality test of note is the Shapiro-Wilk (SW) test, which was developed by Shapiro and Wilk (1965), is based on correlation (Van Heerden, 2015:202), and belongs to the empirical distribution function (EDF) group of tests. The SW test may also be seen as a goodness-of-fit test that evaluates the manner in which the test distribution conforms to a normal distribution with the same mean and standard deviation (Thadewald & Buning, 2007:88; Field, 2009:144). The SW-statistic may be calculated as follows:

$$SW = \frac{\sum_{i=1}^{n} a_i {x_i}^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \tag{5.11}$$

where $x = (x_1, \dots \dots \dots, x_n)$ is a vector of random variables; $x_{()}$ the corresponding ordered vector, and $\bar{x}$ the sample mean. The weights $a_i, i = 1, \dots \dots \dots, n$, are calculated as follows: Let $y = (y_1, \dots \dots \dots, y_n)$ be a vector of random variables from a normal distribution and $y_{()}$ the corresponding ordered vector. The calculation of a_i requires the calculation of the vector of expectation values and the covariance matrix of $y_{()}$: $\acute{m} = (m_1, \ldots \ldots \ldots, m_n)$, where $m_i = E(y_i)$ and V where $v_{ij} = Cov(y_i, y_j)$. The vector a of the weights a_i yields as follows: $a' = m'V^{-1}[(m'V^{-1})(V^{-1}m)]^{-1/2}$. The null hypothesis is rejected if $SW \leq w_{\propto}$ (Thadewald & Buning, 2007:91-92; Toringa & Camps, 2010b:195). As a result, if the test is insignificant $(p > 0.05)$, it means that the data conforms to a normal distribution; and if the test is significant $(p < 0.05)$ the distribution differs significantly from a normal distribution (Field, 2009:144).

Both the third and fourth normality tests in the form of the Anderson-Darling (AD) test (Anderson & Darling, 1952), and the Lilliefors (L) test (Lilliefors, 1967), are based on the empirical distribution function (EDF), which may be written as follows (Toringa & Camps, 2010a:289):

$$\widehat{F_n}(x) = \frac{1}{n}\sum_{i=1}^{n} I\,(X_i \leq x), \tag{5.12}$$

where $I(\cdot)$ is the indicator of the event and X_i is the i^{th} element of the sample to be tested. The EDF function is a step function that increases by $1/n$ at the value of each ordered data point. The determination of normality is done by comparing the EDF function with the standard normal cumulative distribution function (CDF).

The Lilliefors (L) test based on the EDF can be formulated as follows (Toringa & Camps, 2010a:289):

$$L = \underset{1 \leq i \leq N}{max} \left|F(Y_i) - \hat{F}(X_i)\right|, \tag{5.13}$$

where $\hat{F}(X_i)$ is the value of the i^{th} element of the EDF of the sample X, and $F(Y_i)$ is the value of the i^{th} element of the normal CDF with mean $(\bar{Y})$ and variance (σ_y^2) equal to:

$$\bar{Y} = \frac{1}{N}\sum_{i=1}^{N} X_i, \tag{5.14}$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(X_i - \bar{X})^2, \tag{5.15}$$

where N denotes the number of observations and $\bar{X}$ the sample mean of X. The L confidence values are obtained from the CDF of the test results when applied to a normal distribution. Due to the standardisation of the data – irrespective of the mean and variance – the L test is capable of evaluating normality of any normal distribution (Van Heerden, 2015:200). The L test does, however, include a challenge when the critical values are calculated, since the test statistics do not follow a known distribution. As a result, the application of simulations (such as Monte Carlo simulations) is required to estimate confidence values (Toringa & Camps, 2010a:289). Also, the L test tends to be more sensitive near the centre of the distribution than at the tails. The Anderson-Darling (AD) test is however able to address this potential shortcoming through a modification of the L test that allocates more weight to the tail of the distribution. The (AD) test consists of (Toringa & Camps, 2010a:289):

$$AD^{*2} = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)\ [(\ln(\mathrm{F}(\mathrm{X_i})) + \ln(1-(\mathrm{F}(\mathrm{X_i}))], \quad (5.16)$$

where AD^{*2} has to be adjusted to account for sample size, as described in Stephens (1974:732):

$$AD^2 = AD^{*2}\left(1 + \frac{0.75}{n} + \frac{2.25}{n^2}\right). \quad (5.17)$$

The results from the application of all of the tests for normality to the factor and price data are included in Table 5.6a to Table 5.6e below:

Table 5.6a: Normality tests – Influential factors

Variable	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
WM-C	0.893	5.421	0.140	109.530
	Not Normal	Not Normal	Not Normal	Not Normal
IP	0.940	3.810	0.097	13.167
	Not Normal	Not Normal	Not Normal	Not Normal
IPR	0.964	2.252	0.091	12.518
	Not Normal	Not Normal	Not Normal	Not Normal
EP	0.958	2.167	0.101	10.893
	Not Normal	Not Normal	Not Normal	Not Normal
EPR	0.959	2.404	0.092	16.601
	Not Normal	Not Normal	Not Normal	Not Normal
CBOT-C	0.892	7.546	0.158	28.133
	Not Normal	Not Normal	Not Normal	Not Normal
USD/ZAR	0.897	7.940	0.171	24.956
	Not Normal	Not Normal	Not Normal	Not Normal
SUPPLY	0.678	28.081	0.300	163.281
	Not Normal	Not Normal	Not Normal	Not Normal
DEMAND	0.941	4.135	0.113	19.046
	Not Normal	Not Normal	Not Normal	Not Normal
ENDING STOCK	0.979	0.985	0.061	7.252
	Not Normal	Not Normal	Normal	Not Normal
DAYS' STOCK	0.977	1.013	0.055	7.368
	Not Normal	Not Normal	Normal	Not Normal
SOI	0.994	0.411	0.047	0.978
	Normal	Normal	Normal	Normal

Source: Compiled by the author

Table 5.6b: Normality tests – July white maize futures contracts

Variable	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
WM Jul 03	0.838	13.281	0.219	25.034
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 04	0.941	3.775	0.096	21.460
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 05	0.793	18.075	0.269	29.210
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 06	0.963	1.870	0.073	4.340
	Not Normal	Not Normal	Not Normal	Normal
WM Jul 07	0.927	6.069	0.164	14.147
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 08	0.921	5.621	0.167	14.855
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 09	0.943	4.760	0.162	10.680
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 10	0.832	14.676	0.220	25.637
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 11	0.914	6.969	0.156	17.928
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 12	0.947	3.024	0.105	52.432
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 13	0.978	1.100	0.061	8.148
	Not Normal	Not Normal	Normal	Not Normal
WM Jul 14	0.961	3.742	0.142	4.146
	Not Normal	Not Normal	Not Normal	Normal
WM Jul 15	0.895	8.655	0.200	15.113
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 16	0.777	18.966	0.257	35.958
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 17	0.886	8.960	0.170	20.649
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 18	0.981	0.863	0.060	4.685
	Not Normal	Not Normal	Normal	Normal

Source: Compiled by the author

Table 5.6c: Normality tests – July white maize futures contract volatility

Variable	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
WM Jul 03 Vols	0.929	4.225	0.140	14.258
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 04 Vols	0.989	0.751	0.076	0.077
	Normal	Not Normal	Not Normal	Normal
WM Jul 05 Vols	0.958	2.279	0.092	10.094
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 06 Vols	0.905	6.394	0.147	16.740
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 07 Vols	0.949	3.099	0.146	10.963
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 08 Vols	0.959	2.874	0.136	1.984
	Not Normal	Not Normal	Not Normal	Normal
WM Jul 09 Vols	0.964	1.981	0.149	6.394
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 10 Vols	0.925	4.738	0.151	14.225
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 11 Vols	0.935	3.202	0.130	9.349
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 12 Vols	0.905	5.524	0.165	14.459
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 13 Vols	0.810	11.083	0.225	139.715
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 14 Vols	0.873	7.680	0.170	24.010
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 15 Vols	0.802	13.191	0.229	97.048
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 16 Vols	0.950	2.299	0.108	9.500
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 17 Vols	0.919	3.842	0.115	20.185
	Not Normal	Not Normal	Not Normal	Not Normal
WM Jul 18 Vols	0.846	11.927	0.228	22.413
	Not Normal	Not Normal	Not Normal	Not Normal

Source: Compiled by the author

Table 5.6d: Normality tests – March white maize futures contracts

Variable	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
WM Mar 03	0.809	8.792	0.218	16.641
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 04	0.905	3.788	0.169	10.012
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 05	0.898	4.105	0.140	11.488
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 06	0.946	2.062	0.109	7.253
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 07	0.823	7.613	0.237	45.402
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 08	0.974	0.698	0.078	3.452
	Not Normal	Normal	Normal	Normal
WM Mar 09	0.972	0.691	0.062	4.560
	Not Normal	Normal	Normal	Normal
WM Mar 10	0.848	7.868	0.226	14.450
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 11	0.888	5.537	0.199	14.465
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 12	0.969	0.892	0.088	1.275
	Not Normal	Not Normal	Not Normal	Normal
WM Mar 13	0.893	4.871	0.181	11.812
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 14	0.910	3.613	0.181	6.713
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 15	0.829	8.446	0.218	21.534
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 16	0.829	8.178	0.199	15.144
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 17	0.891	4.501	0.195	16.568
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 18	0.965	0.977	0.085	4.638
	Not Normal	Not Normal	Not Normal	Normal

Source: Compiled by the author

Table 5.6e: Normality tests – March white maize futures contract volatility

Variable	Shapiro-Wilk	Anderson-Darling	Lilliefors	Jarque-Bera
WM Mar 03 Vols	0.901	3.279	0.165	21.379
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 04 Vols	0.904	3.566	0.185	12.341
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 05 Vols	0.973	0.534	0.065	3.078
	Not Normal	Normal	Normal	Normal
WM Mar 06 Vols	0.925	2.927	0.183	7.835
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 07 Vols	0.884	2.589	0.156	208.580
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 08 Vols	0.808	6.364	0.245	48.491
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 09 Vols	0.847	5.236	0.272	26.904
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 10 Vols	0.915	3.103	0.171	11.484
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 11 Vols	0.970	1.042	0.109	2.217
	Not Normal	Not Normal	Not Normal	Normal
WM Mar 12 Vols	0.816	3.976	0.171	222.113
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 13 Vols	0.964	1.219	0.140	1.966
	Not Normal	Not Normal	Not Normal	Normal
WM Mar 14 Vols	0.840	7.345	0.264	10.089
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 15 Vols	0.557	16.042	0.313	346.927
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 16 Vols	0.921	2.582	0.125	7.002
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 17 Vols	0.801	7.795	0.293	36.579
	Not Normal	Not Normal	Not Normal	Not Normal
WM Mar 18 Vols	0.841	5.217	0.230	35.582
	Not Normal	Not Normal	Not Normal	Not Normal

Source: Compiled by the author

From the overall descriptive statistics results presented above, it becomes evident that higher moments in the form of skewness and kurtosis (Table 5.5) and non-normality (Table 5.6a to Table 5.6e) are present in the data. With the exclusion of SOI from the factor analysis data, the July 2018 white maize futures contract, the March 2008 and 2009 white maize futures contracts, as well as the March 2005 option volatility data, the rest of the data may be seen as predominantly non-normal. In each of these instances where normality was identified, the consideration that the data may possibly be classified as normal was based on at least one or more of the four normality tests attesting to the notion. The implication of non-normality with regard to the specific methods applied should therefore be considered. As explained at the beginning of Section 5.2.3, the data evaluated in this section is not the data used to compare white maize hedging strategy results by means of performance measures. Therefore, the risk of performance measure biased results due to non-normality (Chapter 4, Section 4.3) should not be considered based on these results, since the specific statistical characteristics of hedging strategy returns are considered in Section 5.5.1 below. However, the impact of non-normality on the proposed methods in the form of data segmentation or clustering and percentile ranking (Section 5.3), should be taken into account when deciding on the specific cluster method applied to the data.

In terms of cluster analysis, several methods can be applied and results may be biased if the method is not able to account for high volatility and the presence of non-normality in the data (De Silva *et al*., 2018:3; Banfield & Raftery, 1993:805). These clustering methods and an applicable method not influenced by non-normality is discussed below. However, the data segmentation by means of percentile ranking is not influenced by the presence of non-normality. Percentile ranking only depends on the data used to compute it and the limit of the ranking always falls between the minimum and the maximum of the data included. As a result, percentiles are not influenced by extreme values, since their calculation are not dependent on a specific probability density function comparison based on normally distributed data (Waltman *et al*., 2012:10). Percentiles rankings are based on the probability density of the specific data included in the analysis and can therefore be calculated even if the data portrays skewness or kurtosis to the extent that it may be classified as not normal.

5.3 Cluster analysis and percentile ranking

One of the main objectives of this study was to find a relevant link or specific similarities in factor and price developments for different seasons. This seasonal similarity identification must be done in an attempt to make an informed decision as to the more applicable or optimal hedging strategy to deploy based on the influential factor similarity found in a specific season. As explained and set out in Section 5.2.1 above, two appropriate methods are proposed to link the influential factors based on their historical influence on market price formation. The first method, called cluster analysis, is based on statistical grouping or pattern recognition methodology, which stems from classification that is based on certain observable characteristics (Everitt, 1992:6; Fukunaga, 1990:508) and is discussed in Section 5.3.1. Thereafter, a practical approach in the form of percentile ranking and the grouping of these rankings is included in an attempt to provide a structured market analysis method, which may be applied to compile a view of the relative development in the influential market price drivers of the SAFEX white maize price (Section 5.3.2).

5.3.1 Cluster analysis

Cluster analysis involves an exploratory analysis of data as an alternative method that aims to order or divide raw data into meaningful groups in an attempt to identify structures or homogenous groups (Jain, 2010:651). Since the analysis is exploratory, no distinction is made between dependent and independent variables. As a result, the absence of categorisation of the data is what distinguishes cluster analysis (sometimes referred to as unsupervised learning) from classified data analysis (supervised learning) (Boongoen & Iam-On, 2018:2). Hence, the main objective of cluster analysis is to discover natural groupings of data by means of a fitting or applicable algorithm.

The applicability of exploratory analysis through the identification of natural groupings led to the application of cluster analysis methodology in various fields of study. These fields include medicine – where similar symptoms or causes of specific illnesses may be grouped (Bredel, *et al*., 2005; Kavadara, *et al*., 2017); marketing – where customers may be segmented based on needs, attitudes, demographics and behaviour (Punj & Stewart, 1983; Helsen & Green, 1991); and applications in education that measure psychological characteristics, aptitude, and achievement (Egan, 1984; Darcan & Badur, 2012. Antonenko, Toy & Niederhauser, 2012). However, it was Stone, Hammer and Marcussen's application of cluster analysis on the Southern Oscillation Index (SOI) (1996:252-255) – whereby they classified SOI behaviour into five clusters or phases – that prompted the idea to implement cluster analysis as an alternative method to find a possible link between the influential factors and consequential seasonal developments. The applicability of the SOI clustering model by Stone, *et al*. (1996) remains relevant, since the method is still applied to distinguish between the main phases of SOI in order to provide forecasts as to expected rainfall patterns. The cluster analysis in this study did not mimic the SOI cluster phases obtained by Stone, *et al*. (1996), but was used to find a potential natural link between the different factors that influence the white maize futures price developments.

Nevertheless, this does not mean that a definite result for this study is to be expected based on the fact that Stone, *et al*. (1996) were able to successfully apply cluster analysis to find the link between similar years based on the different phases of SOI. The results and applicability of cluster techniques tend to be extremely data-dependent and results may differ depending on the type of model applied. Two major challenges are inherent to clustering algorithms. Firstly, different techniques may produce different similarities from the same data set. Secondly, the same algorithm with different parameter settings may identify different groupings within the same data set (Boongoen & Iam-On, 2018:2-3). Considering these two challenges, it is important to consider an applicable method able to combine different clustering approaches into a consensus or more optimal cluster approach. As is the case with the development of theory and model over time, several methods have been tried and tested that led to the categorisation of clustering methods into two general groups. These groups are referred to as relocation and hierarchical clustering methods. Relocation clustering may be further subdivided into the k-means method and the expectation-maximisation (EM) method, whereas the hierarchical methods can be divided into agglomerative or divisive approaches (SPSS, 2001:2). All of these clustering approaches must be discussed to provide the relevant background to the method applied in this study.

The descriptions of the different clustering algorithms are in large part reflected in the naming of the types of algorithms. The first type of clustering method, called relocating clustering, literally involves the specification of the number of clusters and moving each data point from one cluster to the next to find the best groupings through an iterative process (SPSS, 2001:2). The k-means algorithm may be seen as one of the older types of algorithms that was independently developed by Steinhaus (1956), Lloyd (developed 1957, published 1982), Ball and Hall (1965), and MacQueen (1967). The k-means process initiates the iterative process by randomly dividing the data into the specified number of clusters. The subsequent aim of the iterative process is to minimise the total distance between the points in the cluster and the cluster centre (cluster mean). Clusters are optimised by moving data points around in an attempt to minimise the square error of each cluster. As a result, the algorithm aims to minimise a specific mean for each cluster and to maximise the distance between the means of the k-clusters (Jain, 2010:654; Boongoen & Iam-On, 2018:2). In spite of the fact that the k-means algorithm may be seen as an older development, it remains applicable even today, mainly due to its simplicity, efficiency, empirical success (Jain, 2010:653), and its ability to analyse and cluster large data sets (Huang, 1998:301).

One of the main differences between the k-means and the EM algorithm, is that the EM does not include a distance measure. The EM algorithm was developed by Dempster, Laird, and Rubin (1977), and aims to extend the k-means approach by maximising (M) the probability that a specific data point should form part of a cluster. This is done by estimating (E) the mean and standard deviation of each cluster in order to approximate the distribution of the data points in the cluster. The iterative process continues until all data points are assigned to a specific cluster, based on the highest possible probability that each data point belongs to a specific cluster (Meila & Heckermann, 1998:387-388).

The second grouping of clustering methodology, called hierarchical clustering, was developed by Johnson (1967) after the initial work done by Ward (1963). The name hierarchical clustering also refers to the manner in which the method is applied. The application may be explained through the analogy of a tree-like structure. Data points are placed in the form of a two-dimensional tree with branches and leaves. The leaves may be seen as the clusters and the branches as the different types of links or distances between the clusters. When applying agglomerative hierarchical clustering, each leaf will represent a cluster with only one data point, called singleton clusters. Thereafter, an iterative process of merging similar clusters based on specific distance criteria is implemented until relevant clusters are formed (De Silva, Fernando, Wijethunge, Fernando, 2018:2-3). The distance criteria or linkage, as a result, determine the specific agglomerative algorithm applied to measure the dissimilarity based on the Euclidean distance[27] between clusters. Three algorithms in the form of single linkage (SL), complete linkage (CL), and average-linkage (AL) became relevant over time due to its applicability. The SL algorithm applies the distance criteria, so it measures the minimum distance between two data points of opposing clusters. The CL algorithm, on the other hand, applies the distance criteria to measure the maximum distance between data points in the different clusters, whereas the AL algorithm measures average distance between all the data points of opposing clusters as the linkage criterion (Boongoen & Iam-On, 2018:3).

When applying the alternative hierarchical method in the form of the divisive algorithm, the process differs from the agglomerative algorithm, since it follows a top-down approach rather than a bottom-up approach. When applying the divisive algorithm, the tree will initially be made up of a single cluster, after which the cluster is divided into branches or other clusters based on the greatest dissimilarities between the clusters formed. The iterative process continues until relevant clusters are formed. The final visual representation of the cluster tree after the iterative process of optimisation is complete for both an agglomerative and divisive algorithm, is called a dendrogram (De Silva, Fernando, Wijethunge & Fernando, 2018:2-3). The divisive hierarchical clustering algorithm is considered more complex, as it applies a second method to split the initial and corresponding clusters. A popular second method is

[27] The Euclidean distance in this instance refers to the square root of the sums of the squares of the differences between the coordinates of the points in each cluster (Singh, Yadav & Rana, 2013:13).

usually the k-means approach. Yet, results have shown that the divisive algorithm tends to be more accurate than the bottom-up or agglomerative algorithm approach (De Silva, *et al*., 2018:3).

Apart from the finding that divisive hierarchical clustering tends to be more accurate than agglomerative algorithm hierarchical clustering, several other advantages and shortcomings of all of these measures were identified over time. For instance, all of the measures except the EM-algorithm require some form of distance measure. The agglomerative algorithm even makes use of several different measures or linkage methods for the same type of clustering approach. Nonetheless, the end result is not similar, leading directly to different clustering results, even within the same type of approach. The main reason for the difference in clustering allocations is that different algorithms are designed to optimise a specific criterion (Boongoen & Iam-On, 2018:2). In addition, most linkage measures apply Euclidean measures or a simple matching dissimilarity measure to group categorical variables by replacing the mean measure with modes as applied by Huang (1998:289). When variables become mixed, though, the linkage distance takes on various measures that generally consist of the weighted sum of the distances of continuous and categorical variables. The risk of bias is introduced, since the weights are chosen at random and may result in a misrepresentation of clusters (Huang, 1998:286,291,297). Another challenge is that not all the data points in the distributions logically or naturally form part of a cluster. These data points that do not form part of an underlying pattern are usually referred to as noise (Zhang, Ramakrishnan & Livny, 1996). Hierarchical algorithms in particular are known to produce poor clustering links when faced with high dimensional or noisy data (De Silva *et al*., 2018:3).

In cluster analysis terms, high dimensional data means that it becomes difficult to distinguish between the distance between points inside a cluster compared to the distance between points inside and points outside the cluster. As a result, a specific method that is influenced by the presence of high dimensional data may start to fit data points – which would otherwise have been characterised as noise[28] – as part of a cluster and thereby render the clustering process meaningless (Agrawal, Gehrke, Gunopulos & Raghavan, 2005:6). In order to address these challenges, Banfield and Raftery (1993:805) applied a practical model that enabled them to cluster non-Gaussian distributions. The model made use of a decreasing log-likelihood measurement that enabled them to include more than one variable in the form of orientation, shape and size to address linkage. As a result, the model also allowed for the inclusion

[28] Noise in data occurs due to errors in the data collection process as well as errors that may occur when data is stored or processed. These data points have an influence on cluster analysis results, since methods that are unable to account for noise in data tend to include these data values as part of existing clusters, which may distort a potentially meaningful cluster (Garcia, Carvalho & Lorena, 2013:629; Banfield & Raftery,1993:806).

of noise and, in addition, proposed a Bayesian method to identify an appropriate number of clusters. Building on this model, Meila and Heckerman (1998:9) evaluated models known for their ability to handle high dimensional data and developed a likelihood-based linkage measure specifically for agglomerative hierarchical clustering applications.

From these combination type model developments, SPSS (2001:3) extended the model-based linkage measure to include both continuous and categorical data by means of a Two-Step Cluster Analysis. The SPSS model is based on the two-stage Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH) model, developed by Zhang, Ramakrishnan and Livny (1996:103). The BIRCH two-stage model first applies a pre-cluster sequential cluster algorithm, which enables the model to reduce the time it would take to handle large data sets by compressing dense regions and forming sub-clusters. The second step applies hierarchical cluster techniques on the sub-clusters to determine the desired number of clusters. As a result, the SPSS (2001:3) Two-Step Cluster Analysis includes the means to identify the optimal number of clusters through the application of the following process.

The first step is based on a sequential clustering approach and evaluates each data point to determine if the data point belongs to a specific cluster or whether a new cluster should be formed based on a different linkage measure. The step is accomplished practically by constructing a Clustering Feature (CF) tree, as explained by Zhang, *et al*. (1996:105). The mathematical construction of a CF tree starts by correctly defining the concept as follows: Given N d-dimensional data points in a cluster:$\{\vec{X}_i\}$, where

$i = 1,2, \dots \dots \dots, N$, the CF vector of the cluster is defined as a triple: $CF = \left(N, \overrightarrow{LS}, SS\right)$, where N is the number of data points in the cluster, $\overrightarrow{LS}$ is the linear sum of the N data points ($\sum_{i=1}^{N} \vec{X}_i$), and SS is the square sum of the N data points ($\sum_{i=1}^{N} \vec{X}_i^{\,2}$).

From this definition, the CF Additivity Theorem may be applied as follows (Zhang, *et al*., 1996:105): Assume that $CF_1 = \left(N_1, \overrightarrow{LS_1}, SS_1\right)$, and $CF_2 = \left(N_2, \overrightarrow{LS_2}, SS_2\right)$ are the CF vectors of two disjoint clusters. The CF vector that is formed by merging the clusters is:

$$CF_1 + CF_2 = \left(N_1 + N_2, \overrightarrow{LS}_1 + \overrightarrow{LS}_2, SS_1 + SS_2\right). \tag{5.18}$$

The practical construction of the CF tree entails a dynamic process, whereby each data point is moved recursively from the base or root cluster (node) along the CF tree. If the data point falls within the linkage criterion, the cluster absorbs the data point where after the CF tree is updated. However, if the data point does not fall within the linkage criterion, it forms a separate cluster by dividing an existing cluster into two groups based on the data points furthest from each other. This process may cause the CF tree to expand to the extent beyond the maximum number of available levels. In this case, the CF tree expands by increasing the threshold linkage criterion in order to allow for the inclusion of more data points in the existing clusters (Zhang, *et al*., 1996:106).

The second step builds on the results of the first step by using the clusters formed during the first step as input. The reduction of the initial data points into sub-clusters reduces the iterations required and optimises the effectiveness of traditional clustering methods. The second step applies the agglomerative hierarchical clustering method to refine the initial clusters formed in the first step by establishing the chosen linkage criterion between the two closest clusters in each stage of the hierarchical clustering process (SPSS, 2001:4). In both the pre-cluster and hierarchical cluster steps, the chosen linkage criterion will be defined as the corresponding decrease in log-likelihood when data points are combined into a single cluster (SPSS, 2001:5). After the relevant data points are divided into the specified clusters it will be important to determine if the process may be seen as meaningful and the division of factors into the clusters was fitting.

A useful test performed by the Two-Step Cluster Analysis is the generation of the silhouette coefficient used to quantify the "goodness" of a cluster solution and measures for both cohesion (similarity of a data point to own cluster) and separation (similarity of data point to other clusters) (Arbuckle, 2010:397). For every factor in a specific cluster that is generated, one can compute the average distance to all other factors in its cluster and the average distance to all factors in each of the other clusters. For each factor that is selected for the cluster analysis, the silhouette measure is the difference between the smallest average between cluster distance and the average within cluster distance, divided by the larger of the two distances. If the within-cluster distances are small and the between cluster distances are large, this will result in a silhouette measure close to the maximum value of 1 (Arbuckle, 2010:397). If the silhouette measure is negative, the average distance of a case to members of its own cluster is larger than the average distance to cases in other clusters which is an undesirable feature (Arbuckle, 2010:397). The silhouette measure for a cluster is the average of the silhouette measures for the data points within the cluster. The silhouette measure ranges from –1 to +1 were a value between -1 and 0.1 are considered a poor fit, 0.1 – 0.5 a fair fit and a value between 0.5 and 1 a good fit (Arbuckle, 2010:397).

Another important step in the cluster analysis process is to validate whether the clusters are significantly different from one another by means of an Analysis of Variance (ANOVA) (Field, 2013:430). Only if clusters exhibit significantly different means, are they distinguishable (Field, 2013:430). ANOVA compares the variance between the different groups with the variability within each of the groups and are used for the case of a quantitative outcome with a categorical explanatory variable that was two or more categories (in this case the number of clusters if more than two) (Pallant, 2013:258). During the process of ANOVA in SPSS an *F-ratio* is calculated, which represents the variance between the groups divided by the variance within the groups (Pallant, 2013:258). A large *F-ratio* indicates that there is more variability between the groups, which is caused by the independent variable, than there is within each group (Pallant, 2013:258). If the *F-ratio* is significant ($p < 0.005$) one can reject the null hypothesis of assuming equal means (Pallant 2013:258). The *F-ratio* however does not explain which of the groups differ. In order to test which groups are significantly different it is necessary to conduct post-hoc tests. If equal variances is assumed it is argued by Field (2013) and Pallant (2013) that the Bonferroni test is selected due to its ability to handle relative small data sets and control well for *Type 1* error rate. If equal variances are not assumed, Field (2013) and Pallant (2013) suggest the use of the Games-Howell post-hoc test. Post-hoc tests in general are designed to help protect against the likelihood of *Type 1* error and to determine which groups differ.

To conclude – based on the background and literature on cluster analysis presented above, this study applied the SPSS Two-Step Cluster Analysis in order to find possible clusters in the factors that influence the July white maize futures price. The reason for applying the specific method stems from the method's ability to account for non-normality that was identified in the statistical description of the factor data (Table 5.6a), as well as the method's ability to handle possible noise that may form part of the data due to process or source errors. Careful consideration and analysis of the output of several cluster analyses pertaining to the influential factor data revealed that further analysis was required, which led to the introduction of an alternative confirmatory method in order to link seasons by means of the influential factor data. The requirement of additional techniques and methods to improve the preliminary clustering results was confirmed by Steinbach, Ertoz and Kumar (2004:275). One of the main reasons identified was that cluster analysis takes the features as given and proceeds to implement a method from that point. The applicability of the analysis would therefore depend on existing or logical confirmatory results based on the opinion or expertise of the person conducting the analysis.

As a result, one of the risks of cluster analysis is that the person analysing the results may induce human error or bias by accepting a clustering result without being able to logically confirm its applicability. In the case of the specific application of cluster analysis in this study, no other study exists (based on the literature review conducted in this regard) that may be used to confirm or contest the cluster results obtained. In order to address this possible shortcoming, a practical percentile ranking approach to link seasons based on the similarities between seasons at a specific point in time was included. The inclusion of both the cluster analysis approach and percentile ranking approach is done in an attempt to establish consensus as to the similarities between seasons (market characteristics).

5.3.2 Percentile rank and grouping analysis

The inclusion of a percentile rank and grouping analysis approach stem from the applicability of the approach to ascertain how a specific measurement compares to the rest of the measurements in the same group (Thurstone, 1922:225). This early definition of percentile ranking and the calculation of percentiles have since been expanded to include several common applications. Percentiles may be used to provide a fairly accurate visual representation of a frequency distribution. Percentiles are frequently applied for the interpretation of test scores. The ranking of percentiles provides an indication of where an individual ranks relative to the rest of the subjects evaluated by means of the test (Kurtz & Mayo, 1979:145-146). Percentile rankings are also applied to determine how students' achievements have improved relative to other students with similar past scores (Castellano, 2011:1).

From this basic introduction, it makes sense to continue by first explaining the concept of quintiles, which is a collective term for quartiles, deciles and percentiles. All three terms provide a description of the manner in which a frequency distribution can be subdivided (Steyn, Smit, Du Toit & Strasheim, 1998:107-108). Figure 5.10 below provides a visual description of the relationship between the different quintiles for the same frequency distribution.

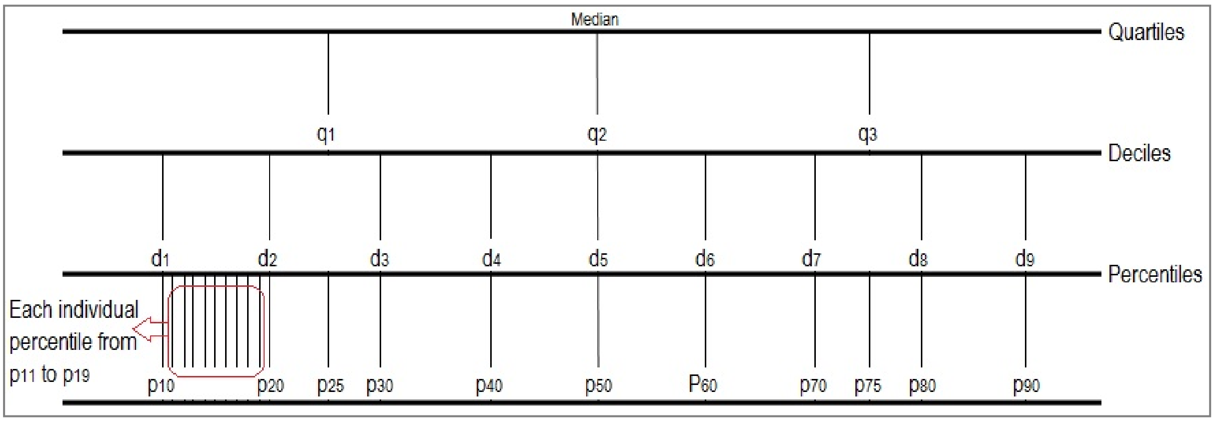

Figure 5.10: Visual description of quartiles, deciles and percentiles
Source: Compiled by the author from Steyn, *et al*. (1998:108)

A practical application and interpretation example of percentiles may be provided by means of the ranking of exam results, which is displayed visually by the histogram in Figure 5.11.

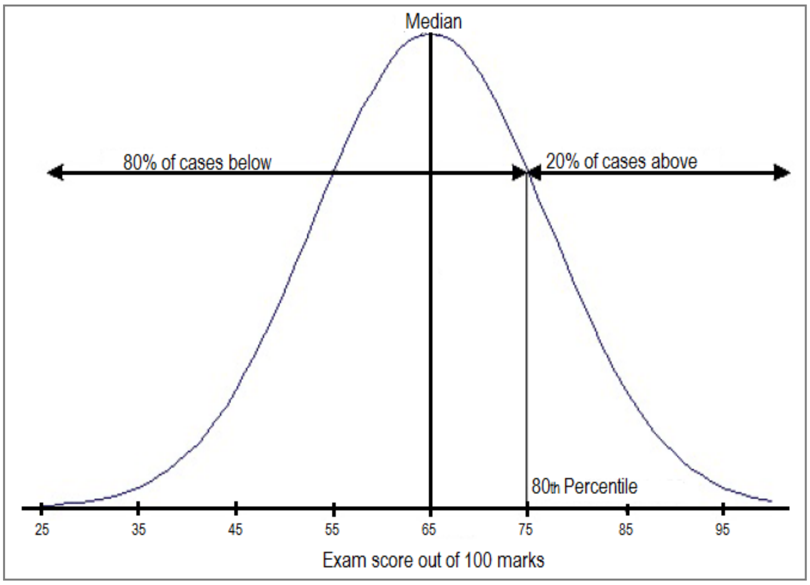

Figure 5.11: Histogram of exam scores achieved
Source: Compiled by the author, from histogram concept in Steyn *et al*. (1998:112)

The histogram shows the frequency of the different scores achieved with the median score or 50th percentile shown as 65 marks. The 80th percentile in the example was calculated as a mark of 75. Practically, this means that 80% of all the exam scores were below 75 marks. As a result, when assigning a percentile value to an exam score, the score is ranked relative to the other scores in the distribution. Such a process of ranking values in a distribution by means of percentiles is called percentile ranking (Dunn, 2001:115). In order to find the value of the i_{th} percentile, the following formula may be applied (Steyn *et al*., 1998:113):

$$p_i = k_l + \frac{(k_u - k_l)\left(\frac{in}{100} - F_{kl}\right)}{f_{p_i}}, \tag{5.19}$$

where, p_i is the i_{th} percentile; k_l is the lower limit of the class containing p_i; k_u is the upper limit of the class containing p_i; F_{kl} is the cumulative frequency below k_l; and f_{p_i} is the frequency of the interval containing p_i.

The idea of applying this method to rank all of the monthly data points of each factor influencing the July white maize futures contract price arose from its effectiveness in ranking values according to the relative value of each individual data point in terms of the distribution in which it lies. The aim of the ranking is to assess the value of each data point in relation to the appropriate value history of the influencing factors. The goal is to identify similar rankings at a specific point in time in order to link seasons on the basis of this similarity. The ranking and grouping of rankings allowed for meaningful interpretation of the factor data and was done as follows.

The monthly data points of all 12 factors (Section 5.2.1) were arranged chronologically from January 2001 up to and including July 2018. Percentile ranking was applied to the monthly data from August 2002 based on the data points from January 2001 up to and including August 2002. Each subsequent month was added to the distribution to calculate the percentile ranking of that month based on the values of the preceding months from January 2001. Percentile ranking was utilised in this manner up to and including December 2005 (60th data point), after which a rolling window of percentile ranking was implemented. This means that the January 2006 percentile ranking was based on the distribution of the 60 data points from February 2001 up to and including January 2006. The 60-month or five-year rolling window was chosen to account for the effect factors such as inflation may have on market prices over time, or an increase in the utilisation of white maize that may skew the percentile ranking of the distribution. The five-year rolling window may be linked to the manner in which agricultural data are compared on a regular basis. Supply and demand balance sheets usually base a projection of yield, demand, and even expected exports on the five-year average of the actual figures of these variables. The United States Department of Agriculture (USDA) specifically compares each weekly evaluation of crop conditions or progress with the five-year average of these values (USDA, 2018).

Following the percentile ranking of each monthly value for all of the different factors, the percentile rankings will be grouped by assigning a value ranging from 1 to 10 to each percentile rank based on the ranges provided in Table 5.7 below:

Table 5.7: Percentile rank grouping ranges

Percentile rank range	Grouping rank
$0.000 \geq x \leq 0.099$	1
$0.100 \geq x \leq 0.199$	2
$0.200 \geq x \leq 0.299$	3
$0.300 \geq x \leq 0.399$	4
$0.400 \geq x \leq 0.499$	5
$0.500 \geq x \leq 0.599$	6
$0.600 \geq x \leq 0.699$	7
$0.700 \geq x \leq 0.799$	8
$0.800 \geq x \leq 0.899$	9
$0.900 \geq x \leq 1.000$	10

Source: Compiled by the author

Note: x denotes each individual percentile rank to be grouped based on the specified range containing the value.

Based on the grouping rank value of the percentile rank range (Table 5.7) for each factor included in the study at a specific point in time, a table (Table 5.8 below included as an example) may be constructed to summarise and compare the grouping rank value of each month for different years over time. The table for each factor is constructed according to a production season, starting in August, prior to the planting window of a new production year and finishing in July when the July white maize futures enter the delivery month. Table 5.8 below is an example of the percentile rank grouping analysis for the July white maize futures price for each season from the 2002/2003 production year up to and including the 2017/2018 production year. From this analysis, the purpose is to compare the relative price level of the July white maize futures contract with the relative value of each individual influential market price driver for each season in an attempt to identify similar price developments in different seasons based on specific dominant influential market price drivers.

In order to establish a model capable of providing a meaningful comparison of all the relevant factors included, a filter model was constructed. The aim of the filter model was to compare the relative grouping of rank values (based on Table 5.7 above) for the different seasons by only including the average relative grouping values from August to October for each production season. The comparison only includes the average of these three months, since a decision on an applicable hedging strategy (Section 5.4) has to be made at the beginning of each production season according to the known or available data for each factor at that point in time. The practical construction of the filter model was done in two basic steps.

In the first step, the average grouping rank from August to October for each factor for each production season was calculated. An example of this calculation based on the July white maize futures contract is included as part of Table 5.8 below and highlighted in green. Step two entailed converting the average relative grouping values from August to October for each individual factor into three main groups to identify three levels or scenarios for each factor (Table 5.9 below).

Table 5.8: Percentile grouping monthly values for each July white maize futures contract

July WM	August	September	October	Average grouping rank	November	December	January	February	March	April	May	June	July
WM Jul 2002/2003	9	10	10	9.67	10	7	5	4	2	1	5	3	2
WM Jul 2003/2004	5	5	4	4.67	4	6	7	6	6	6	6	3	2
WM Jul 2004/2005	6	5	6	5.67	4	2	1	1	1	1	1	1	1
WM Jul 2005/2006	2	4	4	3.33	5	7	5	7	7	6	8	8	8
WM Jul 2006/2007	7	6	7	6.67	8	8	8	10	10	9	9	9	9
WM Jul 2007/2008	9	9	9	9.00	9	9	9	10	10	10	10	10	10
WM Jul 2008/2009	10	10	10	10.00	9	9	8	7	7	6	7	6	4
WM Jul 2009/2010	6	5	6	5.67	7	7	3	3	3	3	2	2	2
WM Jul 2010/2011	5	4	5	4.67	4	3	6	8	6	7	8	9	9
WM Jul 2011/2012	10	8	9	9.00	10	10	10	10	10	10	10	10	10
WM Jul 2012/2013	10	9	10	9.67	10	8	8	9	10	10	10	9	10
WM Jul 2013/2014	9	8	8	8.33	8	9	9	8	8	7	5	5	4
WM Jul 2014/2015	5	5	6	5.33	6	8	7	10	10	10	10	10	10
WM Jul 2015/2016	10	10	10	10.00	10	10	10	10	10	10	10	10	9
WM Jul 2016/2017	8	8	7	7.67	7	7	3	1	2	1	1	1	1
WM Jul 2017/2018	3	3	5	3.67	3	3	3	2	3	5	5	4	5

Source: Compiled by the author

Table 5.9: Average relative value groupings levels

Percentile grouping range	Grouping levels
$0.000 \geq x \leq 3.999$	Low
$4.000 \geq x \leq 7.999$	Medium
$8.000 \geq x \leq 10.000$	High

Source: Compiled by the author

The result of the average relative value groupings for each factor (Table 5.9) formed the main inputs for the filter model, which was used to link different seasons based on grouping value similarities. Table 5.10 below provides an example of the filter model by including the grouping values (Table 5.9) of the July white maize futures contracts based on the average grouping ranks calculated in Table 5.8. The filter model example in Table 5.10 also includes the actual inputs pertaining to the additional factors in the form of the general price trend, historical and expected marketing year-end stock levels (stock-to-usage), input cost in relation to the price level at the point when a production decision must be made, as well as instances of and expectations of possible El Niño and La Niña events, as discussed in Section 5.2.2 above.

Table 5.10: Filter model example

Production year	Main trend	Stock-to-usage	Input cost ratio	El Niño / La Niña	July white maize grouping levels
2002-2003	Downward	39%	73%	Moderate El Niño	High
2003-2004	Upward (Trend turn)	45%	36%	Neutral	Medium
2004-2005	Downward	37%	37%	Weak El Niño	Medium
2005-2006	Upward	32%	29%	Weak La Niña	Low
2006-2007	Upward	11%	38%	Weak El Niño	Medium
2007-2008	Upward	11%	31%	Strong La Niña	High
2008-2009	Downward (Trend turn)	22%	38%	Weak La Niña	High
2009-2010	Downward	22%	32%	Moderate El Niño	Medium
2010-2011	Upward (Trend turn)	7%	26%	Strong La Niña	Medium
2011-2012	Upward	11%	31%	Moderate La Niña	High
2012-2013	Upward	5%	37%	Neutral	High
2013-2014	Upward	19%	31%	Neutral	High
2014-2015	Upward (Trend turn)	27%	27%	Weak El Niño	Medium
2015-2016	Upward	12%	40%	Very Strong El Niño	High
2016-2017	Downward	33%	37%	Weak La Niña	Medium
2017-2018	Upward (Trend turn)	23%	27%	Weak La Niña	Low

Source: Compiled by the author

Hence, the filter model design may be seen as the main summary of the factors evaluated in terms of their status at a specific point in time (August to October) at the start of a new production season. This is also the time when a pre-season hedging strategy must be decided, which requires weighing up various hedging strategy alternatives in order to identify more optimal strategies for each production season. The following section includes a thorough explanation of the hedging strategies included as part of the evaluation in the study.

5.4 Evaluating hedging strategies

The evaluation of hedging strategies was another main objective of this research. Several alternative international and local hedging strategies were included in the literature review in Chapter 4, Sections 4.2.2.1 and 4.2.2.2. The review of these strategies formed the foundation for the 10 strategies included in the evaluation in Section 5.4.2 below. Apart from the applicable hedging strategies, the literature discussed in Chapter 4 (Section 4.2.2) also showed that the success of a hedging strategy depends in large part on the point of view from which the strategy is evaluated. The main considerations in terms of hedging strategies are the ability to reduce risk and to ensure profitability. The strategy that is able to significantly reduce price risk in a particular season may not necessarily be the most profitable. In order to address both points of view, the 10 hedging strategies included below were evaluated on the basis of risk reduction and profitability. The profitability of each strategy was evaluated by measuring the realised daily strategy price against an applicable input cost calculation (Section 5.4.3) for the specific production season. As a result, a daily return (realised daily strategy price minus input cost) could be calculated. Each final realised strategy price minus the relevant input cost, enabled the calculation of seasonal strategy profitability, whereas the risk-reducing capability of a hedging strategy could be evaluated by ranking the strategy returns for each season by means of the different risk-adjusted performance measures (Section 6).

In order to facilitate the calculation of the daily returns for the 10 white maize hedging strategies included in the study for each of the production seasons from 2001 to 2018, a thorough methodological procedure for each strategy is provided in Section 5.4.2 (subdivided into Sections 5.4.2.1 to 5.4.2.10). Each of the derivative instruments applied in the strategies was explained in Chapter 2 (Section 2.3.3.2 & Section 2.3.3.3). Nevertheless, it is important to first provide the Black (1976) model (Section 5.4.1) that was used to value options in several of the strategies, included in Section 5.4.2 below.

5.4.1 Option price valuation – the Black (1976) model

The original Black and Scholes (1973) model was extended by Black (1976) to specifically value options on commodity futures. The original Black and Scholes (1973) model was applicable to European options for a security of which the return was risk neutral (risk-free rate) with a consequent constant volatility. In addition, the Black (1976) model was modified to not require a risk-free rate as input. SAFEX, which facilitates American-style options, adopted the adapted Black (1976) model that is better suited for the pricing of commodity-type contracts (JSE, 2012e: A1). The Black (1976) model, otherwise known as the Fisher-Black model, was used to value white maize options that formed part of the hedging strategies, as discussed in Section 5.4.2. The model may be presented as follows (JSE, 2012e:A1):

It is required to find the option value V,

$$V = BLK[F, K, \sigma', T', T], \tag{5.20}$$

where F is the value of one futures contract; K is the value of one futures contract at the option's strike price; σ' is the volatility expressed as a percentage per annum; T' is the time to expiry in days; and T is the type of option, either put or call.

The applicable units are normalised by putting:

$$T = \frac{T'}{365}, \tag{5.21}$$

$$\sigma = \frac{\sigma'}{100}. \tag{5.22}$$

Also, calculate the basic call price, C', using Black's (1976) formula:

$$C' = MAX[F - K, 0] \ if \ T = 0, otherwise \ C' = F \times N[d_1] - K \times N[d_2], \tag{5.23}$$

where the values for d_1 and d_2 in Equation 5.23 are calculated as follows:

$$d_1 = \frac{\ln\left(\frac{F}{K}\right) + \frac{\sigma^2 T}{2}}{\sigma\sqrt{T}}, \tag{5.24}$$

$$d_2 = d_1 - \sigma\sqrt{T}, \tag{5.25}$$

and the function $N\ [\bullet]$ in equation 5.23 is the Cumulative Normal Integral. $N\ [d]$ is calculated by the following polynomial approximation:

Let $z = * \ d \ *$ and then find:

$$N(z) = 1 - \frac{1}{\sqrt{2\pi}} e^{\frac{x^2}{2}} (b_1 k + b_2 k^2 + b_3 k^3 + b_4 k^4 + b_4 k^4 + b_5 k^5), \tag{5.26}$$

where $= \frac{1}{1+a.z}$, and $a = 0.2316419$; $b_1 = 0.31938153$; $b_2 = -0.356563782$; $b_3 = 1.781477937$; $b_4 = -1.821255978$; $b_5 = 1.330274429$.

Then: $N[d]$

$$= N(z) \ if \ \ d > 0;$$
$$= 0.5 \ if \ \ d = 0;$$
$$= 1 - N(z) \ if \ d = 0.$$

Finally, to calculate call and put values based on formula 5.20:

If $T = Call$, V is the call value found above, adjusted so that it cannot be less than the option's intrinsic value:

$$V = MAX\,[C', F - K]. \tag{5.27}$$

If $T = Put$, V is found from:

$$V = MAX\,[C' - F + K, K - F]. \tag{5.28}$$

The value of V is rounded to the nearest whole number, with fractional values of 0.500 and above being rounded upwards.

5.4.2 Hedging strategy implementation

The methods for evaluating each of the hedging strategies is explained individually, but there are general standardisation criteria that must be included to create a uniform evaluation period. The timeline in Figure 5.12 below aims to standardise the evaluation period.

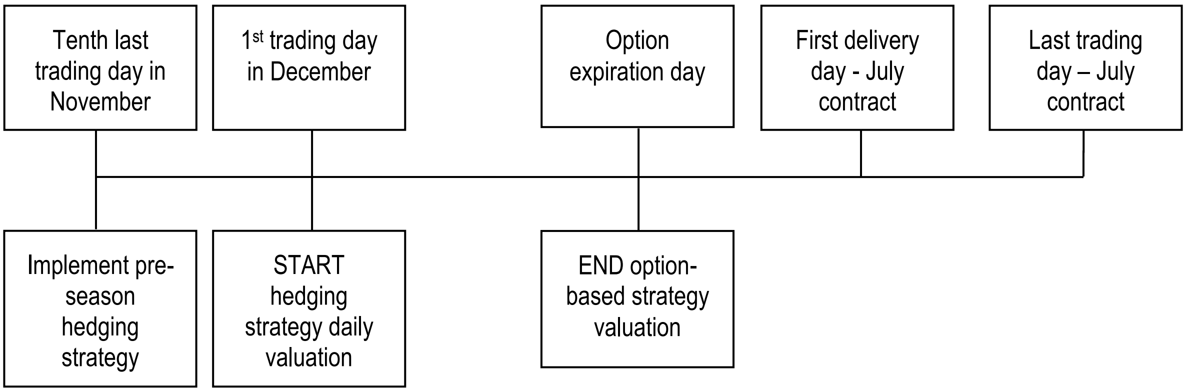

Figure 5.12: General hedging strategy timeline
Source: Compiled by the author

The timeline in Figure 5.12 shows that the initial hedging implementation, specifically for all pre-season strategies that require hedging during the planting period, is at the end of November; more specifically, the last two trading weeks of November. This time period was chosen since it coincides with the main planting window for the western part of the South African production region (Figure 5.13) and therefore the planting window for white maize. Also, the general seasonal average price for the July contract (Figure 5.14) shows that prices tend to increase throughout the planting window for the 5-year, 10-year and 15-year average July white maize futures contract price. The main reason for the price increase may be attributed to the increase in production uncertainty for the new crop, as it should still be planted on time to ensure optimal production and supply potential.

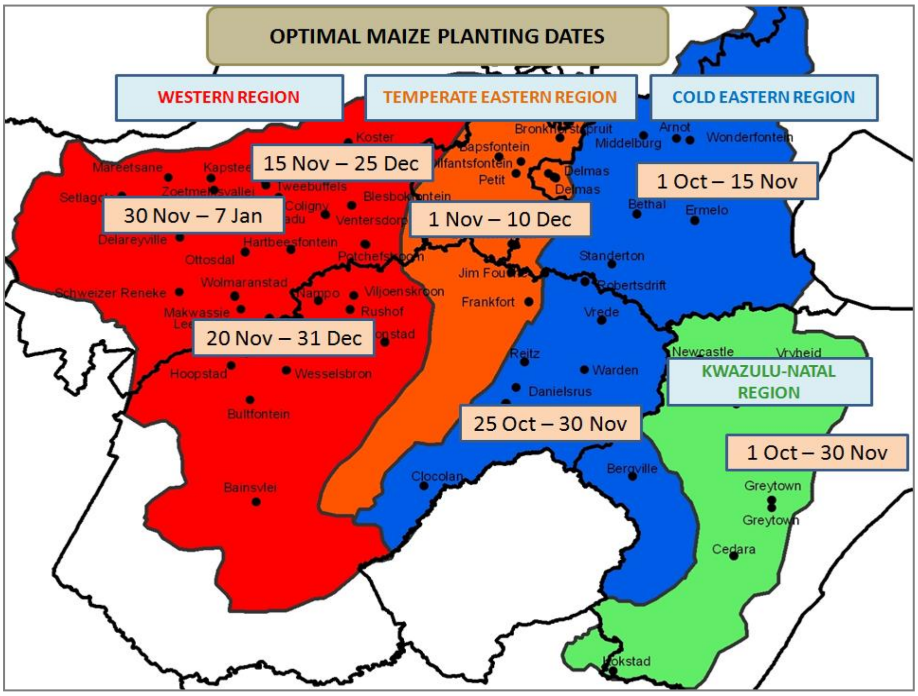

Figure 5.13: Optimal maize planting dates
Source: Agbiz (2018)

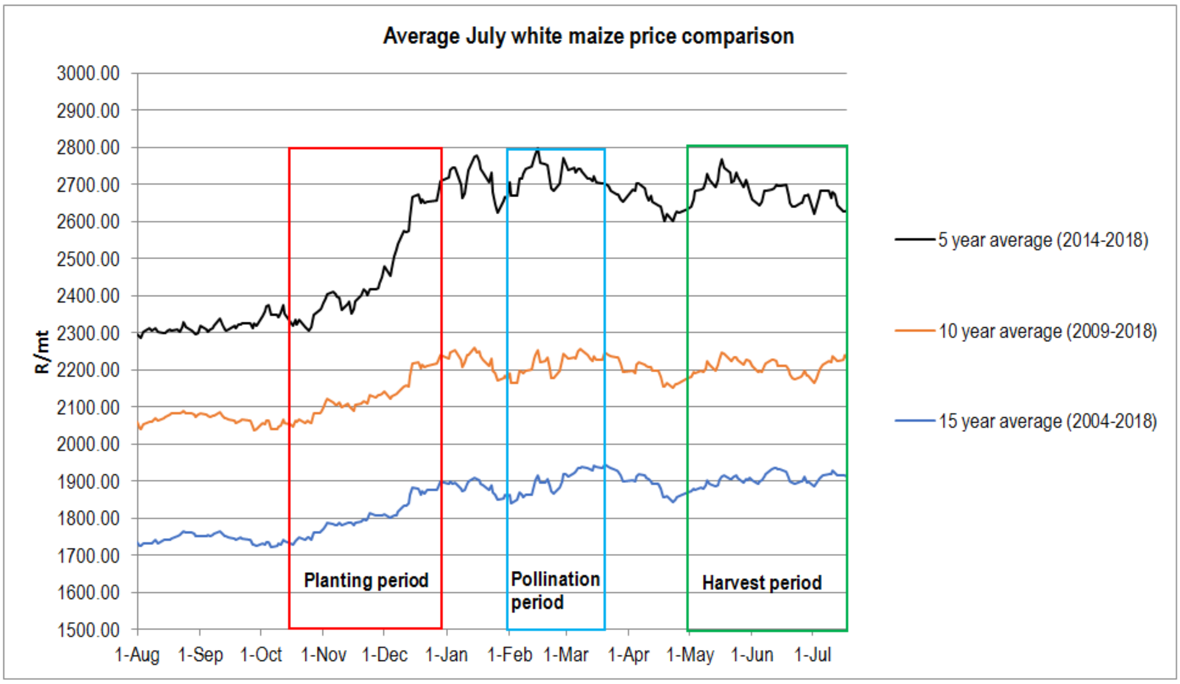

Figure 5.14: July contract seasonal price trend
Source: Compiled by the author. Daily average seasonal price calculated from individual July contract prices obtained from Thomson Reuters (2018)

Apart from the initial implementation period, all strategies – irrespective of whether they are pre-season hedging strategies or not – are valued on a daily basis. The first valuation is on the first trading day in November and then on each trading day until the day the option expires. The final contract price or final valuation day is always on the day after option expiration. This allows the full implementation of each strategy in the instance where produce remains un-hedged after option expiration. The calculation for the final contract price is specified for each strategy below. Where applicable, strategies are visually illustrated to provide the necessary insight into the valuation of a strategy at different price levels.

The 10 strategies are divided into subsections, but are distinguished as follows. Strategy 1 (Section 5.4.2.1) is the benchmark strategy, where a producer does not implement any hedging strategy. Strategy 2 (Section 5.4.2.2) and Strategy 3 (Section 5.4.2.3) are hedging alternatives through option contracts, which can be implemented by individual producers during the planting window. Strategy 4 (Section 5.4.2.4) and Strategy 5 (Section 5.4.2.5) are also strategies that can be implemented by individual producers, but hedging occurs throughout the season by means of short futures contracts. Strategy 6 (Section 5.4.2.6), Strategy 7 (Section 5.4.2.7) and Strategy 8 (Section 5.4.2.8) are option-based portfolio-type strategies. In practical terms, this means that it may be difficult for an individual producer to implement the strategies, as they require more tonnage to implement than the average producer may have available. Al three these strategies (Strategy 6 to 8) establish a hedge for all tonnages during the planting window, and thereafter aim to increase the original hedge level by reducing hedging cost and capturing upward price movement if it occurs. Strategy 9 (Section 5.4.2.9) is an option-based strategy that may be implemented by an individual producer and establishes a hedge during the planting window with a significant decrease in option cost. The risks of reducing option cost significantly at the beginning of a production season are shown through the results of this strategy. Strategy 10 (Section 5.4.2.10) aims to include technical analysis as a sell signal tool in order to establish short futures contracts as a hedge when the signals occur.

5.4.2.1 Strategy 1 - Benchmark strategy

Strydom *et al*. (2010:5) and Venter *et al*. (2012:4) refer to this strategy as the *Spot Strategy*. The same base strategy was also included in an earlier evaluation by Scheepers (2005:40). The strategy is included to evaluate a no-hedge strategy in comparison with the rest of the strategies that involve complete or at least partial hedging prior to harvest. As a result, this strategy may be seen as a baseline strategy, but requires daily valuations nonetheless in order to facilitate the calculation of returns and the subsequent performance measure comparative analysis (Section 5.5). In this specific instance, where no hedging is done by means of a derivative instrument (that can be valued on a daily basis), the daily strategy valuation simply follows an accounting principle approach.

Within the accounting approach, the un-hedged produce is valued against the daily mark-to-market price that is representative if all produce were sold on that specific day. Valuations are done from the first trading day in December and the final valuation for each contract is the first trading day after option expiration. The strategy price for the first trading day after option expiration is the average mark-to-market price from the first trading day after option expiration up to and including the last trading day for the July contract. The average mark-to-market price calculation over the specified period is done to provide a representative producer selling price during the harvest period.

However, the complete opposite of the benchmark strategy in terms of price risk management is a strategy where all produce are hedged in advance during the planting window. Buying a put option, as explained by Geyser (2013:81) and Hull (2005:181-182), provides the necessary minimum price and enables the producer to benefit from upward price movements during the rest of the production cycle.

5.4.2.2 Strategy 2 - Minimum price strategy

Buying a put option during the planting window when production certainty is low remains one of the few methods for hedging price risk to avoid potentially costly contract buy-outs. This strategy was also examined in the studies done by Strydom *et al*. (2010:5) and Venter *et al*. (2012:5). In both these studies results showed that this strategy reduced income variability and provided producers with the means to manage downward price risk, with producers still able to take part in upward price movements.

The strategy is implemented as follows: The average mark-to-market price for the last two weeks (last 10 trading days) of November is calculated. This price level is used as a benchmark and rounded to the nearest at-the-money even R20 option strike above the calculated average price. This strike level and applicable option cost is used as the initial hedge. The strategy is subsequently valued on every trading day from the first trading day in December up to and including the first trading day after option expiration. The valuation also depends on whether the futures market price is above or below the set put option strike price. If the futures price is above the put option strike price (out-of-the-money), the mark-to-market futures price for the day minus the put option premium valuation is used as the strategy price for the day. The put option premium valuation is what the net option cost payable would be if the original put option were sold back on that day and any remaining option cost were retrieved. However, if the futures price is below the put option strike price level (in-the-money), the strategy is valued as the put option strike price level minus the put option premium valuation.

The strategy valuation on the day after option expiration depends on whether the options expired in-the-money or out-of-the-money. If the options expired in-the-money, the strategy price is merely the option strike price level minus the option premium valuation on option expiration day. However, if the options expired out-of-the-money, the produce is effectively un-hedged, and futures contracts have to be sold to hedge the applicable produce. The strategy price, in this instance, would be the average July contract futures price mark-to-market from the day after option expiration up to and including the last trading day in June. The applicable realised put option cost would then be subtracted from this average futures price.

The put option or minimum price strategy is one of the more risk-averse strategies, which inevitably requires payment of an applicable option premium that may be seen as a risk premium. Despite all of the benefits, producers who are less risk-averse remain reluctant to make use of this strategy, mainly due to the premium cost involved. As a result, several combinations have evolved in an attempt to reduce the cost of hedging.

5.4.2.3 Strategy 3 – Minimum / Maximum price (collar) strategy

The minimum / maximum price strategy is a strategy employed by several producers with the main aim of reducing the cost, by simply hedging with a minimum price. This option-based strategy was described by Geyser (2013:145) and is implemented by buying a put option and selling a call option for every maize future equivalent hedged during or just after planting.

This strategy is implemented by calculating the average mark-to-market price for the last two weeks of November. This price level is used as a benchmark and rounded to the nearest at-the-money even R20 option strike above the calculated average price. Put options are bought at this strike level and out-of-the-money call options are sold. The strike of the out-of-the-money call option is set at the strike price level, which reduces the put option cost by half. These strike levels and applicable net option cost (put option cost minus call option income) are used as the initial hedging implementation. The strategy is then valued on every trading day from the first trading day in December up to and including the first trading day after option expiration. The valuation also depends on the July contract futures price in relation to the set option strike levels. This correlation and the three resulting scenarios are illustrated by means of Regions A to C in Figure 5.14 below.

If the July contract futures price for any of the valuation days is marked to market in Region A – which is below the minimum price level – the strategy price is the long put option strike price minus the net option cost. Both the put and call options are valued on the day to determine the net option cost. In the instance where the July contract futures price is *above* the long put option strike price level and *below* the short call option strike price level (Region B), both options may be deemed out-of-the-money. The strategy is valued against the July contract futures price marked-to-market and the applicable net option cost is subtracted. The last scenario is where the July contract futures price is above the short call strike price level. Then the strategy price is the maximum price or short call strike price minus the net option cost value. Depending on the regions, this valuation procedure is followed up to and including option expiration day.

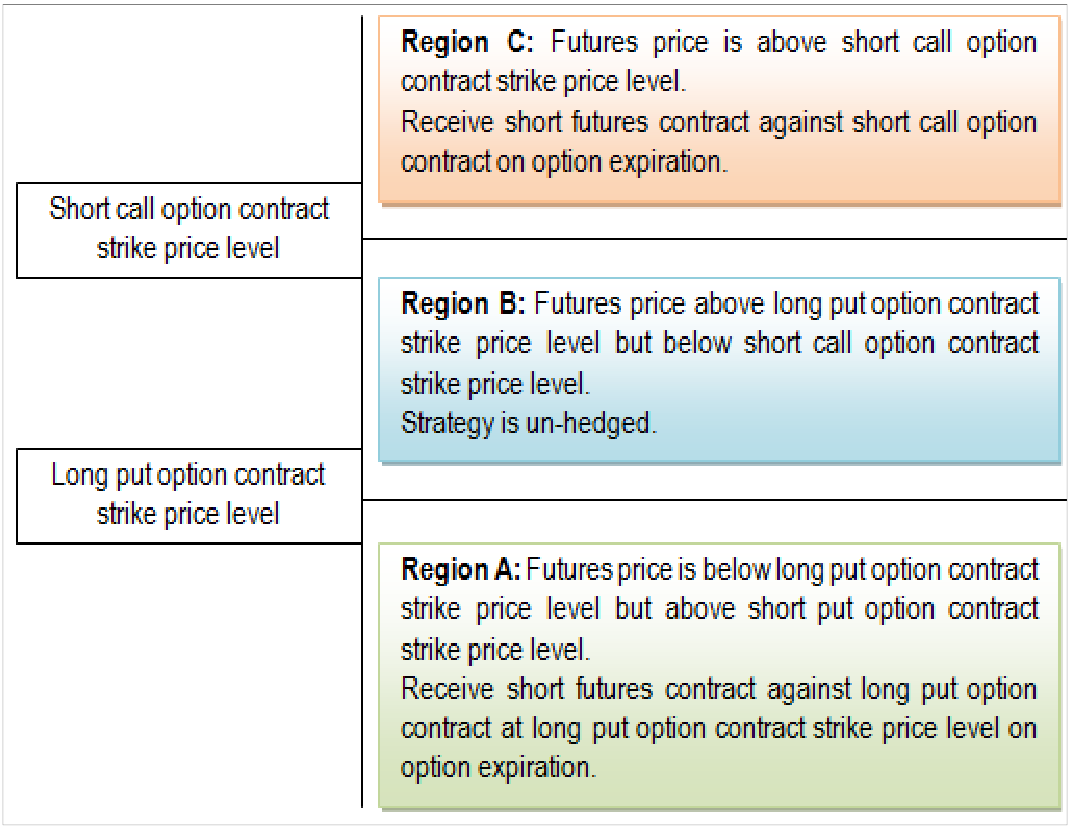

Figure 5.15: The min/max strategy scenarios
Source: Compiled by the author

If the July contract were trading in either of these regions on option expiration day, the strategy valuation of the day after option expiration is valued in the same manner as Figure 5.15 describes for Region A and Region C. If the July contract price were trading in Region B on option expiration, produce would effectively be un-hedged and futures contracts would have to be sold to hedge the applicable produce. In this instance, the strategy price would be the average July contract futures price marked-to-market from the day after option expiration up to and including the last trading day in June. The applicable realised net option cost would be subtracted from this average futures price.

Another popular hedging approach producers employ to avoid option cost, is to hedge by means of fixed price or short futures contracts throughout the production season from planting up to and including the harvest period. Two popular methods are included in the form of Strategy 4 and Strategy 5.

5.4.2.4 Strategy 4 – Three-segment strategy

This was the third similar strategy examined by Strydom *et al*. (2010:5) and Venter *et al*. (2012:5). In this strategy, maize producers sell their crop in three equal segments by means of short futures. The first third is sold during planting, the second third in February after pollination, and the last third during or after harvest in July. In this strategy, a maize producer is protected against declining prices for each segment hedged by means of short futures. However, the maize producer cannot benefit from rising prices after futures have been sold in the different hedging segments. The main reason for the three hedging segments also becomes evident in Figure 5.14. Prices tend to increase during the planting window due to production uncertainty. Producers who hedge by means of futures contracts during this window are also confronted with the possibility that they may not have the produce available to deliver against the short futures contracts during harvest if conditions do not remain favourable for planting. This is why only one third is initially hedged, with the second third following after pollination, when production certainty is slightly better. The last third is hedged during or after harvest, when the produce is deliverable and certain.

This strategy is initiated by calculating the average mark-to-market price for the last two weeks of November. This average price is the hedging level for the first third of expected produce. The remaining two thirds remain un-hedged and valued based on the same accounting principle used in Strategy 1. As a result, the un-hedged produce is valued against the daily mark-to-market price, which is viewed as the representative if all produce were sold on that specific day. Thus the strategy price valuation on the first trading day of December is the weighted average between the hedged third and the mark-to-market valued (un-hedged) two thirds. This valuation remains in place up to the first trading day in March. At that point the average mark-to-market price for the first two weeks of March is used as the short futures hedging level for the second third of expected produce. The strategy price from the first trading day in March is therefore the weighted average price between the third hedged during planting, the third hedged after pollination and the mark-to-market valued (un-hedged) last third. The short futures hedge level for the last third is the average mark-to-market price from the first trading day after option expiration up to and including the last trading day for the July contract. The average mark-to-market price calculation over the specified period is calculated to provide a representative producer selling price during the harvest period. The final weighted strategy price between the three respective hedge levels is the strategy price on the day after option expiration.

The three-segment strategy arguably has the ability to significantly reduce the cost of hedging when compared to option-based strategies. But the risk remains that at least a third of expected produce may already have been sold before traditional seasonal trend shifts, outside market influences significantly affect prices, or other fundamental factors cause unexpected volatility. As a result, a similar strategy evolved that is based on the same method of selling produce in equal segments.

5.4.2.5 Strategy 5 – Twelve-segment strategy

This strategy was included as a variation by Strydom *et al*. (2010:6) and the aim is to sell the total produce in 12 equal segments or three-week intervals from planting to harvest by means of short futures contracts. The initial implementation procedure is similar to the procedure explained in Strategy 4. The initial implementation of the strategy entails calculating the average mark-to-market price for the last two weeks of November. This average price is the hedging level for the first segment of expected produce. The remaining segments remain un-hedged and valued based on the same accounting principle used in Strategy 1. As a result, the un-hedged produce is valued against the daily marked-to-market price. The strategy price valuation on the first trading day of December is the weighted average between the hedged segment and the marked-to-market valued (un-hedged) segments. This valuation remains in place for three weeks until the last hedging date. At that point, the average mark-to-market price of the day is used as the short futures hedging level for the second segment of expected produce. The strategy price from the second hedging day is the weighted average price between the first hedged segment, the second hedged segment, and the mark-to-market value (un-hedged) of the last 10 segments. This process repeats itself every three weeks until the last segment is hedged by means of short futures contracts. The last segment price is the average mark-to-market price from the first trading day after option expiration up to and including the last trading day for the July contract. The average mark-to-market price is calculated over the specified period to provide a representative producer selling price during the harvest period. The final weighted strategy price between the 12 respective hedge levels is the strategy price on the day after option expiration.

The twelve-segment strategy also reduces the cost of hedging when compared to an option-based strategy, and due to the shorter time span between hedging intervals, the strategy may capture more interim market movements than the three-segment strategy. The main risk with both the three-segment (Strategy 4) and twelve-segment (Strategy 5) strategies is that prices may decline throughout the season, which means that prices become fixed at lower levels throughout the production season. Yet this risk may be addressed by implementing alternative strategies that establish a minimum price level during planting, but aims to reduce option cost and increase the average hedge level if the market presents these opportunities. Strategies 6, 7 and 8 are portfolio-based strategy variations, which are able to meet these requirements. It should be noted that since these strategies are portfolio-based, they require a minimum tonnage to execute efficiently. Individual producers may therefore not necessarily have the required tonnage to implement these strategies, but when collective hedging (producers hedging together as part of a portfolio) is implemented, the strategies may be effective. Nevertheless, from an individual producer's point of view, the results of these strategies should be seen as a potential advantage earned by actively managing option-based strategies.

5.4.2.6 Strategy 6 – Actively managed put option strategy

This strategy is an adaptation of the maximum price call option strategy described by Rossouw (2007:83-87). The original maximum price strategy was implemented from the hedging perspective of an end-user or buyer of maize, whereas the strategy included in this study was adapted to hedge by means of put options or minimum prices from a producer's perspective. The aim was to establish a minimum price hedge level, reduce option cost, and capture possible upward price movements above the hedge level at a specific point in time. This strategy can better be explained by means of the graphic representation in Figure 5.16:

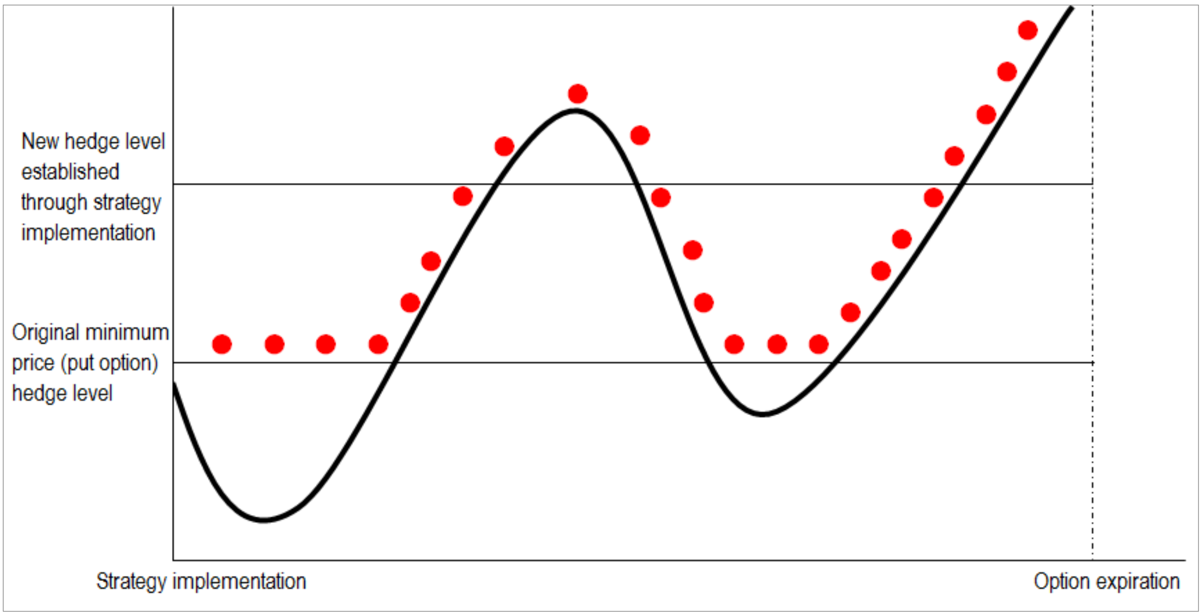

Figure 5.16: Actively managed minimum price strategy
Source: Compiled by the author, adapted from Rossouw (2007:85)

This strategy commences during the planting window. At-the-money put options are purchased for the total expected crop to be hedged. In order to structure the minimum price to be representative of the market, the average mark-to-market price for the last two weeks of November is calculated. This price level is used as a benchmark and rounded to the nearest at-the-money even R20 option strike below the calculated average price. This strike level and applicable option cost is used as the initial hedging implementation from the first trading day in December.

The strategy is then executed as follows: If the futures price is below or equal to the minimum price strike level, nothing is done, since the put options are in-the-money and the average minimum price still protects the producer from any downside price risk. But if the futures price increases to above the minimum price hedge level, the amount of trading days left to option expiration must be determined. If, for example, there are 50 trading days left and the number of put option contracts in the strategy is 100, two of the put option contracts are sold back into the market to retrieve some option cost. The hedge is maintained by selling two futures contracts above the average minimum price strike level. As a result, a new weighted average hedge level between the minimum price strike levels and the short futures price levels is calculated to determine a new strategy hedge level. By repeating this calculation each time the futures price is above the average strategy hedge level, the average strategy price is increased to a higher price level than the original minimum price hedge level. In addition, hedging cost or strategy option cost is reduced.

The daily valuation from the first trading day in December up to and including the first trading day after option expiration depends on the following scenarios. In the instance where the strategy only includes minimum prices at that point in time, the valuation depends on whether the futures market price is above or below the set put option strike price level. If the futures price is above the put option strike price level (out-of-the-money), the mark-to-market futures price for the day minus the put option premium valuation is used as the strategy price for the day. If the futures price is below the put option strike price level (in-the-money), the strategy is valued as the put option strike price level minus the put option premium valuation. In the instance where any or some put options have already been replaced by fixed prices, the above valuation for the remaining put options applies, whereas the applicable short futures hedges are valued and fixed against the specific mark-to-market for the day on which they are implemented. The strategy price for the day is the weighted average price between the put option strike price valuation and the short futures hedging levels minus the applicable option cost valuation.

The strategy valuation on the day after option expiration depends on whether there were any open put options on option expiration day and if the options expired in-the-money or out-of-the-money. If the options expired in-the-money, they are merely exercised and become short futures contracts at the original option strike price. The strategy price then becomes the weighted average hedge level between the different short futures hedge levels minus the weighted average option cost realised through the buying and selling of put options based on the strategy implementation criteria. If the options expired out-of-the-money, the produce is un-hedged and futures contracts have to be sold to hedge the applicable produce. The strategy price for this un-hedged portion is the average July contract futures price mark-to-market from the day after option expiration up to and including the last trading day in June. In this instance, the final strategy price becomes the weighted average between the average July contract futures price mark-to-market from the day after option expiration up to and including the last trading day in June and the short futures hedge levels implemented throughout the strategy. The applicable put option cost realised through the buying and selling of put options based on the strategy implementation criteria is subtracted from this average hedge level.

The actively managed put option strategy does adhere to the principles discussed in Chapter 4 (Section 4.2.2.1), since all expected produce remains hedged and any potential upward market movement is captured by means of a structured hedging plan. The main drawback of the strategy may however be the same as the simple put option strategy (Strategy 2). This shortcoming is that the strategy may become expensive in terms of option cost in years when prices mainly trade sideways or downward after the initial hedge is implemented. As a result, it makes sense to evaluate alternative strategies that may reduce option cost even more, but still follow the principles applied in the actively managed put option strategy.

5.4.2.7 Strategy 7 – Out-of-the-money July contract actively managed synthetic minimum price strategy

This strategy is a variation of the minimum price strategy, which may also be seen as a combination of Strategy 2 and Strategy 6. Strategy 7 entails that a producer hedges all produce by means of July short futures contracts during the planting window, but also purchases out-of-the-money call options against the July futures contract for every short futures contract. As a result, this strategy may also be linked to the proposed call option strategy by Scheepers (2005:48), where a call option was bought to enable the hedger to take part in any upward market movement. The out-of-the-money call option implemented in this strategy, however, does not allow the hedger to take part in immediate upward price movements, since the hedger would only benefit when the futures price rises above the call strike price level. Nevertheless, the out-of-the-money call option addresses the shortcomings of an at-the-money put option, as option cost is reduced due to implementation. Another aspect that may further reduce option cost is active management of the out-of-the-money call options in order to capture upward market movement if it occurs. This explanation of this strategy is enhanced by the graphical representation in Figure 5.17.

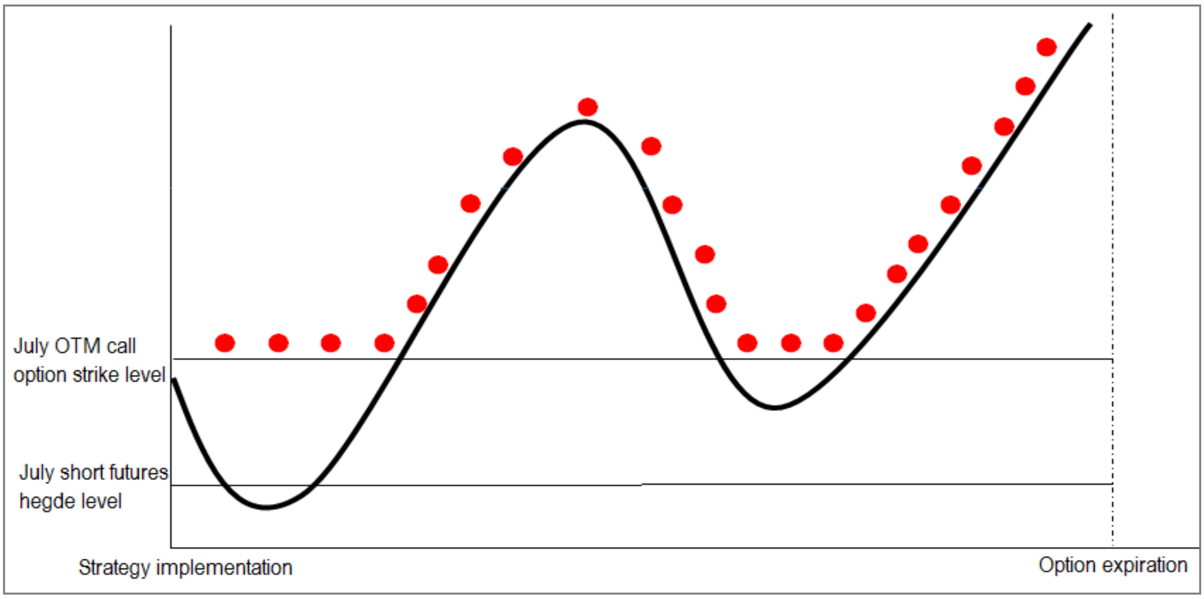

Figure 5.17: Actively managed out-of-the-money synthetic minimum price strategy
Source: Compiled by the author

On the commencement date of this strategy, short futures contracts are sold for the expected crop to be hedged. In order to structure the short futures hedging level according to a market representative level, the average mark-to-market price for the last two weeks of November is calculated. This price is used as the short futures hedge level. In addition, out-of-the-money call options are bought against the July contract at the strike price level, which reduces option cost by half when compared to an at-the-money put option. This short futures hedge level and applicable option cost is implemented as initial hedge.

The strategy is then executed as follows: If the futures price is below the call option strike price level, nothing is done, since the short futures contracts maintain the hedge and the call options remain out-of-the-money. However, if the futures price increases to above the call option strike price level and the option value is greater than the original option premium when the calls were purchased, the number of trading days left to option expiration must be determined. If, for instance, there are 50 trading days left and the number of call option contracts in the strategy is 100, two of the call option contracts would be sold back into the market to retrieve some option cost and capture upward market movement in the value of the call option. By repeating this calculation each time the futures price is above the call option strike price hedge level with the call option value greater than the original option cost, value is added to the original short futures hedge level and hedging cost or strategy option cost is reduced.

The daily valuation from the first trading day in December up to and including the first trading day after option expiration depends on the following scenarios: In the instance where the July futures price is below the call option strike price level, the short futures hedge level minus the applicable call option premium would be the strategy price. In the instance where the futures price has risen above the call option strike price level and some of the call options were sold back, a calculation is done to compare option premium expenditure against option income. Initially, the option income is smaller than the option cost, but the net effect is still a reduction in option cost. However, if the futures price keeps increasing, more and more call options are sold back and option income becomes greater than option premium expenditure. As a result, the daily valuation is dependent on whether a net option cost or net option income remains. In either instance, the cost is subtracted or income is added to the short futures hedge level to value the strategy.

The strategy valuation on the day after option expiration depends on whether there are any call options remaining, and whether they expired in-the-money or out-of-the-money. If the options expired in-the-money, they are merely exercised and become long futures contracts at the original option strike price. These long futures have to be closed out by means of short futures positions to capture the available margin movement from the in-the-money call options. The short futures close-out level is the July contract futures price marked-to-market from the day after option expiration up to and including the last trading day in June. The profit (or loss, if the market price declined) captured in this calculation is then added to the net option cost or income. The resulting strategy price is the initial short futures hedge level minus (or plus) the net call option premium cost (or income) realised by means of the strategy.

The main risk of this strategy is that the futures market price never reaches the out-of-the-money call strike price level. Another variation of this strategy is to buy at-the-money call options, but in an earlier futures month in order to reduce the time value of an option premium (Chapter 2, Section 2.3.3.3), and thus reduce option cost.

5.4.2.8 Strategy 8 – At-the-money March contract actively managed synthetic minimum price strategy

The strategy entails that a producer hedge all produce by means of July short futures contracts during the planting window, but also purchases at-the-money call options for every short futures contract against the March futures contract. This strategy may also be linked to the call option strategy of Scheepers (2005:48), where a call option is bought to enable the hedger to take part in any upward market movement. The March futures contract option cost is smaller than the July at-the-money call option, which immediately reduces option cost. Also, the March futures contract tends to capture upward market movement due to drought or pollination problems. The difference between Scheepers' (2005) strategy and the strategy included in this study, is that the call options in this instance are not merely left to expire; they are actively managed to capture any upward market movement that may occur.

In the implementation of this strategy, short futures contracts are sold to hedge the expected crop. The short futures hedging level is structured according to a market representative level by calculating the average mark-to-market price for the last two weeks of November. This price level is used as the short futures hedge level. In addition, at-the-money call options are bought against the March contract at that point in time. The average mark-to-market price for the March contract in the last two weeks of October is used to determine an appropriate strike price level at an even R20 option strike below the calculated average price. The July short futures hedge level and applicable March option cost is used for initial implementation of the hedge.

The strategy is then executed as follows: The July short futures contracts remain in place, with the only actively managed part of the strategy being the March call options. If the March futures price is below the March call option strike price level, nothing is done, since the July short futures contracts maintain the hedge and the call options remain out-of-the-money. However, if the March futures price increases to above the call option strike price level, the number of trading days left to option expiration must be determined. If there are 50 trading days left and the number of call option contracts in the strategy is 100, two of the call option contracts will be sold back into the market to retrieve some option cost and capture upward market movement in the value of the call option. Yet again, the option contracts are only sold back if the option value is greater than the premium when the calls were purchased. This calculation is executed every time the futures price is above the call option strike price hedge level, which adds value to the original short futures hedge level, and the hedging cost or strategy option cost is reduced.

The daily valuation from the first trading day in December up to and including the first trading day after option expiration in March depends on the following scenarios. In the instance where the March futures price is below the call option strike price level, the strategy price is the July short futures hedge level minus the applicable March call option premium. In the instance where the March futures price rises above the March call option strike price level and some of the call options are sold back, a calculation is done to compare option premium expenditure against option income. Initially, the option income is smaller than the option cost, but the net effect is still a reduction in option cost. However, if the futures price keeps rising, more call options are sold back according to the specified strategy and option income becomes greater than option premium expenditure. As a result, the daily valuation would depend on whether a net option cost or net option income remains. In either instance the strategy is valued by the cost being subtracted from or income added to the July short futures hedge level.

Strategy valuation on the day after the March option expiration depends on any remaining call option contracts and whether they expired in-the-money or out-of-the-money. If the options expired in-the-money, they are merely exercised and become long futures contracts at the original option strike price. These long futures contracts have to be closed out by means of short futures positions to capture the available margin movement from the in-the-money call option contracts. The short futures close-out level is the March contract futures price mark-to-market from the day after option expiration up to and including the last trading day in February. The profit (or loss if the market price went down) captured in this calculation is added to the net option cost or income. Then the strategy price is the initial July short futures hedge level minus (or plus) the net March call option premium cost (or income) realised by means of the strategy.

All of the strategies presented above may be linked to specific previous studies that were discussed in Chapter 4, Section 4.2.2. These strategies mostly include or at least encapsulate most of the traditional hedging strategy variations. None of the strategies presented included structured option-based strategies (regularly applied by producers in practice) that aim to further reduce option cost, but carry the risk of leaving hedged produce un-hedged as the season progresses. Also, none of the strategies presented above includes technical analysis (as discussed in Chapter 3, Section 3.2.5) as a tool by which to implement a hedging decision. As a result, Strategy 9 includes an option-based strategy that significantly reduces option cost, but also introduces the risk of becoming un-hedged. Furthermore, Strategy 10 includes technical analysis as a hedging decision or timing tool.

5.4.2.9 Strategy 9 – Three-way options-based strategy

The strategy is an extension of the minimum / maximum option-based strategy included as Strategy 3 above. As a result, this strategy is also implemented by buying a put option and selling a call option for every maize futures equivalent to be hedged during or just after planting. This strategy adds an additional short put option contract below long put option in the minimum / maximum strategy to reduce option cost even further. The strategy implementation and valuation is explained by means of the graphical representation in Figure 5.18.

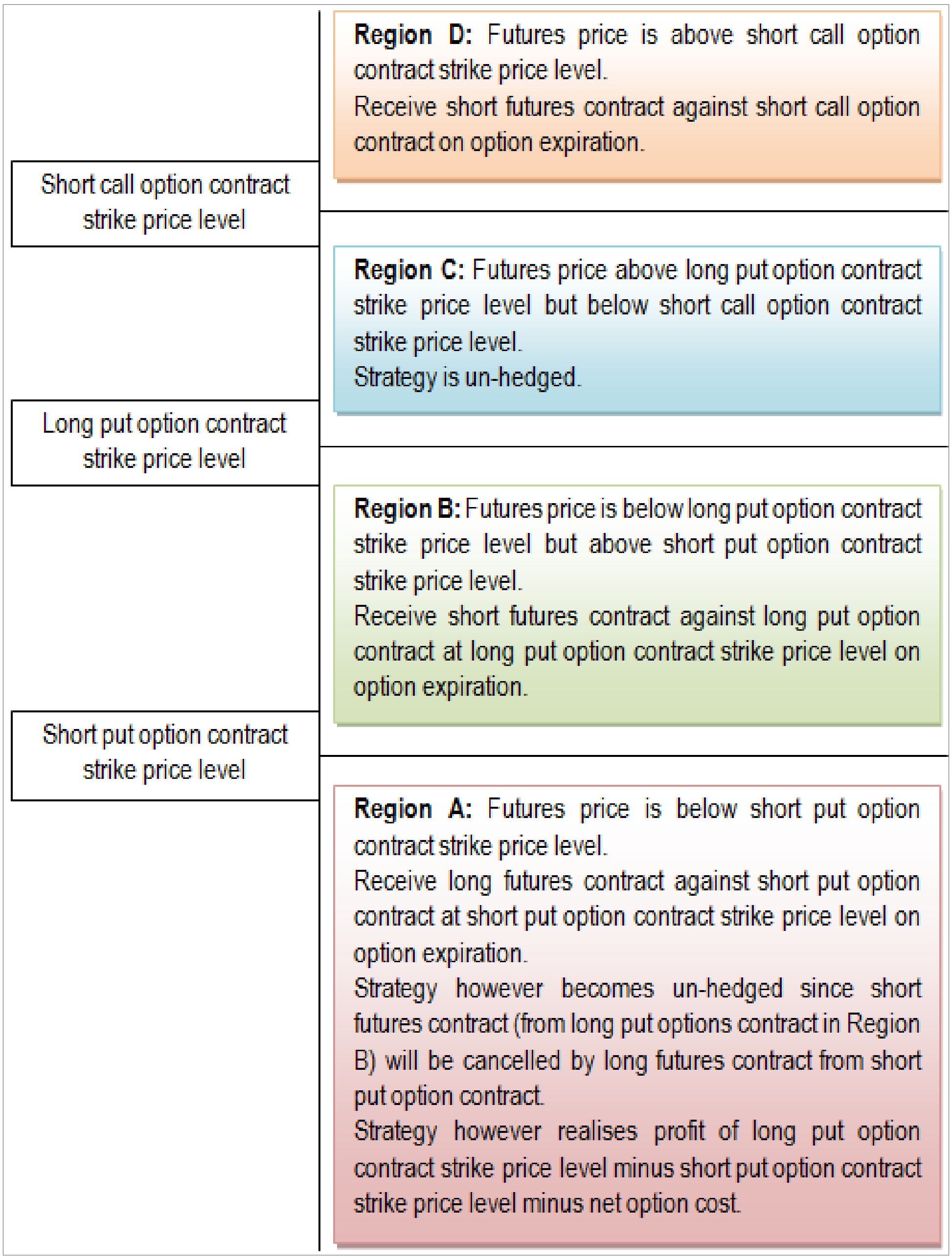

Figure 5.18: Three-way options-based strategy
Source: Compiled by the author

The strategy is implemented by calculating the average mark-to-market price for the last two weeks of November. This price level is used as a benchmark and rounded to the nearest at-the-money even R20 option strike above the calculated average price. Put options are bought at this strike level and out-of-the-money call options are sold above the long put option strike price level. In addition, out-of-the-money put options are sold below the long put option strike price level. The strike price of the out-of-the-money call and put options is set at the strike price level, which reduces the put option cost to a maximum of R20/mt or R2000/contract, but no less than R0/mt. The strike price difference between the long put option strike price and each of the short options strike levels is set at equal intervals or price differences when the calculation is made to reduce the structure option cost to a maximum of R20/mt. These strike price levels and applicable net option cost (long put option cost minus short call and short put option income) are used as the initial hedging implementation. From here, the strategy is valued on every trading day from the first trading day in December up to and including the first trading day after option expiration. The valuation also depends on the July contract futures price in relation to the set option strike levels. This relation and the four resulting scenarios may be explained by means of Regions A to D in Figure 5.18 above.

If the July contract futures price for any of the valuation days is marked-to-market in Region B, which is below the long put strike price level but above the short put strike price level, the strategy price would be the long put option strike price minus the net option cost. All the options in the strategy are valued on the day to determine the net option cost. In the instance where the July contract futures price is above the long put option strike price level and below the short call option strike price level (Region C), both options may be deemed out-of-the-money. The strategy is then valued against the July contract futures price mark-to-market and the applicable net option cost is subtracted. If the July futures price increases to above the short call strike price level into Region D, the strategy price would be the maximum price or short call strike price minus the net option cost value. The final valuation region would be the instance where the July futures price falls below the short put strike price level (Region A). At these price levels, the strategy may be seen as un-hedged, since both the long put and short put options are in-the-money and are exercised to become their respective short and long futures contracts on option expiration. The difference between the long put strike price and the short put strike price may, however, be seen as a strategy income when the July futures price falls below the short put strike price level. In Region A, the strategy is valued against the July contract futures price mark-to-market. The strategy profit should also be added to the July futures mark-to-market price level and the applicable net option cost deducted. Depending on the various applicable regions, this valuation procedure is applied up to and including option expiration day.

On the day after option expiration, the strategy is valued in the same manner as described for Region B if the July contract were trading in either of these regions on option expiration day. If the July contract price were trading in Region C on option expiration, produce would effectively be un-hedged and futures contracts would have to be sold to hedge the applicable produce. The strategy price in this instance would be the average July contract futures price marked-to-market from the day after option expiration up to and including the last trading day in June. The applicable realised net option cost is subtracted from this average futures price. If the July contract price were trading in Region A on option expiration, produce would also be un-hedged and futures contracts would have to be sold to hedge the applicable produce. The strategy price in this instance would be the average July contract futures price mark-to-market from the day after option expiration up to and including the last trading day in June. The strategy profit would also be added to the average July futures marked-to-market price level and the applicable net option cost deducted to value the strategy.

The last strategy uses technical analysis as decision tool for implementing a hedging decision. This strategy is similar to Strategy 4 and Strategy 5, where hedging by means of short futures contracts is done throughout the season. Hedging on the basis of technical analysis does however hold some uncertainty in that a hedger may never be sure how many sell signals the model will generate within a specific season. As a result, the technical analysis model applied should be based on specific research results that may provide the hedger with known probabilities of the expected number of hedging events. The specific technical analysis model included in this study is the composite indicator model developed specifically for white maize by Geldenhuys (2013). The model and strategy are explained in the rest of this section.

5.4.2.10 Strategy 10 – Hedging based on technical analysis

The first part of the strategy covers the necessary methodology behind the composite technical indicator, followed by an explanation of the strategy valuation based on the technical analysis of sell signals. The composite technical indicator developed for white maize by Geldenhuys (2013:103) was implemented in this study. The composite indicator was the optimal choice after evaluating several individual technical indicator sell signals, as well as other combinations of the indicators evaluated. The key to the composite indicator's superior results is its ability to take the type of market into account and assign more weight to indicators that are statistically more suited to the type of market.

Achelis (2001:35-36) identifies two types of markets in the form of trending and trading markets. Trading markets are when prices stay within a specific price range or trade sideways, whereas trending markets occur when prices continue in either an upward or downward trend within a specific time period or season evaluated. It is not always easy to distinguish between a trading or trending market, but over time certain technical indicators have been developed to help identify the type of market.

The specific indicator applied by Geldenhuys (2013:43) was the Directional Movement Index (DMI), which was originally developed by Wilder (1978:35-47). The general DMI(x) that continuously evaluates an x period data interval may be calculated by means of the following steps (the time period in the analysis is set to daily mark-to-market prices of the July white maize futures contract):

i. Calculate the directional movement (DM) for each of the daily intervals. Both equations 5.29 (DM plus) and 5.30 (DM minus) are calculated, but only the greatest absolute value difference is kept as the DM value for the daily interval,

$$+DM_t = High_t - High_{t-1}, \tag{5.29}$$

$$-DM_t = Low_t - Low_{t-1}. \tag{5.30}$$

ii. Also, for the first x days, calculate an x–day sum of the +DM and –DM daily calculations in step 1,

$$+DM_x = \sum_{i=1}^{x}(+DM_i), \tag{5.31}$$

$$-DM_x = \sum_{i=1}^{x}(-DM_i). \tag{5.32}$$

iii. In addition, calculate the subsequent x–day +DM and -DM by means of the following:

$$+DM_{x_t} = \left(+DM_{x_{t-1}}\right) - \left(\frac{+DM_{x_{t-1}}}{x}\right) + \left(+DM_{1_t}\right), \text{ and} \tag{5.33}$$

$$-DM_{x_t} = \left(-DM_{x_{t-1}}\right) - \left(\frac{-DM_{x_{t-1}}}{x}\right) + \left(-DM_{1_t}\right). \tag{5.34}$$

iv. Then, a true range (TR) can be calculated for the current day, which is the greatest absolute value of the following three equations:

$$TR_t = High_t - Low_t, \tag{5.35}$$

$$TR_t = High_t - Close_{t-1}, \text{ and} \tag{5.36}$$

$$TR_t = Low_t - Close_{t-1}. \tag{5.37}$$

v. The same step as step ii now applies for the true range, since it is necessary to also calculate an x-day sum TR that only applies to the first x days of the analysis:

$$+TR_x = \sum_{i=1}^{x} TR_i. \tag{5.38}$$

vi. Subsequently, the x-day TR applicable after the first x days of the analysis should also be calculated:

$$TR_{x_t} = \left(TR_{x_{t-1}}\right) - \left(\frac{TR_{x_{t-1}}}{x}\right) + \left(TR_{1_t}\right). \tag{5.39}$$

vii. The results from the calculations of the first six steps may now be used to calculate the directional indicator (DI) as follows:

$$+DI_x = \frac{+DM_x}{TR_x}, \tag{5.40}$$

$$-DI_x = \frac{-DM_x}{TR_x}. \tag{5.41}$$

viii. All of these steps lead up to the calculation of the Directional Movement Index (DMI) value:

$$DX_t = \frac{(+DI_x)-(-DI_x)}{(+DI_x)+(-DI_x)} \times 100. \tag{5.42}$$

The DMI value in itself does not show the strength of a trend. This may be accomplished by analysing the Average Directional Movement Index (ADX) line in the following step (Alexander, 1997:86; Colby, 2003:212).

ix. Calculate the first ADX by means of Equation 5.42, after which subsequent ADX values may be calculated through Equation 5.43.

$$ADX_t = \sum_{i=t}^{t-(x-1)} DX_i, \tag{5.43}$$

$$ADX_t = \frac{(ADX_{t-1} \times (x-1)) + DX_t}{x}. \tag{5.44}$$

The values generated by means of Equations 5.43 and 5.44 forms a line that is called the ADX line. The ADX values and subsequent line may be interpreted as follows (Colby, 2003:213; Murphy, 1986:468; Wilder, 1978:47):

- If the ADX value is above 25, the DMI index calculation indicates a possible trending market. Important to note, though, is that it does not distinguish between an upward or downward trend, only that a trend is present.

- If the ADX value falls below 25, the DMI calculation indicates a possible trendless or trading market.

The result obtained from the DMI and ADX calculations makes it possible to identify the type of market with more certainty. As a result, it enables the application of technical indicators that are better suited to identifying sell or buy signals in a specific type of market. These indicators, known as leading indicators, tend to lead the market price in order to predict price reversals based on overbought[29] and oversold[30] market conditions. The two leading indicators included in the analysis by Geldenhuys (2013:48-50) were the Relative Strength Index (RSI) and the Stochastic Oscillator (Stoch). Yet these indicators may not necessarily be ideal when identifying buying or selling opportunities in a market that is trending. Leading indicators usually create false signals in a trending market, which becomes overbought or oversold for extended periods of time and may lead to buying or selling decisions against a trend (Geldenhuys, 2013:68). As a result, two lagging indicators in the form of the exponentially weighted moving average (EMA) and the moving average convergence divergence (MACD) were included to more conclusively identify buy or sell signals in trending markets. These indicators follow the market price or the trend and generate buy or sell signals after a change in price direction or trend occurs (Murphy, 1986:33). This may result in late signals, but significantly reduces the risk of false signals in trending markets.

The study by Geldenhuys (2013:102) followed these guidelines in order to develop the composite indicator, which assigns more weight to indicators that are better suited for the type of market. The composite indicator nevertheless included all four of the indicators mentioned above and built on the premise that the best sell signal would arguably be where all four indicators give the same signal irrespective of market type or conditions. The weighting of the different indicators in the composite indicator was done as follows:

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29 An overbought market is associated with a market where the number of buyers outweighs the number of sellers within a specific time period. The buying support in the market usually leads to price peaks within the specific time period that necessitate price corrections to re-balance the buyers and sellers (Meyers, 1994:299).

30 An oversold market is exactly the opposite of an overbought market, where the number of sellers significantly outweighs the number of buyers in the specified time period. The selling pressure in the market usually leads to price troughs within the specific time period, which necessitates price corrections to re-balance the buyers and sellers (Meyers, 1994:299).

- In the instance where the ADX value was below 25 and a trading market was identified, the RSI and Stoch were assigned an individual weight of 0.3 respectively, whereas the EMA and MACD were assigned a weight of 0.2 each.
- In a trending market, where the ADX value went above 25, the value was broken up into three value areas in order to rank the strength of the trend and assign more specific weights to the applicable indicators. If the ADX value ranged between 25 and 50, the RSI and Stoch were each assigned a weight of 0.25 and the EMA and MACD were assigned a weight of 0.25, respectively. If the ADX value ranged between 50 and 75, the RSI and Stoch were each assigned a weight of 0.225 and the EMA and MACD were assigned a weight of 0.275, respectively. In the final instance where the ADX value ranged between 75 and 100, the RSI and Stoch were each assigned a weight of 0.2 and the EMA and MACD were assigned a weight of 0.3, respectively.

Each of the leading (*i* and *ii)* and lagging indicators (*iii* and *iv*) that form part of the composite indicator also require individual value calculations, which form the basis of each indicator's decision criteria in order to generate a value that will be multiplied by the respective weights as stipulated above. Each of these indicator value calculations are presented below and are followed by interpretations that focus mainly on the identification of sell signals through the calculation to identify short futures hedging opportunities.

i Leading indicator – Relative Strength Index (RSI)

The RSI indicator compares the strength of the underlying price relative to itself (Achelis, 2001:297). The mathematical calculation of the RSI value is as follows (Colby, 2003:610; Whistler, 2004:38):

$$\text{RSI}=100-\left[{}^{100}\big/_{(1+RS)}\right], \tag{5.45}$$

where:

$RS = \frac{Average\ of\ n\ days'higher\ closing\ prices}{Average\ of\ n\ days\ lower\ closing\ prices}$,

with n indicating the number of days in the rolling window evaluation period.

The RSI rolling window evaluation period included in the study was set at the default period of 14 days (Wilder, 1978:65). An overbought level, which indicates sell signals, was set at specific levels depending on the type of market. Geldenhuys (2013:75) optimised sell signals in a trending market when the RSI crossed back through an upper limit value of 70% from above, whereas sell signals in a trading market was optimised when the RSI crossed an upper limit of 55% from above.

ii Leading indicator – Stochastic Oscillator (Stoch)

The indicator provides a comparison of recent market lows and highs relative to closing prices (Achelis, 2001:321; Alexander, 1997:96). The theory behind the comparison is that closing prices are closer to recent highs when prices increase, whereas closing prices are closer to recent lows when prices decrease. The stochastic oscillator equation includes the calculation of two lines, namely the %K and %D lines. These lines are formed through the calculation of the following values over time (Meyers, 1994:165; Whistler, 2004:34):

$$\%K = 100 \times \left[{}^{(C - L)}\!/_{(H - L)}\right], \tag{5.46}$$

where C represents the most recent closing price over the time interval evaluated, L represents the lowest low value over the time interval evaluated, and H represents the highest high over the time interval evaluated.

The %K line, however, tends to capture market volatility, since the line provides a rolling window of the market movement in relation to the most recent highs and lows. The inclusion of a three-period moving average of the %K line in the form of the %D line smooths any erratic movements and facilitates buy and sell signal identification (Murphy, 1986:304; Whistler, 2004:35). The analysis by Geldenhuys (2013:78) set the time periods for the %K line at 14 days and the %D line kept at the default three-day moving average. Sell signals in a trending market were optimised when the %K line crossed the %D line from above and confirmed or acted on when the %K value crossed the 80% upper oscillator limit from above. Sell signals in a trading market were optimised and acted on in the same manner, but the upper oscillator limit was set to a value of 75%.

iii Lagging indicator – Exponentially weighted moving average (EMA)

A moving average provides an average value of the data over a specific time frame. In the simplest form, all the values in the time frame contribute equally to the calculation of the average value and once a new value is added to the average calculation, the oldest value is not taken into account in the calculation. Over time, a rolling window of average value calculation forms a smoothed line, which is the moving average of the underlying data for a specified time period (Achelis, 2001:27; Murphy, 1986:234; Whistler, 2004:30). It is, however, the characteristic of equal weighting that causes the moving average line to lag behind a more volatile price move, which may lead to late buy or sell signals (Murphy, 1986:238; Whistler, 2004:31). In order to address this shortcoming, the exponential moving average (EMA) was developed to assign more weight to the latest data in the evaluation time period without discarding the older data. The calculation of the EMA may be done as follows (Colby, 2003:262):

$$EMA = (C - E_p)K + E_p, \tag{5.47}$$

where C represents the closing price for the current period, E_p represents the exponential moving average of the previous period, $K = {}^{2}/_{(n+1)}$ represents the exponential smoothing constant, and n represents the total number of periods included in the EMA calculation.

The EMA included by Geldenhuys (2013:80) was a 20-period EMA, which was optimised to avoid false or delayed sell signals. Sell signals were generated once the July futures contract daily closing price crossed the EMA line from above or more specifically when the July futures contract closing price value dropped below the EMA value.

iv Lagging indicator – Moving Average Convergence Divergence (MACD)

The MACD was developed by Appel (2005) with the main aim of indicating changes in price momentum. As a result, the indicator also shows the direction of a trend and is suited to identify changes in the momentum or trend (Achelis, 2001:199; Reuters, 1999:104). The MACD line is calculated by subtracting a longer period EMA (Equation 5.47) from a shorter period EMA. Thereafter, a signal line or trigger line is calculated, which is the average of the MACD line for a specific period. The trigger line fulfils the same function for the MACD as the %D line does for the %K line in the stochastic oscillator calculation. As a result, a crossover of the MACD through the trigger line from above may be seen as a sell signal (Alexander, 1997:88,143; Colby, 2003:412; Murphy, 1986:313; Reuters, 1999:104). In the analysis by Geldenhuys (2013:81), the longer period EMA was set to 26 days, the shorter to 12 days, and the trigger line to a nine-day average of the MACD.

All of the indicator values should be calculated and evaluated on a daily basis based on the sell signal rules explained for each of the individual indicators. A value of one should be assigned to an indicator if a sell signal is generated and a value of zero should be assigned to an indicator if no sell signal is present. Each of the individual indicator values assigned must then be multiplied by their respective weights depending on the applicable market as explained above (Geldenhuys, 2013:103). The sum of the indicator values multiplied by their respective weights should then be added to derive a composite indicator value. The sell signal of the composite indicator was optimised and set to a composite indicator sell signal value of 40. This means that a sell signal is generated when all the indicators in conjunction generate a sell signal and the composite indicator reaches a value of 40.

The sell signals generated by means of the composite indicator will be used as a timing tool to hedge produce by means of short futures contracts in order to implement the proposed hedging strategy. The main challenge to overcome, however, is the fact that the number of sell signals generated throughout the production season is unknown. In order to address this unknown, certain decision rules have to be introduced to standardise the analysis based on historical results. As a result, the strategy was implemented on the first three sell signals generated from the beginning of the last two weeks in November up to and including option expiration day for the July white maize futures contract in June. The three sell signals were identified from the average number (3.769 sell signals) and standard deviation value (1.739) of sell signals generated by means of the composite technical indicator for each season over time (Geldenhuys, 2013:105). Based on the three sell signal decision, the strategy mostly followed the same implementation principles as described in the three hedge strategy (Strategy 4).

The initial implementation of the strategy was done by implementing the composite technical indicator evaluation from 1 August each season. The first sell signal generated from the beginning of the last two weeks in November was applied as the hedging implementation of the first third of expected produce by means of short futures contracts against mark-to-market price value on the sell signal day. The remaining two thirds was un-hedged and valued based on the accounting principle of all the un-hedged produce being valued against the daily mark-to-market price. Thus the strategy price valuation on the first trading day of December was the weighted average between the hedged third and the marked-to-market valued (un-hedged) two thirds. This valuation remained in place up to the day when a potential second sell signal was generated. From that point in time, the strategy price was the weighted average price between the third hedged during the first sell signal, the third hedged at the second sell signal, and the marked-to-market valued (un-hedged) last third. The last third would accordingly be hedged if a third sell signal were generated and the strategy price would be the weighted average price of the three sell signal price levels. However, it is possible for the composite indicator not to generate a second or third sell signal. In this instance, the un-hedged produce would be valued against the average mark-to-market price from the first trading day after option expiration up to and including the last trading day for the July contract. The average marked-to-market price calculation over the specified period is done to provide a representative producer selling price during the harvest period.

To summarise – 10 strategies were presented and their implementation, as well as valuation procedure, were explained. Basic strategies were included by means of Strategy 1 and Strategy 2, whereas Strategy 3 already included a basic option strategy to reduce option cost. Thus Strategy 3 was confronted with the risk that, in the event that futures prices rose above the maximum price level, the producer would not be able to take part in upward price movements. Strategy 4 and Strategy 5 dealt with the alternative of avoiding option cost completely, but as a result included the risk of futures prices trending lower during the course of the production season, which lead to a lower final strategy hedging price level. Strategies 6, 7 and 8 included more dynamic or actively managed hedging strategies in an attempt to reduce option cost without bearing the risk of realising a lower final strategy hedging price level if prices trended lower throughout the production season. These three strategies nevertheless also included the risk that option cost may not be significantly reduced through the strategy implementation in production seasons where prices tended to trade sideways. In an attempt to counter this risk, Strategy 9 was included to reduce option cost even further. This strategy would also be perfectly suited to a production season where prices traded sideways. However, this advantage brought with it the risk of produce becoming un-hedged depending on market movement. As a result, this strategy did not necessarily adhere to the core of price risk management through derivative instruments and tends to include a more speculative hedging element. Arguably, leaving a percentage of expected produce un-hedged and only hedging a percentage at a specific point in time throughout the season, Strategies 4, 5 and 10 also beared the risk of un-hedged produce during seasons where futures prices tended to decrease throughout the production season.

As a result, all of these strategies deployed by producers include different elements of risk, which may be linked to the type of season and price development within different seasons. It is therefore only sensible to compare these strategies for all of the different seasons in order to determine which of the strategies performed the best in terms of price as well as profitability. A comparison in terms of price may be done by evaluating the highest realised strategy price for each season over time. The profitability comparison, however, requires comparison between the daily strategy price valuations of each strategy and the relevant input cost calculation for each season.

5.4.3 Input cost calculation

Calculating a relevant input cost figure for each season necessitates a specific demarcation, since inputs and the associated cost may differ significantly between producers based on type of production (dry-land vs. irrigation), cultivation practices, and production area. The demarcation for this study was already done in Chapter 1 (Section 1.5). As a result, the input cost calculation was based on the predominantly dry-land white maize production area of the central and northern Free State. The input cost calculation per metric tonne for the region was generalised based on the 5-year average yield obtained from Grain SA (2018b). The input cost calculation per hectare was based on variable direct and indirect input costs required to prepare the land, plant, manage and harvest the crop. Capital cost, such as fixed improvements, machinery and equipment cost or depreciation was excluded. Table 5.11 below provides a breakdown of the main inputs included in the calculation.

Table 5.11: Input cost calculation for white maize in central and northern Free State 2016-17

Production year	2016/17
A. Direct variable costs (R/hectare)	
Seed	855.59
Fertiliser & Lime	2482.08
Fuel	757.70
Weed control	714.65
Pest control	0.00
Repairs and parts	569.51
Total Cost A	5379.53
B. Indirect variable costs (R/hectare)	
Crop insurance	86.68
Casual labour	55.73
Permanent labour	310.54
License and Insurance	84.56
Marketing cost	68.89
Drying and cleaning cost	35.90
Interest on production credit	510.19
Contract work	241.60
Other cost	539.16
Total Cost B	1933.25
Total variable cost (A+B)	7312.78
Yield (mt/ha)	6.50
Input Cost (R/ton)	1124.57

Source: Compiled by the author, adapted from Grain SA (2018b) general calculation

Based on the daily strategy price valuation for each hedging strategy, thoroughly explained in Section 5.4.2 above, a return could be calculated by subtracting the relevant input cost (Section 5.4.3) for the applicable production year. The returns for each production year could then be evaluated and compared by means of the proposed performance measures discussed in the following section.

5.5 Performance measurement evaluation of hedging strategy returns

The comparison of the 10 hedging strategies described above (Section 5.4.2.1 to 5.4.2.10) was done by means of applicable performance measures, which were included as part of the in-depth literature review in Chapter 4, Section 4.3. Consequently, Section 5.5.2 below focuses on the method and interpretation of specific measures, since not all measures apply, due to certain constraints when applying these measures to the agricultural commodity market. It is, however, relevant to first determine if the return data may be classified as normally distributed or not (Section 5.5.1), since return distributions classified as non-normal may lead to biased performance measure results for specific performance measures (Leland, 1998:5-6; Harding 2002:1; Brooks & Kat, 2002:37; Goetzmann, Ingersoll & Ross, 2002:8; Ronaldo & Favre, 2003:2; Pedersen & Rudholm-Alfvin, 2003:168; Bailey, Li & Zhang, 2004:3; Eling & Schuhmacher, 2007:2645; Liang and Park, 2007:359; Zakamouline, 2010:4; Van Heerden, 2015:210).

5.5.1 Evaluating the skewness, kurtosis and normality of hedging strategy returns

The statistical characteristics in terms of skewness (S), kurtosis (K) and the consequent presence of normality was evaluated by means of the same measures included in Section 5.2.3 above. The presence of normality was not seen as a prerequisite for the inclusion of certain measures, neither was it used as criteria to exclude other measures. The aim was to arrive at a consensus to rank hedging-strategy performance based on the conformation by different measures. It was however important to consider the presence of non-normality and the implications thereof to avoid biased results by giving preference to measures able to account for the presence of higher moments (Bacon, 2009:12; Wiesinger, 2010:26). Table 5.12 below provides a summary of the basic descriptive statistics and includes higher moments, such as skewness (S) and kurtosis (K), as well as normality tests results based on the Jarque-Bera (JB), Shapiro-Wilk (SW), Lilliefors (L) and Anderson-Darling (AD) tests. These calculations were done for each of the 10 strategies for which return data were compiled for all 16 production seasons from 2003 up to and including 2018.

From the results presented in Table 5.12 below, the following ways of presenting the data were included to provide an all-inclusive summary. In the event where it was not possible to determine skewness (S) and kurtosis (K) or to evaluate normality, an (*) was added. The main reason which made it impossible to determine or evaluate these values was due to a constant return for the greatest part of the return data evaluated. A constant return occurred when a strategy price remained constant for the greatest part of the evaluation period. There are a few specific strategies where a constant strategy price may occur. For example, the strategy price may remain constant in Strategy 7 and

Strategy 8 where the price is fixed during the planting window by means of short futures contracts and call options are bought to take part in upward market price movement. In these instances, the strategy price would remain constant if the market price decreased throughout the season and the strategy price remained fixed at the short futures contract price level minus the long call option premium cost.

Similarly, Strategy 2 (buy and hold put option contracts) may also realise a constant return if prices decreased significantly after the put option contracts were bought and the market price dropped below the average put option contract strike price level minus the relevant option cost. Other instances where it was not possible to determine skewness (S), kurtosis (K), or evaluate normality, was when the July futures contract increased significantly after the strategies were implemented. Strategies that are not able to take part in upward price movements consequently realise a constant return. The option strategy presented in Strategy 9 included a short call option contract level, which resulted in a short futures contract or fixed strategy price if the market price surpassed the short call option contract strike price level. Similarly, Strategy 10 may be subject to three sell signals in short succession, resulting in a fixed or constant strategy price for the rest of the production season.

The inability to determine skewness (S), kurtosis (K), or evaluate normality for all strategies in all the production years presented did, however, not limit an evaluation of the distributions or normality assumptions of the return data. In terms of skewness (S), the return data could not be classified as predominantly positively or negatively skew, but skewness could be observed throughout. Similarly, when evaluating kurtosis (K), the return data could not be classified as predominantly leptokurtic of platykurtic, but the values were far removed from a normal distribution kurtosis of three. As a result, in terms of skewness (S) and kurtosis (K), the return data already showed the presence of non-normality. The presence of non-normality was confirmed by the four tests for normality, which showed that the return data were predominantly non-normal. In exceptions where normality was identified, the test value was highlighted in green.

Table 5.12: Descriptive statistics and normality test results – hedging strategy returns

2003 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.20	1.76	1.75	2.16	0.82	1.76	1.90	1.88	0.57	0.85
Maximum	2.21	2.12	2.08	2.49	2.20	1.77	1.90	1.88	2.13	2.21
Median	0.60	1.76	1.90	2.32	0.95	1.77	1.90	1.88	0.97	1.12
Mean	0.86	1.77	1.89	2.31	1.17	1.77	1.90	1.88	1.16	1.30
Standard deviation	0.56	0.06	0.04	0.07	0.37	0.00	0.00	0.00	0.45	0.37
Skewness	0.77	5.64	2.05	-0.14	1.01	-7.75	*	-8.21	0.56	0.77
Kurtosis	-0.85	29.94	13.82	0.03	-0.26	62.10	*	65.96	-1.23	-0.82
Shapiro-Wilk	0.85	0.16	0.50	0.97	0.80	0.13	*	*	*	*
Anderson-Darling	8.64	50.91	26.58	1.34	11.72	+Infinity	*	*	*	*
Lilliefors	0.23	0.54	0.43	0.10	0.26	0.53	*	*	*	*
Jarque-Bera	17.50	5843.76	1185.86	0.49	23.71	23383.97	*	*	*	*
Normality consensus	Non-normal	Non-normal	Non-normal	Normal	Non-normal	Non-normal	*	Leptokurtic	Platykurtic	Platykurtic

2004 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.35	0.30	0.39	0.50	0.50	0.30	0.39	0.37	0.47	0.51
Maximum	1.39	1.22	0.77	1.08	1.21	0.67	0.52	0.77	0.78	1.12
Median	0.74	0.61	0.57	0.65	0.81	0.61	0.51	0.77	0.72	0.89
Mean	0.79	0.66	0.61	0.70	0.85	0.55	0.49	0.67	0.66	0.90
Standard deviation	0.22	0.22	0.11	0.14	0.13	0.13	0.05	0.14	0.09	0.11
Skewness	0.70	0.65	-0.12	1.06	0.69	-0.76	-0.94	-1.04	-0.42	-0.75
Kurtosis	-0.12	-0.49	-1.21	0.19	1.01	-1.00	-0.80	-0.61	-1.18	2.44
Shapiro-Wilk	0.94	0.94	0.90	0.88	0.88	0.81	0.73	0.69	0.86	0.91
Anderson-Darling	3.05	2.57	6.55	6.94	7.68	10.59	16.09	20.10	8.33	4.24
Lilliefors	0.12	0.11	0.21	0.19	0.20	0.20	0.29	0.35	0.26	0.16
Jarque-Bera	11.49	11.10	8.88	26.38	16.85	19.19	24.34	27.36	12.20	47.48
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2005 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	-0.17	0.42	0.47	0.10	0.01	0.42	0.53	0.49	0.13	-0.17
Maximum	0.49	0.42	0.55	0.55	0.51	0.42	0.53	0.49	0.51	0.49
Median	-0.07	0.42	0.55	0.16	0.11	0.42	0.53	0.49	0.23	-0.09
Mean	0.01	0.42	0.54	0.22	0.14	0.42	0.53	0.49	0.27	0.01
Standard deviation	0.18	0.00	0.02	0.13	0.13	0.00	0.00	0.00	0.10	0.19
Skewness	1.38	*	-2.20	1.38	1.41	*	*	*	0.97	1.38
Kurtosis	0.47	*	3.72	0.42	0.79	*	*	*	-0.41	0.45
Shapiro-Wilk	0.75	*	0.54	0.72	0.78	*	*	*	0.84	0.74
Anderson-Darling	15.08	*	29.15	17.14	12.28	*	*	*	9.52	16.07
Lilliefors	0.30	*	0.39	0.31	0.29	*	*	*	0.26	0.29
Jarque-Bera	45.44	*	193.46	45.54	50.34	*	*	*	23.10	5.99
Normality consensus	Non-normal	*	Non-normal	Non-normal	Non-normal	*	*	*	Non-normal	Non-normal

2006 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.35	0.21	0.21	0.37	0.42	0.21	0.31	0.26	0.21	0.42
Maximum	1.00	0.73	0.63	0.68	0.70	0.67	0.35	0.32	0.76	0.72
Median	0.62	0.46	0.47	0.55	0.59	0.35	0.31	0.32	0.55	0.62
Mean	0.63	0.47	0.49	0.54	0.57	0.39	0.31	0.31	0.55	0.62
Standard deviation	0.13	0.11	0.09	0.06	0.05	0.12	0.01	0.01	0.10	0.05
Skewness	0.40	-0.11	-0.17	-0.59	-1.03	0.65	4.33	-2.43	-0.40	-0.57
Kurtosis	0.10	0.38	0.68	0.00	0.82	-0.48	18.84	4.56	0.71	1.20
Shapiro-Wilk	0.97	0.97	0.88	0.95	0.88	0.94	0.28	0.48	0.93	0.97
Anderson-Darling	1.61	0.94	6.69	2.91	7.69	2.68	44.54	33.19	3.26	1.10
Lilliefors	0.10	0.06	0.17	0.14	0.22	0.13	0.50	0.42	0.14	0.12
Jarque-Bera	3.71	1.09	3.35	8.04	28.43	11.01	2472.38	255.87	6.50	15.85
Normality consensus	Normal	Normal	Normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2007 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.71	0.54	0.56	0.73	0.71	0.54	0.66	0.61	0.57	0.71
Maximum	1.79	1.57	1.07	1.45	1.37	1.11	0.91	0.74	1.11	1.79
Median	1.32	1.10	1.01	1.26	1.17	0.72	0.76	0.74	1.06	1.33
Mean	1.23	1.05	0.93	1.13	1.07	0.75	0.76	0.69	0.97	1.23
Standard deviation	0.32	0.27	0.14	0.24	0.20	0.17	0.09	0.06	0.14	0.32
Skewness	-0.13	-0.06	-1.10	-0.47	-0.41	0.43	0.12	-0.42	-1.21	-0.13
Kurtosis	-1.24	-0.84	0.11	-1.50	-1.30	-1.18	-1.69	-1.81	0.43	-1.21
Shapiro-Wilk	0.92	0.96	0.73	0.82	0.87	0.89	0.82	0.63	0.73	0.91
Anderson-Darling	4.37	1.78	17.34	11.46	8.45	5.22	10.25	25.68	17.09	4.75
Lilliefors	0.16	0.12	0.38	0.27	0.26	0.16	0.22	0.39	0.39	0.16
Jarque-Bera	9.37	4.22	28.49	18.25	13.92	12.54	17.08	23.31	35.49	8.92
Normality consensus	Non-normal	Normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2008 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.29	0.29	0.31	0.33	0.30	0.29	0.36	0.32	0.29	0.29
Maximum	1.00	0.85	0.59	0.70	0.60	0.56	0.44	0.32	0.64	0.55
Median	0.65	0.52	0.55	0.58	0.55	0.34	0.36	0.32	0.61	0.51
Mean	0.60	0.49	0.48	0.53	0.51	0.37	0.38	0.32	0.52	0.48
Standard deviation	0.17	0.14	0.10	0.09	0.08	0.08	0.02	0.00	0.12	0.06
Skewness	0.14	0.19	-0.65	-0.29	-0.56	0.70	0.78	*	-0.68	-0.96
Kurtosis	-0.85	-0.39	-1.18	-1.28	-1.10	-0.91	-0.58	*	-1.16	-0.02
Shapiro-Wilk	0.95	0.93	0.79	0.91	0.87	0.85	0.80	*	*	*
Anderson-Darling	2.51	2.68	11.82	5.53	7.34	7.65	11.84	*	*	*
Lilliefors	0.12	0.15	0.31	0.20	0.23	0.19	0.26	*	*	*
Jarque-Bera	4.57	1.74	17.65	11.47	14.26	16.02	15.88	*	*	*
Normality consensus	Normal	Normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	*	Platykurtic	Platykurtic

2009 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.21	0.48	0.48	0.43	0.41	0.48	0.57	0.54	0.47	0.21
Maximum	0.69	0.68	0.67	0.68	0.67	0.49	0.57	0.54	0.67	0.69
Median	0.41	0.48	0.56	0.49	0.48	0.49	0.57	0.54	0.55	0.41
Mean	0.44	0.49	0.55	0.52	0.50	0.49	0.57	0.54	0.54	0.44
Standard deviation	0.10	0.03	0.03	0.06	0.06	0.00	0.00	0.00	0.04	0.10
Skewness	0.68	5.65	0.30	1.06	1.10	-1.43	*	-2.21	0.28	0.68
Kurtosis	-0.34	29.91	3.15	-0.20	0.12	0.21	*	2.87	0.50	-0.34
Shapiro-Wilk	0.92	0.16	0.75	0.83	0.85	0.55	*	*	*	*
Anderson-Darling	5.33	51.78	14.29	10.51	9.69	31.20	*	*	*	*
Lilliefors	0.18	0.54	0.31	0.25	0.28	0.47	*	*	*	*
Jarque-Bera	11.42	5919.70	59.37	26.03	28.21	47.40	*	*	*	*
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	*	Platykurtic	Platykurtic	Platykurtic

2010 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.04	0.41	0.41	0.25	0.25	0.41	0.50	0.47	0.27	0.44
Maximum	0.70	0.64	0.61	0.66	0.69	0.44	0.50	0.47	0.65	0.66
Median	0.15	0.41	0.50	0.29	0.31	0.44	0.50	0.47	0.38	0.46
Mean	0.25	0.43	0.51	0.36	0.37	0.43	0.50	0.47	0.40	0.50
Standard deviation	0.20	0.07	0.04	0.13	0.13	0.01	0.00	0.00	0.10	0.06
Skewness	1.19	2.25	1.36	1.25	1.34	-2.70	*	-2.84	1.33	1.29
Kurtosis	-0.17	3.12	2.01	-0.10	0.15	5.89	*	6.47	0.83	0.09
Shapiro-Wilk	0.76	0.40	0.64	0.72	0.71	0.41	*	*	*	*
Anderson-Darling	14.80	43.04	26.59	17.68	18.22	39.64	*	*	*	*
Lilliefors	0.24	0.52	0.45	0.26	0.31	0.49	*	*	*	*
Jarque-Bera	33.66	176.26	67.05	36.72	42.16	375.68	*	*	*	*
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	*	Leptokurtic	Platykurtic	Platykurtic

2011 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.21	0.15	0.15	0.24	0.23	0.15	0.21	0.20	0.16	0.25
Maximum	0.70	0.56	0.44	0.52	0.52	0.52	0.28	0.29	0.49	0.53
Median	0.53	0.40	0.41	0.44	0.45	0.26	0.23	0.29	0.46	0.48
Mean	0.49	0.38	0.36	0.41	0.41	0.28	0.23	0.25	0.40	0.43
Standard deviation	0.13	0.10	0.08	0.07	0.07	0.11	0.02	0.04	0.10	0.08
Skewness	-0.47	-0.81	-1.18	-0.78	-0.94	0.59	0.56	-0.59	-1.15	-0.90
Kurtosis	-1.05	0.07	0.31	-0.88	-0.58	-0.79	-0.96	-1.58	0.11	-0.84
Shapiro-Wilk	0.92	0.92	0.78	0.85	0.82	0.91	0.87	0.66	0.77	0.76
Anderson-Darling	4.20	3.31	12.27	8.87	11.70	3.74	5.93	22.64	13.55	15.58
Lilliefors	0.16	0.13	0.33	0.22	0.25	0.12	0.17	0.37	0.35	0.27
Jarque-Bera	11.62	15.40	33.04	18.73	22.38	11.93	12.72	22.64	31.10	23.20
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2012 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.64	0.55	0.56	0.67	0.65	0.55	0.63	0.59	0.56	0.66
Maximum	1.15	0.90	0.90	0.91	0.91	0.85	0.64	0.64	0.96	0.77
Median	0.82	0.71	0.74	0.80	0.82	0.65	0.63	0.64	0.79	0.73
Mean	0.83	0.71	0.74	0.79	0.81	0.67	0.64	0.63	0.79	0.73
Standard deviation	0.09	0.08	0.07	0.05	0.05	0.08	0.00	0.02	0.08	0.01
Skewness	0.81	-0.04	0.00	-0.23	-0.70	0.23	0.30	-1.50	-0.61	-2.26
Kurtosis	0.74	0.28	1.79	-0.22	0.65	-1.28	-1.83	0.49	1.91	8.90
Shapiro-Wilk	0.95	0.97	0.83	0.99	0.95	0.93	0.68	0.57	0.88	0.66
Anderson-Darling	2.28	1.47	10.37	0.66	2.29	3.31	20.68	29.66	5.99	19.67
Lilliefors	0.11	0.10	0.21	0.08	0.17	0.11	0.34	0.43	0.14	0.33
Jarque-Bera	18.43	0.49	18.65	1.50	13.90	10.87	21.67	54.08	29.92	580.39
Normality consensus	Non-normal	Normal	Non-normal	Normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2013 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.52	0.81	0.82	0.67	0.60	0.81	0.89	0.86	0.71	0.59
Maximum	1.01	0.95	0.98	0.98	0.97	0.84	0.89	0.86	1.02	0.96
Median	0.79	0.81	0.88	0.89	0.78	0.81	0.89	0.86	0.87	0.77
Mean	0.80	0.82	0.88	0.86	0.77	0.82	0.89	0.86	0.87	0.75
Standard deviation	0.11	0.03	0.02	0.07	0.06	0.01	0.00	0.00	0.06	0.06
Skewness	-0.14	4.40	1.54	-0.65	-0.03	1.15	*	*	0.07	0.11
Kurtosis	-0.57	18.12	5.75	-0.44	0.78	1.05	*	*	0.07	2.32
Shapiro-Wilk	0.98	0.24	0.74	0.93	0.97	0.77	*	*	*	*
Anderson-Darling	0.66	47.67	12.78	3.27	1.48	12.41	*	*	*	*
Lilliefors	0.06	0.53	0.32	0.16	0.11	0.29	*	*	*	*
Jarque-Bera	2.35	2334.09	244.75	10.98	3.49	36.57	*	*	*	*
Normality consensus	Normal	Non-normal	Non-normal	Non-normal	Normal	Non-normal	*	*	Platykurtic	Platykurtic

2014 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.30	0.44	0.48	0.49	0.57	0.44	0.51	0.48	0.52	0.30
Maximum	0.86	0.76	0.73	0.77	0.81	0.52	0.51	0.78	0.77	0.86
Median	0.60	0.53	0.57	0.59	0.62	0.52	0.51	0.78	0.60	0.60
Mean	0.58	0.54	0.57	0.60	0.63	0.50	0.51	0.70	0.60	0.58
Standard deviation	0.12	0.09	0.06	0.06	0.05	0.03	0.00	0.11	0.06	0.12
Skewness	-0.07	0.42	1.04	0.84	1.31	-1.15	-1.30	-0.97	1.15	-0.07
Kurtosis	-0.40	-0.61	1.33	0.58	1.39	-0.26	-0.22	-0.76	1.46	-0.40
Shapiro-Wilk	0.95	0.92	0.84	0.93	0.87	0.71	0.56	0.70	0.84	0.95
Anderson-Darling	2.64	3.36	7.08	2.58	5.08	17.21	30.58	18.95	6.74	2.64
Lilliefors	0.15	0.18	0.16	0.11	0.17	0.29	0.45	0.35	0.18	0.15
Jarque-Bera	1.02	6.08	34.84	17.93	49.91	30.56	38.95	24.89	42.28	1.02
Normality consensus	Normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Normal

2015 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.32	0.25	0.27	0.33	0.34	0.25	0.30	0.28	0.28	0.37
Maximum	1.14	0.97	0.50	0.78	0.76	0.73	0.60	0.47	0.52	0.43
Median	0.77	0.67	0.45	0.65	0.63	0.39	0.38	0.47	0.49	0.41
Mean	0.70	0.62	0.43	0.58	0.57	0.42	0.40	0.40	0.46	0.41
Standard deviation	0.22	0.19	0.05	0.14	0.12	0.14	0.09	0.08	0.06	0.01
Skewness	-0.45	-0.42	-1.19	-0.64	-0.66	0.51	0.55	-0.57	-1.18	-2.99
Kurtosis	-1.27	-1.22	0.58	-1.33	-1.20	-0.99	-1.04	-1.60	0.20	14.78
Shapiro-Wilk	0.87	0.90	0.76	0.80	0.82	0.91	0.86	0.67	0.72	0.43
Anderson-Darling	7.72	6.31	16.87	12.70	12.14	4.29	6.58	22.36	19.41	34.83
Lilliefors	0.20	0.17	0.39	0.29	0.31	0.15	0.18	0.38	0.41	0.47
Jarque-Bera	14.11	12.67	34.68	19.62	18.49	11.74	13.22	22.50	32.69	1471.50
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal

2016 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.96	0.90	0.84	0.91	0.95	0.62	0.72	0.66	0.87	0.96
Maximum	1.92	1.74	1.08	1.55	1.73	1.66	1.25	1.26	1.11	1.92
Median	1.73	1.55	1.00	1.44	1.58	1.12	0.96	1.26	1.05	1.75
Mean	1.66	1.49	1.00	1.39	1.55	1.11	0.95	1.11	1.04	1.68
Standard deviation	0.21	0.18	0.03	0.14	0.16	0.32	0.16	0.22	0.03	0.21
Skewness	-1.79	-1.56	-3.21	-2.16	-2.22	0.04	0.08	-1.05	-4.13	-2.04
Kurtosis	2.81	1.95	13.23	3.88	4.44	-1.25	-1.19	-0.57	18.70	3.52
Shapiro-Wilk	0.79	0.83	0.41	0.68	0.69	0.94	0.95	0.69	0.35	0.72
Anderson-Darling	9.81	8.18	36.40	17.16	15.66	1.92	1.88	20.01	37.93	14.33
Lilliefors	0.21	0.20	0.48	0.28	0.32	0.07	0.08	0.35	0.49	0.24
Jarque-Bera	121.63	79.80	1270.42	197.48	231.71	9.22	8.52	27.98	2454.54	170.71
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Normal	Non-normal	Non-normal	Non-normal	Non-normal

2017 Production year										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.02	0.38	0.39	0.24	0.23	0.38	0.47	0.37	0.24	0.02
Maximum	0.78	0.68	0.61	0.70	0.76	0.41	0.47	0.37	0.66	0.78
Median	0.17	0.38	0.47	0.30	0.30	0.41	0.47	0.37	0.38	0.18
Mean	0.25	0.40	0.48	0.36	0.36	0.41	0.47	0.37	0.39	0.26
Standard deviation	0.19	0.06	0.04	0.12	0.12	0.01	0.00	0.00	0.09	0.18
Skewness	1.11	3.32	1.46	1.29	1.58	-2.93	*	-8.61	1.01	1.24
Kurtosis	0.27	9.50	4.44	0.55	1.58	6.95	*	82.36	1.23	0.52
Shapiro-Wilk	0.87	0.31	0.64	0.80	0.76	0.36	*	*	*	*
Anderson-Darling	6.41	45.83	23.85	10.63	13.12	42.42	*	*	*	*
Lilliefors	0.17	0.53	0.43	0.24	0.27	0.51	*	*	*	*
Jarque-Bera	28.71	772.00	162.27	39.80	71.46	475.25	*	*	*	*
Normality consensus	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	Non-normal	*	Leptokurtic	Platykurtic	Platykurtic

2018 Production year.										
Statistic	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
Minimum	0.11	0.13	0.14	0.15	0.14	0.13	0.19	0.16	0.13	0.11
Maximum	0.29	0.25	0.26	0.28	0.27	0.15	0.19	0.16	0.29	0.29
Median	0.20	0.13	0.18	0.21	0.19	0.13	0.19	0.16	0.22	0.20
Mean	0.20	0.14	0.19	0.21	0.19	0.13	0.19	0.16	0.21	0.19
Standard deviation	0.05	0.03	0.03	0.02	0.02	0.01	0.00	0.00	0.05	0.04
Skewness	-0.08	2.83	0.73	-0.16	0.52	1.32	*	*	-0.05	-0.21
Kurtosis	-0.86	8.07	0.25	0.09	1.25	0.23	*	*	-1.01	-0.58
Shapiro-Wilk	0.98	0.46	0.88	0.97	0.93	0.71	*	*	*	*
Anderson-Darling	0.72	33.19	7.83	1.49	2.85	18.56	*	*	*	*
Lilliefors	0.06	0.48	0.30	0.10	0.13	0.38	*	*	*	*
Jarque-Bera	4.47	567.13	12.88	0.66	15.54	40.99	*	*	*	*
Normality consensus	Normal	Non-normal	Non-normal	Normal	Non-normal	Non-normal	*	*	Platykurtic	Platykurtic

Source: Compiled by the author

Consequently, the evaluation reported by Table 5.12, which includes the descriptive statistics and normality evaluations of the returns of 10 hedging strategies for 16 production seasons, shows that the return data are predominantly non-normal. In each of the instances where normality was identified, the consideration that the data may be classified as normal was based on at least one (highlighted in green) of the four normality test results. The presence of non-normality as a result emphasises the requirement from literature (Chapter 4, Section 4.3) to apply several types of performance measures, even if the measure is unable to evaluate non-normal data effectively, in order to reach consensus through similarities in performance measure rankings. As a result, the following subsection provides a summary of the performance measures included in the evaluation to determine which strategy performed optimally in terms of a risk-weighted return for each of the production years.

5.5.2 Performance measures

The specific performance measures included in the evaluation are presented in Table 5.13, which was derived from Table 4.2 in Chapter 4, Section 4.3. It should however be emphasised that a thorough literature review of these measures was included in Chapter 4 (Section 4.3) and that this section only focuses on the measures included in the evaluation and specifically how the measure rankings were combined to reach consensus.

Table 5.13: Performance measures included

Measurement approach	Equation	Variables
Traditional performance measures	Sharpe ratio = $\frac{R_{p-}r_f}{\sigma_p}$ (4.1) (Sharpe, 1966:122).	R_p is the portfolio return, r_f the risk-free rate and σ_p the portfolio standard deviation.
Measuring performance based on lower partial moments (LPMs).	Lower Partial Moment: $LPM_{ni}(\tau) = \frac{1}{T}\sum_{t=1}^{T} \max[\tau - r_{it}, 0]^n$ (4.4) Only negative returns or returns lower than a benchmark or acceptable return is used to measure risk. A minimum acceptable return may be a risk-free rate, average return or even zero (Sortino & Van der Meer, 1991:29).	The minimum acceptable return *r* for security *i* is represented by τ with the order *n* of the LPM, which may differ between ratios. A higher order would be more applicable as investor risk aversion increases.
Measuring performance based on lower partial moments (LPMs).	Omega = $\frac{\int_{\tau}^{b}(1-F(x))dx}{\int_{a}^{\tau}F(x)dx}$ (4.5.1) (Keating & Shadwick, 2002a:3) applied by (Eling & Schumacher, 2007:2635) as: Omega = $\frac{r_i^d-\tau}{LPM_{ni}(\tau)} + 1$ (4.5.2)	Omega deploys a LPM of order 1, which relates to expected shortfall from τ.
	Sortino = $\frac{r_i^d-\tau}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.6) (Sortino & Van der Meer, 1991:29).	Sortino deploys a LPM of order 2, which relates to the semi-variance from τ, therefore only including the negative returns as a risk measure.
	Kappa 3 = $\frac{r_i^d-\tau}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.7) (Kaplan & Knowles, 2004:3).	Kappa 3 may be seen as a generalised measure, usually deploying a LPM of order 3. Kappa of order 1 may be seen as Omega and Kappa of order 2 as the Sortino ratio.
	Upside Potential Ratio = $\frac{\sum_{t=1}^{T} t^{+}\frac{1}{T}(R_t-R_{mar})}{\sum_{t=1}^{T} t^{-}\frac{1}{T}(R_t-R_{mar})^2}$ (4.8.1) (Sortino, Van der Meer & Platinga, 1999:52), applied by (Eling & Schumacher, 2007:2635) as: UPR = $\frac{HPM_{1i}(\tau)}{\sqrt[n]{LPM_{ni}(\tau)}}$ (4.8.2), whereby the ratio combines the Higher Partial Moment (HPM) of order 1 with the LPM of order 2.	Where T is the number of periods in the sample, R_t is the return of an investment in period t, and t^{+}=1 if $R_t > R_{mar}$, t^{+}=0 if $R_t \leq R_{mar}$, t^{-}=1 if $R_t \leq R_{mar}$ and t^{-}=0 if $R_t > R_{mar}$.
Performance measurement based on drawdown.	Calmar ratio = $\frac{r_i^d-r_f}{-MD_{i1}}$ (4.9) (Young, 1991:40).	Where r_i^d represents the average return, r_f the risk-free rate, and MD_{i1} the lowest return or maximum possible loss incurred in the time period considered.

Measurement approach	Equation	Variables
Performance measurement on the basis of Value-at-Risk (VaR).	VaR is the loss value with a known probability an investor is willing to accept over a specific time period. Standard Value at Risk may be written as: $VaR_i = -(r_i^d + z_\alpha * \sigma_i)$ (4.12), and under the condition that the VaR is exceeded: $CVaR_i = E[-r_{it} \mid r_{it} \leq -VaR_i]$ (4.13), and when the return distribution is non-normal: $MVaR_i = -(r_i^d + \sigma_i * (z_\alpha + (z_\alpha^2 - 1) * \frac{S_i}{6} + (z_\alpha^3 - 3 * z_\alpha) * \frac{E_i}{24} - (2 * z_\alpha^3 - 5 * z_\alpha) * (\frac{S_i^2}{36})$ (4.14).	Where z_α is the α-quintile of the standard normal distribution. S_i is the skewness and E_i the kurtosis of the return distribution.
	Excess return on VaR = $\frac{r_i^d - r^f}{VaR_i}$ (4.15) (Dowd, 2000:216).	
	Conditional Sharpe ratio = $\frac{r_i^d - r^f}{CVaR_i}$ (4.16) (Agarwal & Naik, 2004:85).	
	Modified Sharpe ratio = $\frac{r_i^d - r^f}{MVaR_i}$ (4.17) (Gregoriou & Gueyie, 2003:81).	

Source: Compiled by author

An evaluation of Table 5.13 shows that specific measures were excluded from the original Table 4.2. Traditional measures in the form of the Treynor ratio and Jensens α are both excluded. The main reason for their exclusion is that the agricultural market does not have a market index or tradable market representative contract that could be used to calculate the risk measure beta (β). Two other measures excluded are the Sterling and Burke measures, which are based on drawdown. These measures are similar to the well-known and more regularly applied Calmar ratio, which also forms part of the drawdown type measures approach. As a result and in order to include a drawdown measure approach, the Calmar ratio is included regardless of the finding by Eling and Schumacher (2007:2639) that these measures produce similar results as the Sharpe ratio. Other relevant measures (able to account for the presence of higher moments) in the form of Omega, Sortino, Kappa 3 and the Upside Potential Ratio are also included in the evaluation. Furthermore, all the relevant or well-known measures based on VaR and usually applied in literature are also included.

Arguably, the implementation of specific measures, such as the Sharp ratio, Omega and Upside Potential Ratio requires the additional calculation input of either a relevant risk-free rate or threshold value. In terms of an applicable risk-free rate or, rather, a risk-free rate proxy, Van Heerden (2016:577) evaluated 21 separate proxies to determine which of these rates included the least amount of variability in return and did not show correlation with market returns. Results confirmed that it remains problematic to identify an optimal risk-free rate proxy, since all of the proxies evaluated included return volatility and showed a degree of correlation with market proxy returns (Van Heerden, 2016:585). The study nevertheless identified that the application of the 3-month Treasury Bill rate and the 3-month Negotiable Certificate of Deposit (NCD) rate were preferable when considering their stability throughout changing market conditions. These specific rates are however not available in daily intervals and the corresponding 3-month Johannesburg Interbank Average Rate (JIBAR) money-market rate was chosen as risk-free rate proxy for this study. The applicability of this rate to the agricultural market was also considered, since the initial margin requirement (Chapter 2, Section 2.3.3.1) when trading futures or option contracts on SAFEX, is subject to a JIBAR-derived interest rate earning.

When considering a relevant threshold level to interpret measures such as the Sortino, Omega or Upside Potential Ratio it becomes important to consider the implications of a chosen threshold. Common choices include the risk-free rate or a zero value return threshold, which distinguishes between positive and negative returns. The choice of threshold can however cause misleading results, since higher threshold levels can lead to an increase in performance ranking, which may induce additional risk. The misleading result becomes highlighted when an Omega threshold is set too high. Results in these instances showed that the ranking by means of the Omega performance measure may decline, but risk will always be increased (Vilkancas, 2014:262-263). The evaluation of Omega thresholds by Vilkancas (2014:257), however pointed out that conformation by similar performance measures in terms of return rankings provides a comparison to evaluate any misleading results obtained by moving the threshold to higher levels. Consequently, an evaluation of an applicable threshold level for the strategy returns data was conducted. A zero return threshold makes it difficult to apply either the Omega or Upside Potential Ratio, since several strategies in all the applicable seasons only realised positive returns. As a result, it was concluded to include an applicable positive threshold in the form of the company tax rate plus the prime interest rate at the time.

These rates were chosen, since the return data generated was based on the input cost of planting the crop for that particular season. The cost of production did therefore not include an interest rate component, which may be applicable to longer term capital loans or the fact that the income would still be subject to an applicable tax rate. The inclusion of the sum of these rates (company tax rates plus prime interest rate) at the specific points in time as a threshold made it possible to determine and rank strategy performance by means of Sortino, Omega and the Upside Potential Ratio for most production years. Several production seasons, however, provided challenges in this regard where it was not possible to calculate a measure value based on this threshold. The challenges were considered and are presented in Chapter 6, Section 6.3.2. In spite of the challenges presented, changes in the threshold around the said threshold level did not lead to a change in rankings for a specific measure in a specific production season. It was however observed that the separate measures realised different rankings for the same production season, which necessitated a method of achieving ranking consensus.

In order to reach a consensus with regard to the difference in rankings, the following process based on the example of performance measures and strategies as reported in Table 5.14, was followed. Each strategy in a specific season was assigned a ranking number based on the results of the specific performance measure. In other words, a ranking of one would imply a superior strategy, whereas a ranking of 10 would imply the least optimal strategy based on the specific measures ranking (see Table 5.14). The ranking number for each performance measure based on the evaluation of each individual strategy for a specific production season was added to calculate a cumulative rank for each strategy. Based on this cumulative rank, the strategy that achieved the more optimal ranking (lowest ranking number) for most of the individual performance measure rankings, may be identified by means of the lowest cumulative ranking. When considering Table 5.14 below, Strategy 9 may be seen as the more optimal strategy, with the smallest number in terms of cumulative or total ranking (30); and Strategy 6 may be seen as the less optimal strategy, since the total ranking number was the highest (62) for all 10 strategies evaluated.

Table 5.14: Performance measure ranking consensus

Performance Measure	Strat 1	Strat 2	Strat 3	Strat 4	Strat 5	Strat 6	Strat 7	Strat 8	Strat 9	Strat 10
Sharpe	9	2	1	2	9	10	4	8	2	5
Sortino	8	5	3	1	2	4	9	5	4	3
Omega	6	8	1	4	9	3	7	8	4	5
Kappa 3	1	6	6	4	2	4	2	1	4	7
Upside Potential	10	10	4	8	3	7	3	5	3	1
Calmar	6	4	7	10	3	9	10	10	1	5
Excess return on VaR	2	1	3	1	8	10	8	3	10	7
Conditional Sharpe ratio	7	4	3	9	4	10	2	2	1	6
Modified Sharpe ratio	3	3	7	5	5	5	7	8	1	2
Total ranking	52	43	35	44	45	62	52	50	30	41

Source: Compiled by author

As a result, an evaluation of all 10 hedging strategies for each individual production (2003-2018) season may be done by means of the hedging strategy ranking consensus. The ranking consensus may therefore identify the more optimal strategy for each production season. The optimal strategy result for each production season, based on the potential consensus ranking result, was then included in the filter model, which was explained by means of Table 5.10 in Section 5.3.2 above. The similarities between specific production seasons, which could be identified by means of the filter model, were therefore linked to specific strategies that were more optimal to implement in the specific type of season. It should however be noted that similar types of strategies may be identified as more optimal for a specific type of production season. Strategies that are able to provide a hedge with the least amount of option cost are more optimal in a market that trades downward throughout a production season. Conversely, strategies that are able to capture upward market potential when futures market prices tend to increase throughout a production season are more optimal if the expectation is as such. Therefore, the potential logical result presented by means of the individual performance measures as well as the ranking consensus are considered when evaluating results obtained.

5.6 Chapter summary

The reason(s) market prices form in a specific manner may be seen as a foundation on which researchers aim to build their expectation for future price formation. In terms of the South African white maize market, several studies (Chapter 3, Section 3.3.1) aimed to address and identify the influential market price drivers in order to derive an explanatory model or even to identify potential trends that included price seasonality analysis. In this light, the first aim of this chapter was to provide an alternative methodological approach to link or observe the influential market price drivers that characterise each individual season in an attempt to link different production seasons based on similar characteristics. The second aim was to explain the implementation of 10 different types of hedging strategies that may be applied in any given production season. Unfortunately, this does not mean that each strategy is as effective as or more effective than the rest in all of the production seasons. It is not always easy to identify an optimal strategy, which brought about the third aim of this chapter – to identify the optimal white maize hedging strategy for each production season by means of performance measures. Based on these three chapter aims, the proposed methodology addressed the main goal of this study: to link different production seasons based on similar influential market price drivers and to identify a specific or type of white maize hedging strategy that would be more optimal to implement in the specific type of season identified. The steps in the method to reach this goal may be summarised as follows.

The first step (Section 5.2) in the methodology was to identify influential market price drivers or price determinant factors. The main factors were identified from existing literature and the factors included were not only the raw factor values, but also adaptations or alterations of the factor values in order to add perspective to the relative value of the factor values. Raw factor price values included were the white maize continuous price, which forms the basis of price discovery in the South African white maize market; import and export parity price levels, which provide a price range for price formation. However, these raw factor values do not provide a comparative value of the white maize price relative to import and export parity price levels. As a result, these factor price values were adapted by dividing the white maize price by the import and export price levels, respectively. This adaption provided a ratio by which to evaluate whether the white maize price was relatively closer to import or export parity price levels. Two other important determinants of import and export parity in the form of the CBOT continuous maize price, as well as the rand/dollar exchange rate (USD/ZAR) were included. Both of these factors become more important in price formation when the white maize price is relatively closer to import or export parity price levels. In order for prices to move to either import or export parity price levels, the trigger in price formation may predominantly be linked to supply and demand figures or expectations. As a result, several factors, as well as comparative or relative supply and demand factor values, were included. Specific values for supply (acquisition) and demand (utilisation), as well as ending stock, were included to evaluate consensus. In addition, a ratio or relative value in the form of days' stock availability were included to provide conformation of whether supply was relatively high or relatively low in terms of stock availability based on the current tempo of demand. The inevitable reality of supply and demand is that supply, in particular, may be significantly influenced by adverse weather events in the form of drought. A weather or seasonal climate expectation proxy in the form of the Southern Oscillation Index (SOI) was included to confirm potential low supply scenarios. Nevertheless, the SOI value is one of the only inherently forward-looking factors included, since it provides an indication of expected weather phenomena in the form of El Niño or La Niña events.

In an attempt to link different seasons based on monthly factor value similarities, all of these factors were evaluated by means of data clustering and percentile ranking analysis, which may be seen as the second step (Section 5.3) in the methodology. Data clustering is a process that involves exploratory analysis of data, whereby the factor data are grouped in natural groups. With regard to the influential factors, it provides an indication as to which factors are predominantly influencing price formation at a specific point in time. Percentile ranking analysis, on the other hand, provides a relative measure of each new data point to a series of previous data points of the same factor. As a result, it provides a measure to determine if the specific factor data value is relatively high or relatively low compared to the previous factor data values. Based on the results of both of these methods, a filter model was constructed, providing a dynamic summary of all of the factor value percentile ranking groupings at a specific point in time when hedging decisions must be made. The percentile ranking grouping values for different seasons are thereby compared, in order to link different seasons based on similar factor values at a specific point in time. In addition, the influential factor values that were identified by means of cluster analysis as predominant influencers of price formation may provide conformation of the similarities between specific seasons.

Furthermore, four additional seasonal characteristics or single value seasonal influential factors were added to the filter model in an attempt to improve the identification of similar seasonal characteristics. These factors were: the seasonal price trend based on the continuous white maize contract, the end of marketing year realised stock-to-usage level, the Sea Surface Temperature (SST) values, and the relative value of the July white maize futures price compared to input cost. The factor's characteristic or expected value during the planting window was included in the filter model in order to evaluate the market trend, the expected stock-to-usage level, the specific weather phenomena based on SST, and whether a profitable planting decision was possible. From the identification of seasonal similarities, it may become possible to link specific types of seasons with a more optimal hedging strategy for the type of season identified.

Several types of hedging strategies were considered as the third step in the methodology (Section 5.4), with an eventual count of 10 popular hedging strategies identified from literature and adapted for practical application. These strategies included a benchmark strategy, where no pre-season hedging occurs during the planting window and all produce are hedged during the harvest period. Other strategies were based on specific selling periods or time increments by means of short futures contracts, which incur no hedging cost in terms of option cost. Option-based strategies were, however, included based on several different approaches, which comprised the aim to reduce option cost and to capture upward market movements if they occurred. It is not always easy to identify a more optimal strategy for each production season based on the realised strategy price alone, since the strategy in itself may induce a fair amount of risk.

In an attempt to rank the hedging strategy results in a meaningful manner, a fourth step (Section 5.5) in the form of performance measure analysis was included to rank the hedging strategies based on a risk weighted approach. However, some of the performance measures included in the evaluation may induce ranking bias when the distribution of return data is non-normal. As a result, several performance measures were included, known to be able to evaluate return data with higher moment statistical characteristics, as was identified in the statistical analysis of the hedging strategy return data (see Table 5.12). Furthermore, in order to identify consensus between the different types of measures and to adhere to the findings in Chapter 4 (Section 4.3.5), the results obtained by means of all of the measures included in Table 5.13 were considered when determining an optimal white maize hedging strategy for each production season. This consideration was attempted by calculating a cumulative or total rank based on the performance measure ranking for each hedging strategy in a specific production season. The hedging strategy with the lowest cumulative rank (therefore the highest ranking for most of the individual performance measures) was considered as the more optimal hedging strategy for that production season. Finally, but based on a critical evaluation of logical results obtained from the performance measure analysis, the optimal strategy for each production season was added to the filter model (Table 5.10) to facilitate the identification of more optimal hedging strategies for production seasons with similar (specific) characteristics.

To conclude – the methodological approach presented in this chapter aimed to provide a structured approach and appropriate methods to link different production seasons in a structured manner and also to identify more optimal hedging strategies for a specific type of production season expectation. In all of the literature reviewed for this study, none applied the manner in which production seasons are characterised to identity similarities between specific types of seasons. Several hedging strategies based on existing literature, but which had never been implemented on the South African white maize market, were included in this evaluation. The results based on the methodological approach are presented in the following chapter.

CHAPTER 6

Results

"I love it when a plan comes together." – Colonel John "Hannibal" Smith (The A-Team) (1983)

6.1 Introduction

Throughout the course of this study, the literature chapters aimed to provide the necessary background to facilitate an understanding of the inner workings of markets with a specific focus on the South African white maize market. This background, with reference to Chapter 2 (Section 2.3.3 and Section 2.4) and Chapter 4 (Section 4.2.2 and Section 4.3), provided a solid foundation for the process followed in Chapter 5, where the structured methodological approach was presented by means of specific steps. This methodological approach or steps determined the order in which results are presented in this chapter.

Section 6.2 combines the results that are based on the approach as discussed in Section 5.3 and includes a thorough summary of the clustering analysis and percentile ranking analysis results obtained, based on the influential factors (market price drivers) identified in Section 5.2. These results characterise each historical season under evaluation. This characterisation provided by the stance of the influential price determinant factors at a specific point in time are then interpreted to determine a seasonal price formation expectation based on similar characteristics or circumstances in previous production years. The next step is to establish which hedging strategies would perform better during seasons with specific market characteristics in order to link more optimal hedging strategies according to the price formation expectation. This would enable risk managers to identify the best hedging strategy at the beginning of each type of season, and in the process limit their price risk to maximise profits. To accomplish this, Section 6.3 begins by reporting the results obtained from the implementation of the 10 hedging strategies, as discussed in Chapter 5 (Section 5.4). The hedging strategy results also include the results obtained from the ranking analyses carried out according to performance measures, with the latter assisting to establish the best hedging strategies. Section 6.4 then combines the results obtained in an all-inclusive decision-making filter model, which enables the identification of seasonal influential market factor similarities/groupings in order to derive an informed decision as to the optimal hedging strategy to deploy, given the seasonal price formation expectation (Chapter 5, Section 5.3.2). Finally, Section 6.5 contains a summary of the chapter.

6.2 Percentile ranking and cluster analysis results

The results obtained from both the percentile ranking analysis and cluster analysis methods stem from the influential factor monthly data for each of the factors discussed in Chapter 5 (Section 5.2). The first part of this section provides the percentile rank and grouping results (Section 6.2.1), which is followed by the cluster analysis results in Section 6.2.2. The results based on these two methods should, however, not be viewed in isolation. An important synergy between these two methods became evident during the analysis, and it is also presented and explained.

6.2.1 Percentile rank grouping analysis results

Each of the monthly values of the factors identified was assigned a percentile ranking value as explained in Chapter 5 (Section 5.3.2). These percentile values were assigned a grouping rank value by means of the percentile rank grouping ranges provided in Chapter 5 (Table 5.7). The results of these percentile groupings (based on monthly values) for each factor were summarised by means of individual tables of which specific results are included to show how the market factor (market price driver) rankings may be compared with the July white maize futures contract percentile groupings (based on monthly values) (Chapter 5, Table 5.8). It is, however, important to start by reporting, in summary, the individual factor percentile groupings (based on monthly values) in Table 6.1 to provide an overview of how the relative value or levels of these monthly grouping values should be interpreted.

Table 6.1: Percentile groupings interpretation (based on monthly values)

Market factor (market price driver)	Acronym	Interpretation of low value level (closer to zero)	Interpretation of high value level (closer to 10)
White maize continuous price	WM-C	WM-C value is low compared to previous values.	WM-C value is high compared to previous values.
Import parity	IP	IP value is low compared to previous values. IP in itself is low.	IP value is high compared to previous values. IP in itself is high.
Import parity ratio	IPR	Cash prices are relatively far from IP.	Cash prices are relatively close to IP.
Export parity	EP	EP value is low compared to previous values.	EP value is high compared to previous values.
Export parity ratio	EPR	Cash prices are relatively close to EP.	Cash prices are relatively far from EP.
CBOT continuous maize price	CBOT-C	CBOT-C value is low compared to previous values.	CBOT-C value is high compared to previous values.

Market factor (market price driver)	Acronym	Interpretation of low value level (closer to zero)	Interpretation of high value level (closer to 10)
Dollar/Rand currency	USD/ZAR	USD/ZAR value is low compared to previous values. ZAR appreciated against USD.	USD/ZAR value is high compared to previous values. ZAR depreciated against USD.
Acquisition	Supply	Indicates supply is low.	Indicates supply is high.
Utilisation	Demand	Indicates demand is low.	Indicates demand is high.
Carry out / closing stock	Ending stock	Indicates ending stock is low.	Indicates ending stock is high.
Stock availability days	Days stock	Confirms low ending stock and indicates days' stock is low.	Confirms high ending stock and indicates days' stock is high.
Southern Oscillation Index	SOI	Indicates that SOI levels are low, which increases the probability of El Niño type (drier) events.	Indicates that SOI levels are high, which increases the probability of La Niña type (wetter) events.

Source: Compiled by author

The following tables (Table 6.2 to 6.7) provide a summary of the percentile rank grouping levels (based on monthly values) for each market factor. Several figures (Figure 6.1 to 6.14) are also reported where applicable to enhance the understanding of the results reported in these tables. These figures consist of comparisons between the percentile rank grouping (based on monthly values) of specific market factors, and the July white maize futures price percentile rank grouping (based on monthly values) over the same period. The main purpose of comparing the percentile rank grouping values of each individual factor with the July white maize futures price percentile rank grouping value, is to evaluate the logic progression of the percentile rank grouping values. A logical progression enables a meaningful analysis of the influence a specific influential price determinant may have on the July white maize futures price, or, specifically, how the July white maize futures price reacts to changes in the influential price determinant factor percentile rank grouping values. The tables and figures which do not form part of the discussion in this section, or is not referred to specifically for comparative reasons, will not be included in the results or Appendix to this study since they will only lengthen an already extensive result and not necessarily contribute to the readers understanding. However, any relevant table or figure not included will be made available to the reader upon request to the author.

In order to ensure a thorough understanding of this comparison, the first factor in the form of the percentile rank grouping values for the white maize continuous contract price (WM-C) (Table 6.2) is evaluated in detail. An applicable comparison is made to the percentile rank grouping values of the corresponding July white maize futures contract (Chapter 5, Section 5.3.2, Table 5.8 included below for ease of reference) to enhance the explanation. Several production years are included in the comparison to enable the reader to compare and interpret the rest of the percentile rank grouping value tables included as part of the results.

The first important step in the evaluation of any percentile rank grouping value is to refer to the interpretation of the relative factor value (or levels), as provided in Table 6.1 above. From the interpretation of the white maize continuous contract price (WM-C) percentile rank grouping value provided in Table 6.1 above, one can derive that a large value closer to 10 means that the WM-C at that point in time was high compared to previous price values. The actual percentile rank grouping values for WM-C in Table 6.2 below shows that this was the case during the 2007/2008, 2011/2012, as well as the 2015/2016 production years. Conversely, the WM-C percentile rank grouping values (Table 6.2) were low (closer to zero) during the 2004/2005, 2009/2010 and 2017/2018 production years.

Yet interpreting the percentile rank grouping value in isolation only provides an indication of the grouping value at a specific point in time relative to previous factor values. It will therefore be meaningful to compare the development of the percentile rank grouping values of the WM-C with the percentile rank grouping values of the corresponding July white maize futures contract (Table 5.8 below). Such a comparison may provide additional insight into the manner in which relative factor values conform to the price development in the corresponding July white maize futures contract. A visual comparison is also provided for four production years in Figure 6.1 below. From this comparison, it is apparent that the percentile rank grouping values for the WM-C and the corresponding July white maize futures contract show similar development for each of the production years included in Figure 6.1. Furthermore, the development in the percentile rank grouping values for WM-C and the corresponding July white maize futures contract was similar for each of the production seasons included in this analysis (See Appendix Figure A1). This also confirms that the price development in the white maize continuous contract and the corresponding July white maize futures contract are similar. Ultimately, the finding may be justified by means of the result by McCullough (2010:120), which states that price formation in the South African white maize market occurs in the cash or continuous market price development and spills over to the futures market price.

The confirmation of the result obtained through the percentile rank grouping method applied in existing literature provides an initial validation of the applicability of the method. Still, this premise warrants further confirmation, since Auret and Schmitt (2008) as well as Stone *et al*. (1996) and Meyer *et al*. (2006) stated that influential price determinant factors should not be interpreted in isolation. To address this requirement, a comparative evaluation of the percentile rank grouping value of the July white maize futures contract to import and export parity was done to determine if a relatively high July white maize futures contract price could be equated with import parity (IP) and a relatively low July white maize futures contract price with export parity (EP). The value of this specific comparison stems from the finding by Auret and Schmitt (2008:128) that the import parity price of white maize was a significant influential variable included in their final explanatory model. The finding by Meyer, Westhoff, Binfield and Kirsten (2006:370-374), that the market may be characterised based on price levels closer to IP and EP, accentuates the importance of these factors in price formation.

The specific finding by Meyer *et al*. (2006) proved to be applicable, since the comparison of the percentile rank grouping values for IP and EP to the percentile rank grouping values of the July white maize futures contract price did not always provide logical results. For example, the percentile rank grouping values of the July white maize futures contract price during the 2014/2015 production year (Table 5.8) increased to high levels from December 2014 onward. Yet the percentile rank grouping values for IP (Table 6.3a) remained neutral to low until it increased in June 2015. Hence, this instance failed to show a similarity in the development of the July white maize futures contract price and IP. The 2016/2017 production year confirms the opposite scenario, with the percentile rank grouping values of the July white maize futures contract price moving to low values, and the percentile rank grouping values for IP remaining high throughout the production year. A comparison of the percentile rank grouping values of the July white maize futures contract price and the percentile rank grouping values for EP (Table 6.4a) also includes an example in the form of the 2014/2015 production year, where the development in percentile rank grouping values show dissimilarities. As a result, it was important to include the percentile rank grouping values for IPR (Table 6.3b) and EPR (Table 6.4b) in the analysis to determine if prices were closer to import parity (IP) or export parity (EP), as specified by Meyer *et al*. (2006).

To accomplish this analysis, the 2008/2009 and 2016/2017 production years were included as examples to highlight the relevance and information captured by means of the percentile rank grouping method. In considering the representation of the 2008/2009 production year by means of Figure 6.2 and Figure 6.3, the percentile rank grouping values for IP and EP show that the July white maize futures contract moved in accordance with parity price changes. Both IP and EP were on high levels and moved to lower levels during the course of the production year. (The interpretation continues after Figure 6.2).

Table 5.8: Percentile rank grouping monthly values for each July white maize futures contract (WM Jul)

July WM	August	September	October	November	December	January	February	March	April	May	June	July
WM Jul 2002/2003	9	10	10	10	7	5	4	2	1	5	3	2
WM Jul 2003/2004	5	5	4	4	6	7	6	6	6	6	3	2
WM Jul 2004/2005	6	5	6	4	2	1	1	1	1	1	1	1
WM Jul 2005/2006	2	4	4	5	7	5	7	7	6	8	8	8
WM Jul 2006/2007	7	6	7	8	8	8	10	10	9	9	9	9
WM Jul 2007/2008	9	9	9	9	9	9	10	10	10	10	10	10
WM Jul 2008/2009	10	10	10	9	9	8	7	7	6	7	6	4
WM Jul 2009/2010	6	5	6	7	7	3	3	3	3	2	2	2
WM Jul 2010/2011	5	4	5	4	3	6	8	6	7	8	9	9
WM Jul 2011/2012	10	8	9	10	10	10	10	10	10	10	10	10
WM Jul 2012/2013	10	9	10	10	8	8	9	10	10	10	9	10
WM Jul 2013/2014	9	8	8	8	9	9	8	8	7	5	5	4
WM Jul 2014/2015	5	5	6	6	8	7	10	10	10	10	10	10
WM Jul 2015/2016	10	10	10	10	10	10	10	10	10	10	10	9
WM Jul 2016/2017	8	8	7	7	7	3	1	2	1	1	1	1
WM Jul 2017/2018	3	3	5	3	3	3	2	3	5	5	4	5

Source: Compiled by the author

Table 6.2: White maize continuous (WM-C) percentile grouping levels (based on monthly values)

WM-Continuous	August	September	October	November	December	January	February	March	April	May	June	July
WM-C 2002/2003	9	7	9	9	7	5	3	1	1	4	3	3
WM-C 2003/2004	4	4	4	4	6	7	6	6	6	5	4	3
WM-C 2004/2005	5	4	5	4	1	1	1	1	1	1	1	2
WM-C 2005/2006	2	4	4	6	7	6	7	7	7	8	8	8
WM-C 2006/2007	7	7	7	8	8	8	9	10	9	9	9	10
WM-C 2007/2008	10	10	10	10	10	10	9	10	9	9	10	10
WM-C 2008/2009	10	9	9	7	9	8	6	7	6	6	6	5
WM-C 2009/2010	5	5	6	6	7	3	3	3	2	2	2	3
WM-C 2010/2011	3	3	4	4	3	5	6	5	6	7	8	10
WM-C 2011/2012	10	10	10	10	10	10	10	10	9	9	9	10
WM-C 2012/2013	10	9	10	9	8	8	8	9	8	9	8	9
WM-C 2013/2014	9	9	9	10	10	10	10	10	6	5	5	4
WM-C 2014/2015	4	4	5	5	5	5	10	9	9	9	10	10
WM-C 2015/2016	10	10	10	10	10	10	10	10	10	10	10	9
WM-C 2016/2017	9	9	9	9	9	6	7	2	2	1	1	2
WM-C 2017/2018	2	2	3	2	2	2	2	3	4	4	4	4

Source: Compiled by author

Figure 6.1: ***Percentile rank grouping value comparison of white maize continuous (WM-C) with July white maize futures contract (WM Jul) (based on monthly values)***

Source: Compiled by author

Table 6.3a: Import parity (IP) percentile rank grouping levels (based on monthly values)

Import Parity	August	September	October	November	December	January	February	March	April	May	June	July
IP 2002/2003	10	10	7	5	4	4	3	1	1	4	1	1
IP 2003/2004	1	1	2	2	3	5	7	7	9	8	5	3
IP 2004/2005	5	3	3	1	2	5	5	6	5	6	6	6
IP 2005/2006	5	3	5	2	2	1	2	2	4	6	8	8
IP 2006/2007	8	10	10	10	10	10	10	10	10	10	9	10
IP 2007/2008	10	10	10	10	10	10	10	10	10	10	10	10
IP 2008/2009	10	9	9	9	9	9	9	8	8	8	7	7
IP 2009/2010	6	7	7	7	7	6	7	4	4	5	4	4
IP 2010/2011	7	7	8	7	7	9	8	9	10	9	8	9
IP 2011/2012	10	10	10	8	8	7	7	8	8	8	10	10
IP 2012/2013	10	10	10	10	9	10	10	8	9	10	10	8
IP 2013/2014	8	7	7	7	7	9	10	8	8	6	5	5
IP 2014/2015	4	5	6	4	4	4	6	4	3	3	8	7
IP 2015/2016	8	7	9	10	10	10	10	10	9	10	10	9
IP 2016/2017	10	9	6	8	8	8	8	8	6	8	8	9
IP 2017/2018	8	8	9	9	7	6	6	7	8	7	9	8

Source: Compiled by author

Table 6.3b: Import parity ratio (IPR) percentile rank grouping levels (based on monthly values)

Import Parity Ratio	August	September	October	November	December	January	February	March	April	May	June	July
IPR 2002/2003	7	7	9	10	10	7	4	2	2	5	5	5
IPR 2003/2004	5	6	5	5	8	9	5	3	1	2	4	4
IPR 2004/2005	4	6	7	6	2	1	1	1	1	1	1	2
IPR 2005/2006	2	4	4	7	9	8	8	9	7	7	8	7
IPR 2006/2007	5	3	2	4	3	2	6	7	5	5	7	8
IPR 2007/2008	7	8	8	5	5	3	2	2	2	2	2	3
IPR 2008/2009	2	3	3	3	5	3	3	3	4	3	3	5
IPR 2009/2010	5	5	4	6	6	2	1	2	1	1	1	2
IPR 2010/2011	1	1	1	3	2	1	4	2	2	4	6	7
IPR 2011/2012	7	7	9	10	10	10	9	9	8	8	7	9
IPR 2012/2013	9	6	9	8	7	6	6	9	7	4	3	9
IPR 2013/2014	9	10	10	10	10	10	10	10	6	4	4	4
IPR 2014/2015	4	4	5	7	8	7	10	10	10	10	10	10
IPR 2015/2016	10	10	9	8	10	10	10	10	10	10	10	9
IPR 2016/2017	9	8	10	9	9	5	5	1	1	1	1	1
IPR 2017/2018	1	1	1	1	2	2	2	2	2	3	2	3

Source: Compiled by author

Figure 6.2: Percentile rank grouping value comparison of IP and IPR with July white maize futures contract (WM Jul) (based on monthly values)
Source: Compiled by author

Yet the IPR shows that market prices were far from import parity (low IPR grouping values), whereas the EPR shows that prices were actually closer to export parity (low EPR grouping values). Based on the change in the percentile rank grouping values of IPR and EPR over the 2008/2009 season, prices remained far from import parity (IP), but also moved away from export parity (EP) prices to levels higher than EP.

The 2016/2017 production year also provided important insight into the price developments of the July white maize futures contract compared to IP, IPR, EP and EPR (see Figure 6.2 and 6.3). In terms of IP and EP, both these price levels remained high throughout the season, while the July white maize futures price declined throughout the season. An interpretation of IPR reveals that prices were closer to IP (high IPR grouping values) at the beginning of the season, but due to the decline in the white maize price, IPR declined during the second half of the production year. The decline in white maize prices from IP levels to EP levels is confirmed by the EPR, which moved from high percentile rank grouping values (prices far from EP) to low percentile rank grouping values over the course of the season.

As a result, the interpretation of the percentile rank grouping value level of IP, IPR, EP and EPR may be used to evaluate the relative price level of the white maize price in accordance with import and export parity (EP) in itself. Similar percentile rank grouping value results could therefore be used to link production years with similar characteristics, such as when prices were closer to import parity (high IPR grouping values) at a point in time during the season. Such examples include the 2002/2003, 2007/2008, 2011/2012, 2012/2013, 2013/2014, 2015/2016 and 2016/2017 production years (Table 6.3b). Also, seasons when prices were closer to EP and confirmed by low EPR grouping values included the 2008/2009, 2010/2011, 2012/2013 and 2017/2018 production years (Table 6.4b). However, IP, IPR, EP and EPR should never be interpreted in isolation, which was demonstrated when the percentile rank grouping results for the 2012/2013 production year were evaluated. In this specific production year, market prices were both closer to import parity (high IPR values) and export parity (low EPR values) (Figure 6.4 below). Scenarios displaying this type of discrepancy required a wider comparison to additional price determinant influential factors (market drivers) to provide a logical explanation. (The next set of interpretations follows after Figure 6.4).

Table 6.4a: Export parity (EP) percentile rank grouping levels (based on monthly values)

Export Parity	August	September	October	November	December	January	February	March	April	May	June	July
EP 2002/2003	10	10	9	6	5	5	3	2	1	4	1	1
EP 2003/2004	1	1	2	1	1	3	5	5	6	6	1	1
EP 2004/2005	2	1	1	1	1	1	1	1	1	2	1	2
EP 2005/2006	1	1	2	1	2	1	2	2	4	6	6	7
EP 2006/2007	7	7	8	8	8	9	9	8	8	9	7	8
EP 2007/2008	9	9	9	10	10	10	10	10	10	10	10	10
EP 2008/2009	10	9	9	9	9	9	9	8	8	8	7	6
EP 2009/2010	5	6	7	6	7	4	5	3	4	6	4	4
EP 2010/2011	7	8	9	8	9	10	10	10	9	10	9	10
EP 2011/2012	10	9	10	8	10	9	8	9	9	9	10	10
EP 2012/2013	10	10	10	10	9	10	10	9	9	10	10	8
EP 2013/2014	8	6	6	6	6	8	8	8	8	6	4	4
EP 2014/2015	3	3	3	3	3	3	3	3	2	2	7	2
EP 2015/2016	6	5	7	10	10	10	10	10	10	10	10	10
EP 2016/2017	10	9	7	8	8	8	8	8	6	5	5	5
EP 2017/2018	5	4	6	5	2	1	2	4	6	7	8	7

Source: Compiled by author

Table 6.4b: Export parity ratio (EPR) percentile rank grouping levels (based on monthly values)

Export Parity Ratio	August	September	October	November	December	January	February	March	April	May	June	July
EPR 2002/2003	7	7	8	10	10	6	3	1	3	5	5	7
EPR 2003/2004	6	9	6	9	10	10	7	7	4	5	7	8
EPR 2004/2005	7	10	10	10	9	3	1	3	3	3	3	5
EPR 2005/2006	8	10	9	10	10	10	10	10	9	8	8	8
EPR 2006/2007	5	6	4	5	4	3	6	10	8	7	9	10
EPR 2007/2008	8	9	9	6	5	4	1	1	1	1	1	2
EPR 2008/2009	2	3	2	4	4	3	2	4	5	4	5	6
EPR 2009/2010	6	6	5	7	7	4	3	5	3	1	2	3
EPR 2010/2011	1	1	1	1	1	1	1	1	1	1	3	3
EPR 2011/2012	5	7	6	8	7	8	7	6	4	4	2	5
EPR 2012/2013	4	1	3	2	2	1	1	5	2	1	1	7
EPR 2013/2014	7	9	9	10	10	10	9	10	4	4	4	4
EPR 2014/2015	6	6	6	8	9	8	10	10	10	10	10	10
EPR 2015/2016	10	10	9	7	9	10	10	8	8	7	7	7
EPR 2016/2017	5	4	9	8	7	3	4	1	1	1	1	2
EPR 2017/2018	2	2	2	3	4	5	4	3	3	2	1	2

Source: Compiled by author

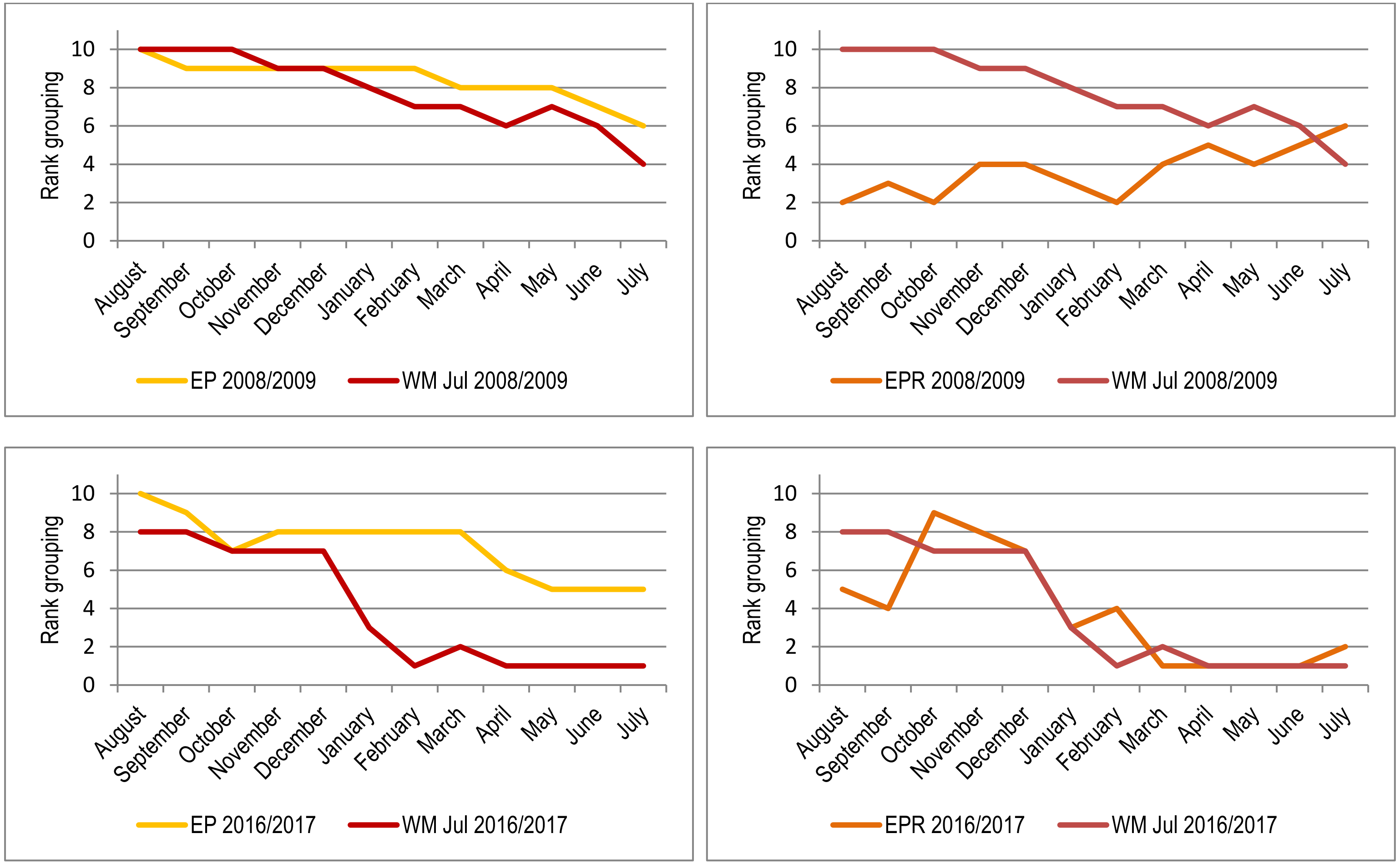


Figure 6.3: Percentile rank grouping value comparison of EP and EPR with July white maize futures contract (WM Jul) (based on monthly values)

Source: Compiled by author

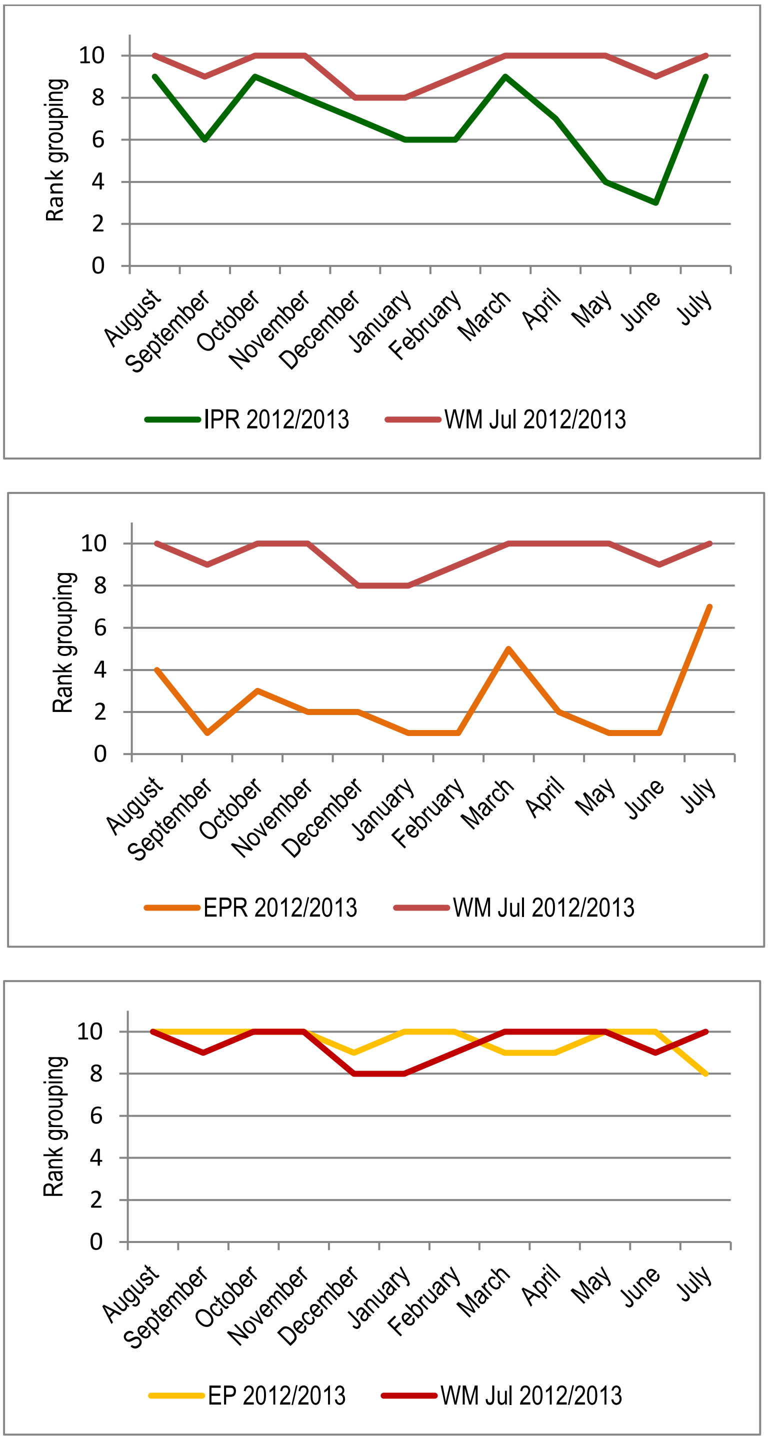


Figure 6.4: Percentile rank grouping value comparison of IPR, EPR and EP with July white maize futures contract (WM Jul) for the 2012/2013 production year

Source: Compiled by author

Figure 6.4 clearly shows that the July white maize futures contract price was actually high (high percentile rank grouping values) for the 2012/2013 production year, but also that prices were closer to export parity (EP) (low EPR percentile rank grouping values). An analysis of the percentile rank grouping values for EP provides the required insight, since export parity (EP) in itself was high, resulting in lower EPR percentile rank grouping values. This example emphasises the necessity of analysing all of the factors as a whole before drawing conclusions about seasonal similarities after a single factor. The specific contrast that showed in the 2012/2013 production year due to both high IP and EP percentile rank grouping values may be clarified even further through an analysis of the CBOT-C price as well as currency price (USD/ZAR) percentile rank grouping levels, since they are key determinants of import and export parity price levels (Auret & Schmitt, 2008:108).

Table 6.5a and Table 6.5b below provide an overview of the percentile rank grouping levels (based on monthly values) for the CBOT-C and USD/ZAR. Higher values for both factors would cause a direct shift to higher values for IP and EP, since CBOT-C and the USD/ZAR are key inputs in the calculation of IP and EP (Chapter 5, Section 5.2.1.2, Table 5.1). Similarly, lower values for CBOT-C and the USD/ZAR would result in lower factor levels for IP and EP. Arguably, these factors are not always high or low (in terms of percentile rank grouping values) at the same time, but when both are high – as in the 2012/2013 production year (Figure 6.5) – both EP and IP would most likely increase. This does not necessarily mean that one could expect high percentile rank grouping values for IP when both CBOT-C and the USD/ZAR are at high percentile rank grouping levels. Figure 6.5 reflects the 2008/2009 production year, a specific season in which such a scenario became evident. During this season, market prices were actually closer to export parity (EP) levels (Figure 6.3, low EPR relative values) from the beginning of the season, but the high percentile rank grouping value level of IP and EP (Figure 6.3) in this case could be attributed to the high percentile rank grouping level of CBOT-C and USD/ZAR.

The results and scenarios presented up to this point show that all of these factors have a definite influence on price formation in the market in real time as the season progresses, even if this influence is brought about through the influence they have on each other. The fundamental factors included in the percentile rank grouping analysis in the form of supply, demand, ending stock, and days' stock are monthly values, which are snapshots of these values as the season progresses (Chapter 5, Section 5.2.1.4). As a result, the relative values (or levels) of these fundamental factors may not necessarily indicate or provide an explanation as to why the July white maize futures contract reacted to market expectations at a specific point in time compared to the more direct and logical influence of factors such as IP, EP, CBOT-C and USD/ZAR. The inclusion of the fundamental factors as part of the percentile rank grouping analysis nevertheless remains important to identify similarities between production years. These similarities between production years are revealed when comparisons are drawn between the percentile rank grouping values (Table 6.5a to Table 6.5d) for supply, demand, ending stock and days' stock. (The next set of interpretations follow after Table 6.6d).

Table 6.5a: CBOT-C percentile rank grouping levels (based on monthly values)

CBOT Continuous	August	September	October	November	December	January	February	March	April	May	June	July
CBOT-C 2002/2003	10	10	10	9	8	8	8	8	8	9	7	4
CBOT-C 2003/2004	8	6	9	9	9	10	10	10	10	10	9	4
CBOT-C 2004/2005	5	3	2	1	3	1	5	4	3	6	4	7
CBOT-C 2005/2006	2	3	1	1	5	6	7	7	8	9	7	8
CBOT-C 2006/2007	6	10	10	10	10	10	10	10	10	10	9	9
CBOT-C 2007/2008	9	9	10	10	10	10	10	10	10	10	10	10
CBOT-C 2008/2009	10	9	8	7	9	8	7	8	8	9	6	6
CBOT-C 2009/2010	5	6	6	8	8	6	7	5	6	5	5	7
CBOT-C 2010/2011	8	9	10	9	10	10	10	10	10	10	9	10
CBOT-C 2011/2012	10	8	9	9	9	9	9	9	9	6	9	10
CBOT-C 2012/2013	10	10	10	9	9	9	9	8	8	7	8	5
CBOT-C 2013/2014	5	4	4	4	4	4	4	5	5	4	3	1
CBOT-C 2014/2015	1	1	2	2	3	2	2	2	1	1	3	2
CBOT-C 2015/2016	1	3	2	2	1	2	1	1	4	4	1	1
CBOT-C 2016/2017	1	1	2	1	2	3	4	3	2	4	4	4
CBOT-C 2017/2018	1	2	2	1	2	4	6	7	8	8	2	6

Source: Compiled by author

Table 6.5b: USD/ZAR percentile rank grouping levels (based on monthly values)

Dollar/Rand	August	September	October	November	December	January	February	March	April	May	June	July
USD/ZAR 2002/2003	8	8	6	5	4	4	3	1	1	4	1	1
USD/ZAR 2003/2004	1	1	1	1	1	2	1	1	2	1	1	1
USD/ZAR 2004/2005	2	1	1	1	1	1	1	2	1	4	3	3
USD/ZAR 2005/2006	2	2	4	3	2	1	2	2	1	5	6	6
USD/ZAR 2006/2007	6	7	7	6	6	7	7	7	6	7	6	7
USD/ZAR 2007/2008	7	5	4	5	6	10	10	10	10	10	10	9
USD/ZAR 2008/2009	10	10	10	10	10	10	10	10	9	9	8	8
USD/ZAR 2009/2010	8	7	8	7	7	7	8	6	6	7	7	5
USD/ZAR 2010/2011	6	3	3	3	1	4	2	1	1	1	1	1
USD/ZAR 2011/2012	3	9	9	9	9	8	6	6	7	9	9	9
USD/ZAR 2012/2013	9	9	9	9	9	9	9	9	9	10	10	10
USD/ZAR 2013/2014	10	10	9	10	10	10	10	10	10	10	10	10
USD/ZAR 2014/2015	10	10	10	10	10	10	10	10	10	10	10	10
USD/ZAR 2015/2016	10	10	10	10	10	10	10	10	10	10	10	9
USD/ZAR 2016/2017	10	8	8	9	8	8	7	8	7	7	7	7
USD/ZAR 2017/2018	6	8	9	8	6	5	5	5	6	6	8	7

Source: Compiled by author

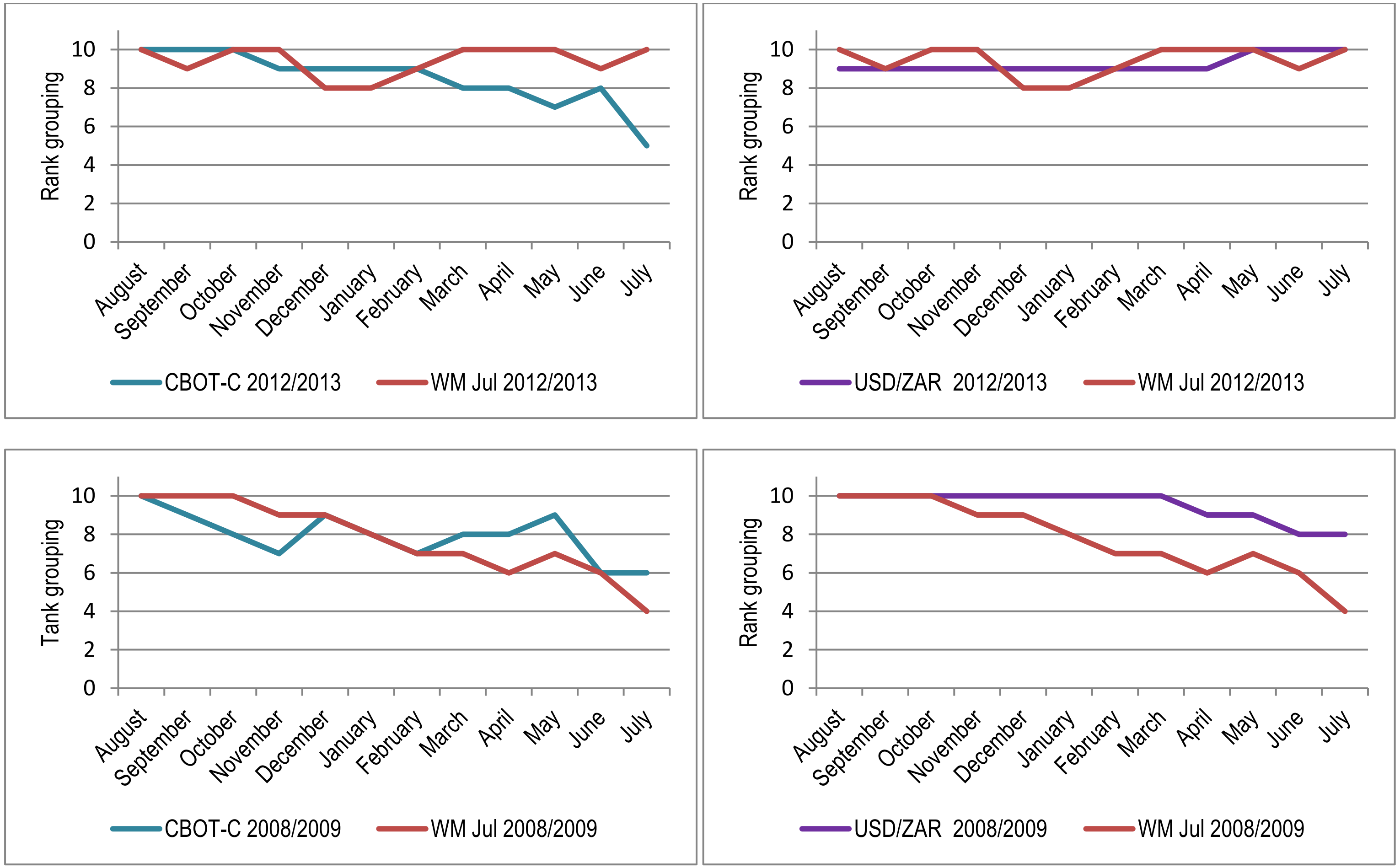


Figure 6.5: ***Percentile rank grouping value comparison of CBOT-C and USD/ZA comparison with July white maize futures contract (WM Jul) (based on monthly values)***

Source: Compiled by author

Table 6.6a: Supply percentile rank grouping levels (based on monthly values)

Supply	August	September	October	November	December	January	February	March	April	May	June	July
Supply 2002/2003	7	6	5	3	1	3	5	7	8	9	10	10
Supply 2003/2004	7	6	4	2	1	1	1	5	6	8	10	10
Supply 2004/2005	8	6	3	3	2	1	1	3	5	7	9	10
Supply 2005/2006	9	7	5	5	4	3	4	3	2	6	8	9
Supply 2006/2007	8	7	6	4	3	4	5	6	7	9	9	8
Supply 2007/2008	7	5	4	4	3	3	5	6	7	8	10	10
Supply 2008/2009	8	6	5	4	2	2	4	4	5	8	10	10
Supply 2009/2010	8	7	5	4	2	2	3	4	6	8	10	10
Supply 2010/2011	8	7	6	4	1	1	3	2	2	7	9	10
Supply 2011/2012	9	7	6	4	2	3	4	6	7	9	10	9
Supply 2012/2013	7	6	5	5	3	4	5	6	7	8	9	9
Supply 2013/2014	7	6	5	3	1	3	4	4	6	8	10	10
Supply 2014/2015	8	6	5	4	3	4	4	3	6	8	9	8
Supply 2015/2016	7	6	6	4	1	4	6	6	7	8	8	9
Supply 2016/2017	8	7	6	7	1	4	5	7	7	9	10	10
Supply 2017/2018	9	6	5	4	1	2	1	2	3	8	9	10

Source: Compiled by author

Table 6.6b: Demand percentile rank grouping levels (based on monthly values)

Demand	August	September	October	November	December	January	February	March	April	May	June	July
Demand 2002/2003	1	1	3	1	1	1	1	4	4	7	6	8
Demand 2003/2004	4	9	10	7	7	5	8	6	5	9	5	3
Demand 2004/2005	7	7	7	7	6	2	9	10	10	10	9	9
Demand 2005/2006	9	9	4	4	1	2	1	4	1	4	2	2
Demand 2006/2007	2	3	8	8	4	10	10	10	10	9	7	5
Demand 2007/2008	4	6	9	9	9	10	9	10	9	10	9	9
Demand 2008/2009	8	8	9	7	7	7	5	9	4	6	6	6
Demand 2009/2010	4	4	6	4	3	1	4	10	9	10	10	10
Demand 2010/2011	10	10	10	10	10	10	10	10	10	10	10	8
Demand 2011/2012	9	8	6	4	3	6	5	8	3	5	1	4
Demand 2012/2013	4	2	5	7	4	6	8	8	8	6	3	6
Demand 2013/2014	4	1	3	4	2	5	3	4	1	3	7	10
Demand 2014/2015	10	10	10	9	8	7	5	6	1	1	1	2
Demand 2015/2016	2	1	2	2	1	1	1	1	1	3	2	1
Demand 2016/2017	2	1	3	5	1	1	1	7	5	8	9	10
Demand 2017/2018	10	10	10	10	9	10	9	10	10	10	9	9

Source: Compiled by author

Table 6.6c: Ending stock percentile rank grouping levels (based on monthly values)

Ending Stock	August	September	October	November	December	January	February	March	April	May	June	July
Ending Stock 2002/2003	10	10	9	7	7	6	5	4	3	6	10	10
Ending Stock 2003/2004	10	10	10	9	8	7	6	5	4	3	8	10
Ending Stock 2004/2005	10	10	9	9	9	8	7	6	4	3	6	9
Ending Stock 2005/2006	10	10	9	8	8	7	5	4	3	2	3	7
Ending Stock 2006/2007	8	8	7	6	5	4	3	1	1	3	5	7
Ending Stock 2007/2008	6	5	4	3	2	1	1	1	1	1	4	9
Ending Stock 2008/2009	10	9	7	6	5	3	2	1	1	1	2	8
Ending Stock 2009/2010	9	9	8	7	6	5	3	2	2	2	7	10
Ending Stock 2010/2011	10	10	10	9	8	7	6	4	2	1	2	6
Ending Stock 2011/2012	8	8	6	5	4	3	2	1	1	3	6	9
Ending Stock 2012/2013	9	8	7	6	5	4	3	2	1	2	5	7
Ending Stock 2013/2014	7	6	5	4	4	2	1	1	1	1	5	10
Ending Stock 2014/2015	10	9	8	7	6	5	4	3	2	4	7	8
Ending Stock 2015/2016	8	7	7	6	5	4	4	3	2	2	3	5
Ending Stock 2016/2017	6	6	5	4	3	2	2	1	1	2	10	10
Ending Stock 2017/2018	10	10	10	10	9	9	8	7	5	5	6	9

Source: Compiled by author

Table 6.6d: Days' Stock percentile rank grouping levels (based on monthly values)

Days' Stock	August	September	October	November	December	January	February	March	April	May	June	July
Days' Stock 2002/2003	10	10	9	9	8	7	6	4	3	6	9	10
Days' Stock 2003/2004	10	10	9	8	7	7	5	5	4	3	7	10
Days' Stock 2004/2005	10	10	9	9	8	8	6	4	2	2	5	9
Days' Stock 2005/2006	10	9	10	9	8	7	7	4	4	3	3	7
Days' Stock 2006/2007	9	9	6	5	5	2	1	1	1	2	4	6
Days' Stock 2007/2008	6	5	3	2	2	1	1	1	1	1	3	7
Days' Stock 2008/2009	8	6	5	5	4	3	2	1	1	1	3	7
Days' Stock 2009/2010	9	9	7	7	6	6	4	2	2	2	5	9
Days' Stock 2010/2011	9	9	7	6	6	5	4	3	2	1	2	5
Days' Stock 2011/2012	6	6	6	5	5	3	2	1	1	3	7	9
Days' Stock 2012/2013	9	8	7	5	5	4	3	2	1	2	6	6
Days' Stock 2013/2014	8	8	5	4	4	2	2	1	1	1	5	8
Days' Stock 2014/2015	9	7	6	6	5	4	4	4	3	4	9	10
Days' Stock 2015/2016	9	10	8	7	6	5	5	4	4	3	4	6
Days' Stock 2016/2017	7	7	5	4	5	3	2	1	1	2	8	10
Days' Stock 2017/2018	10	10	10	8	9	7	6	5	3	3	4	8

Source: Compiled by author

Based on the percentile rank grouping results reported in Table 6.6a, supply is mainly seasonal, reaching high levels during the harvest window from May to July (Chapter 5, Section 5.4.2, Figure 5.14) for each of the production years. Supply gradually declines form August to January, after which the first deliveries, usually from irrigation fields planted earlier, become available on the market from February. In some seasons when imports are required to replenish stock levels, supply may increase when the stock becomes available on the market. Demand, on the other hand (Table 6.6b), may follow a more random pattern. High demand is usually linked to production years when prices are closer to export parity (EP) (low EPR percentile rank grouping value in Table 6.4b) or when white maize substitutes yellow maize in the animal feed market.

The latter scenario occurs when white maize becomes relatively cheaper than yellow maize to the extent that animal feed producers are willing to make use of white instead of yellow maize. The most recent example of both scenarios is shown in Figure 6.6a and Figure 6.6b below. A surplus of white maize produced during the 2016/2017 production year resulted in price declines and WM market prices trading closer to export parity (EP) (low percentile rank grouping values for EPR in Table 6.4b) during the 2017/2018 marketing year. The demand for white maize for human consumption remained high compared to other marketing years (Figure 6.6a) due to the lower market price – see Table 5.8 and Table 6.2, which confirm the low percentile rank grouping value for cash market and futures market white maize prices. Also, a feed switch occurred (Figure 6.6b), since the demand for white maize in the animal feed market was significantly higher than in other marketing years and the demand for yellow maize (traditional animal feed) declined accordingly.

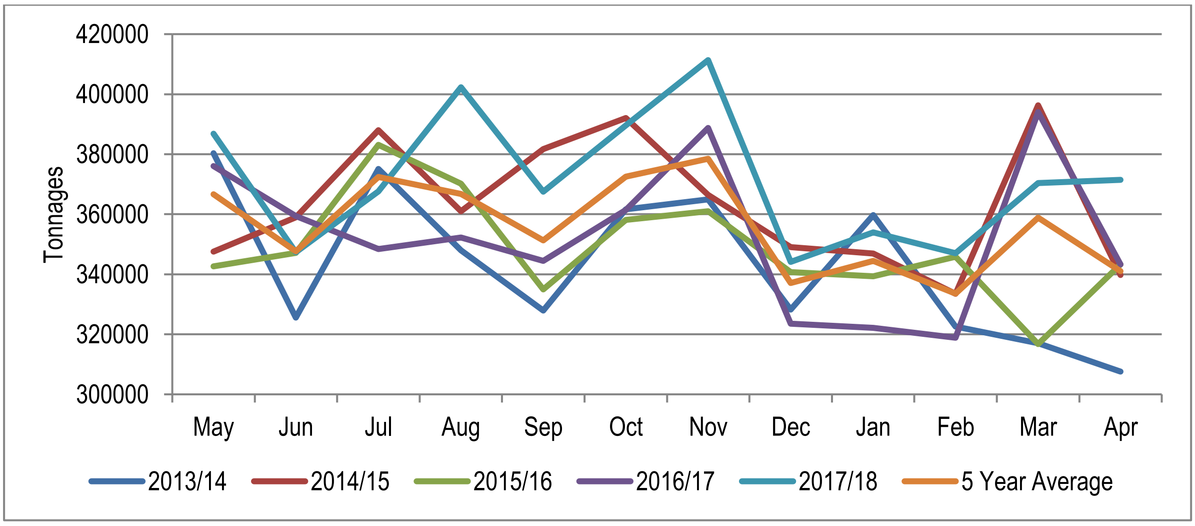


Figure 6.6a: White maize usage for human consumption
Source: Compiled by the author from SAGIS (2018a)

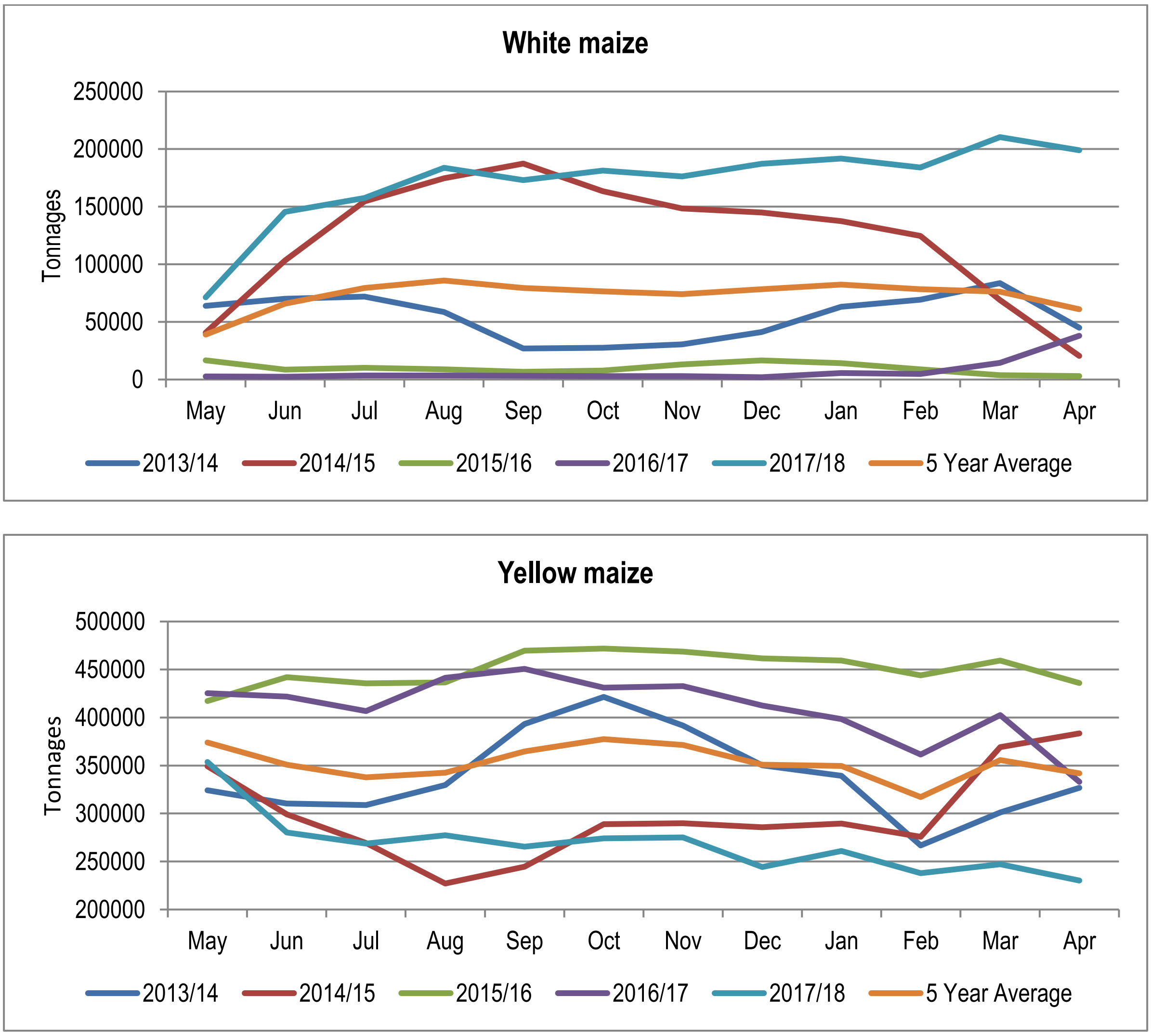


Figure 6.6b: White maize vs yellow maize usage for animal consumption
Source: Compiled by the author from SAGIS (2018a)

Ultimately, the interaction between supply and demand is the basis of the calculation (Chapter 5, Section 5.2.1.4) of available stock in terms of ending stock (Table 6.6c) and days' stock (Table 6.6d) relative values (or levels). The effect of these values on price formation – especially futures price formations – is illustrated in Figure 6.6c below, which shows a comparison of ending stock percentile rank grouping values and the July white maize futures contract percentile rank grouping values from the 2014/2015 production year up to the 2017/2018 production year. From the progression in percentile rank grouping values, it is evident that the July white maize futures contract reacted before the ending stock figure and was based on the expected progression in ending stock. The 2014/2015 production year saw a steady decline in ending stock, which was never fully recouped in the 2015/2016 production year. Ending stock remained low until the 2016/2017 production year harvest fully replenished stock levels, which is shown by the high percentile rank grouping value level for the 2017/2018 production year in Figure 6.6c.

Further conformation is provided by the 2015 July white futures contract, which reacted to the expected reduction in ending stock by increasing to high levels before ending stock reached low levels during the 2014/2015 production year. Prices remained high while ending stock levels remained low in the 2015/2016 production year. The July white maize futures contract nevertheless started to decline long before ending stock was recouped in the 2016/2017 production year, and futures prices remained low and closer to export parity (EP) (Table 6.4b) in the period when white maize ending stock (Table 6.6c) remained ample.

This explanation clearly demonstrates the possibility of linking seasons on the basis of low or high percentile rank grouping value levels of ending stock or days' stock. It is, however, difficult to form a July white maize futures price progression expectation based on monthly supply and demand values, since these monthly updated values always lag price formation. In order to address this shortcoming, one of the additional factors introduced in Chapter 5 (Section 5.2.2.2) aimed to provide an expectation of annual stock-to-usage based on the tempo of usage or expected cumulative supply. If the stock-to-usage expectation for the following production year declines, ending stock or days' stock is also expected to gradually decline and prices to respond upwards for the July white maize futures contract if all other factors remain stable. One additional factor that may have an adverse effect on ending stock is the Southern Oscillation Index (SOI) and the weather phenomena associated with it.

Table 6.7 below provides the percentile rank grouping values (based on monthly values) calculated for SOI. Given the fact that lower SOI percentile rank grouping values indicate an increased probability of a warmer/drier El Niño season and higher SOI percentile rank grouping values indicate an increased probability of a wetter La Niña season, one would expect the July white maize futures contract to react accordingly. A comparison of the SOI and the July white maize futures contract percentile rank grouping values confirms this premise. Figure 6.7 below provides this comparison for the 2015/2016 and 2016/2017 production years. According to Figure 5.7 (Chapter 5, Section 5.2.2.3), the 2015/2016 production year experienced the most intense El Niño event in the past 50 years.

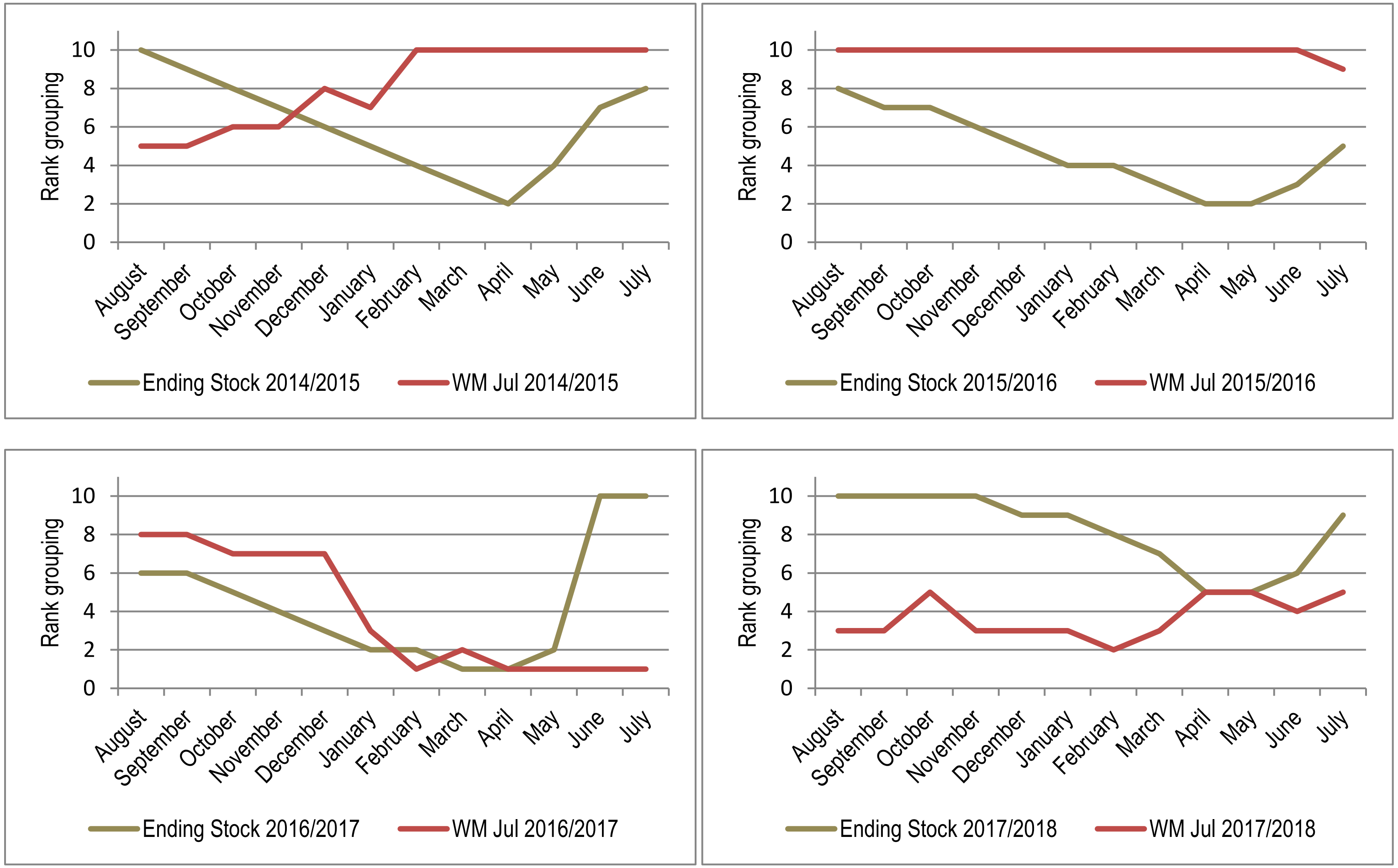


Figure 6.6c: ***Percentile rank grouping value comparison of Ending stock with July white maize futures contract (WM Jul) (based on monthly values)***

Source: Compiled by author

Table 6.7: Southern Oscillation Index (SOI) percentile rank grouping levels (based on monthly values)

Southern Oscillation Index	August	September	October	November	December	January	February	March	April	May	June	July
SOI 2002/2003	1	3	3	5	1	7	3	5	5	6	2	9
SOI 2003/2004	7	7	7	7	10	2	10	7	1	10	1	4
SOI 2004/2005	4	6	6	3	2	8	1	7	2	2	8	8
SOI 2005/2006	5	9	10	7	7	10	7	10	10	3	4	3
SOI 2006/2007	1	5	1	7	5	3	6	7	5	6	9	5
SOI 2007/2008	8	8	9	10	10	10	10	9	8	5	8	8
SOI 2008/2009	9	10	10	10	9	9	10	6	8	4	5	7
SOI 2009/2010	4	8	1	3	2	2	1	2	10	9	7	10
SOI 2010/2011	10	10	10	10	10	10	10	10	10	7	6	8
SOI 2011/2012	7	9	8	9	10	8	6	7	3	5	2	6
SOI 2012/2013	3	7	7	7	2	6	3	8	6	8	9	8
SOI 2013/2014	5	7	5	8	5	9	5	1	7	7	5	4
SOI 2014/2015	2	3	2	2	2	2	6	2	4	1	2	1
SOI 2015/2016	1	1	1	4	2	1	1	4	1	7	7	7
SOI 2016/2017	8	10	4	6	6	6	5	8	3	6	2	8
SOI 2017/2018	7	8	9	9	5	8	3	8	7	7	3	6

Source: Compiled by author

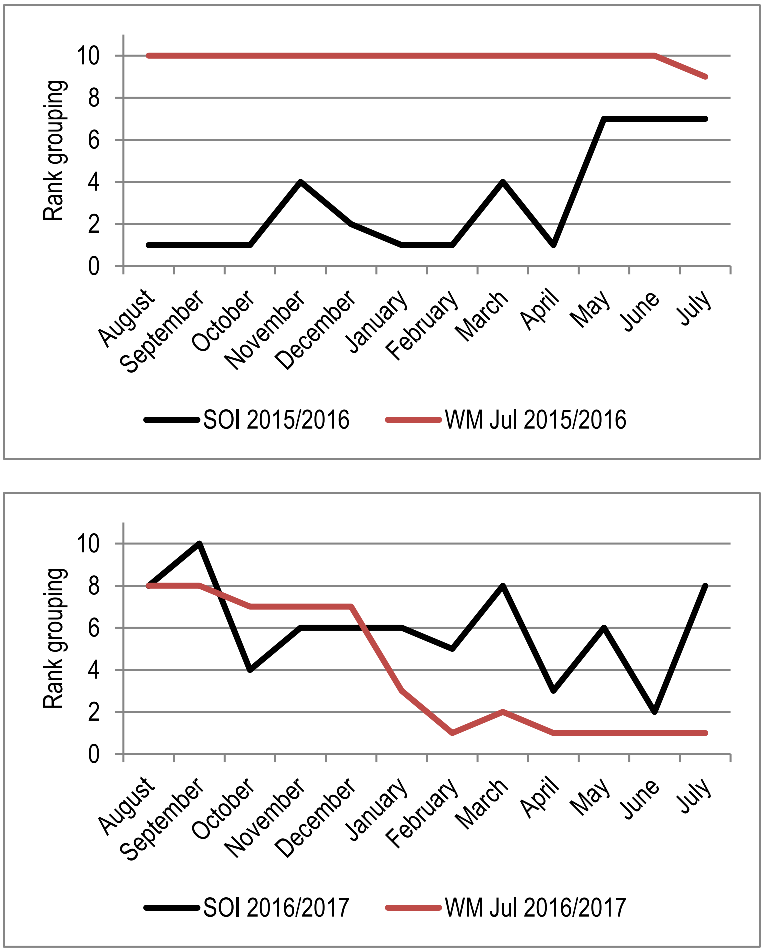


Figure 6.7: Percentile rank grouping value comparison of SOI with July white maize futures contract (WM Jul) (based on monthly values)

Source: Compiled by author

Consequently, the relatively low SOI values of the 2015/2016 season confirm the El Niño effect, and the upward July white maize prices response (high percentile rank grouping values) confirms the logical relationship between this factor and price formation. The following production year (2016/2017) clearly shows an increase in the percentile rank grouping values for SOI, which is confirmed by a La Niña event (Chapter 5, Section 5.2.2.3, Figure 5.7). White maize prices reacted to the implication of the expected improvement in rainfall and production, which caused the percentile rank grouping value of the July white maize futures contract price to decrease accordingly.

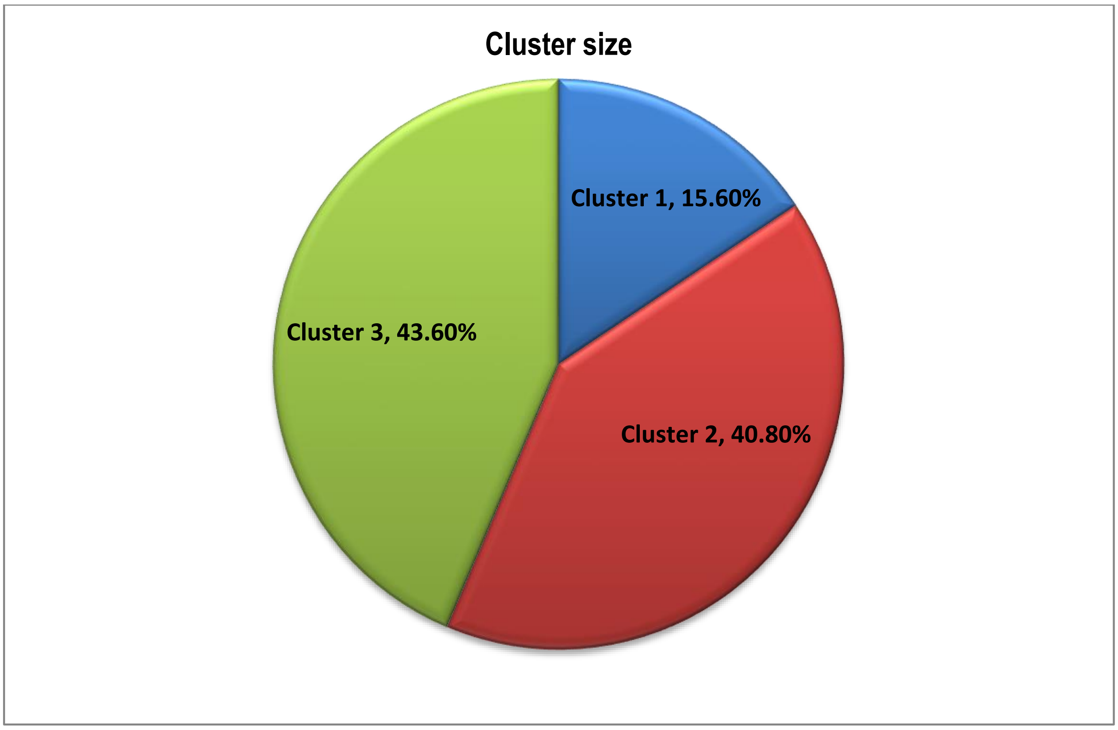
To conclude – the interpretations of the percentile rank grouping values for all the factors provided above confirm that the percentile ranking and grouping method provide the necessary foundation to link similar seasons based on the similarities in the relative factor values. The progression in the factor values throughout any given production year also shows a logical link to price formation in the July white maize futures contract at a specific point in time. However, none of the factors, with the possible exception of the SOI factor, provide the means to make a logical derivation as to the expected price formation of the July white maize futures contract. Furthermore, it became evident that it would be impractical to review each factor in isolation; also, that a review of the mutual interaction of the factor values would be required throughout each production year.

The factor interaction was thoroughly reviewed to evaluate whether similar production years could be linked on the grounds of similar factor interactions. The findings confirmed results by Meyer, Westhoff, Binfield and Kirsten (2006:370-374) that three types of seasons could be identified. The first type of season is characterised by ample supply; market prices tend to be closer to export parity (EP), and there are no imminent weather scares. The second type of season is the complete opposite: supply is low and market prices react to reach price levels closer to import parity (IP). Low supply seasons may also be linked to production years where the impact of drier weather conditions adversely affected production potential. In both season types where market prices are closer to either export or import parity price levels, the influence of the international market price (CBOT-C) and the exchange rate (USD/ZAR) arguably have an influence on price formation. In the third type of season, the market price is not forced to extremes. However, this season is more difficult to characterise, as the influence of the different factors may change as the production year develops. Fortunately, the cluster analysis approach provides the synergy of more important factors conforming at a specific point in time, and is discussed in the following section.

6.2.2 Cluster analysis results

The implementation of the SPSS Two-Step Cluster analysis method (Chapter 5, Section 5.3.1) confirmed the inherent risk of cluster analysis: the possibility to induce bias by accepting or applying an analysis without being able to logically confirm that the results make sense or can be confirmed (Steinbach, Ertoz and Kumar, 2004:275). It is for this reason that the cluster analysis results followed the percentile rank grouping results; the percentile rank grouping results provided the means to test whether the results of the cluster analysis were logical. Therefore, the results of several alternative Two-Step Cluster analyses (hereafter referred to as cluster analysis method or simply cluster analysis) were considered and interpreted to find the most intuitively logical result.

The first and most basic alternative was to introduce all the monthly data of all of the market factors (Table 6.1) to the cluster analysis method in order to let the two-step process identify the optimal number of clusters in the first step, and cluster the relevant factors in the identified number of clusters in step two. Three clusters were identified by the SPSS (2017) software, along with the cluster sizes, factors to be included in each cluster, and importance ranking or predictor performance of the factors in each cluster (Figure 6.8). The silhouette coefficient was calculated at 0.4, thus indicating a fair fit.



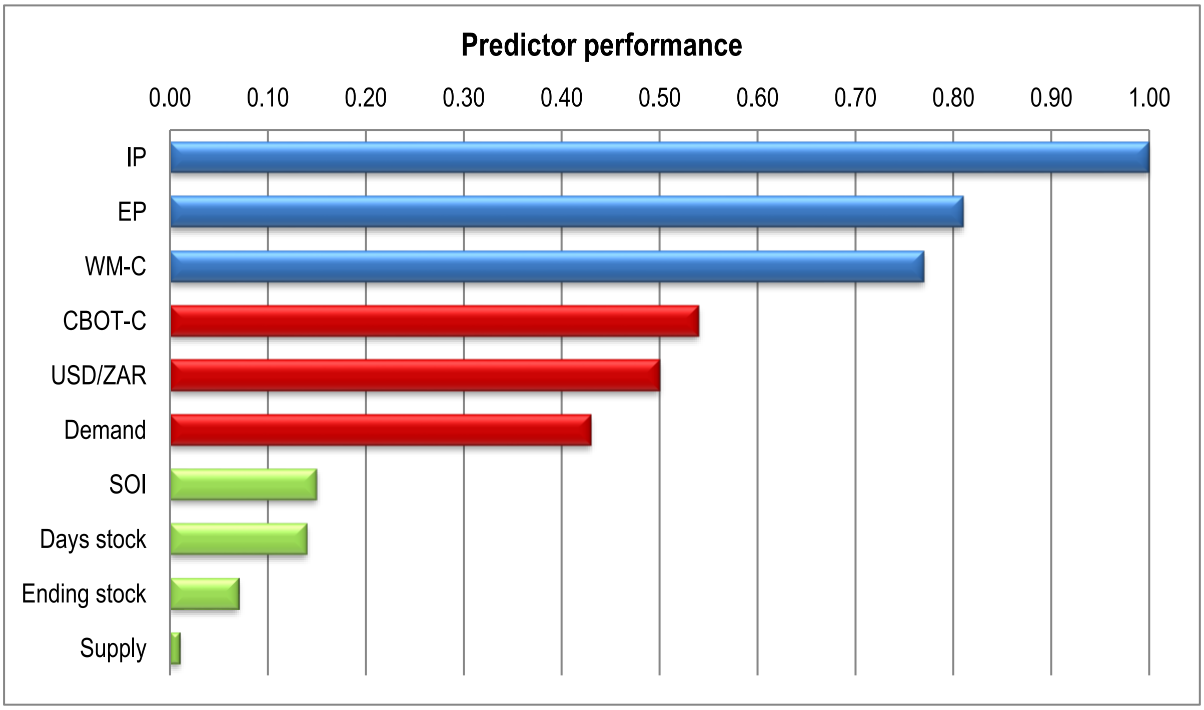


Figure 6.8: Two-Step Cluster analysis – three clusters
Source: Compiled by author from SPSS (2017) results

In order to determine if the three clusters formed were significantly different, a one-way analysis of variance (ANOVA) was conducted to explore the impact of the three clusters on the July white maize futures contract price. There was a statistically significant difference at the $p < 0.05$ in the July price for white maize between the different clusters:

$F\ (2{,}208) = 78.553,\ p < 0.05.$

The descriptive statistics of the analysis is provided in Table 6.8a below. The main result of the analysis in this regard was that the three clusters were significantly different from one another.

Table 6.8a: Three-cluster ANOVA descriptive statistics

Cluster	N	Mean	Std. Deviation
1	33	3036.727	1035.387
2	86	1891.709	293.649
3	92	1261.674	821.687
	df	**F-Ratio**	**Sig.**
Between Groups	2	78.553	0.000*
Within Groups	208		

* The mean difference is significant at the 0.05 level.
Source: Compiled by author from SPSS (2017) results

In order to confirm the statistically significant independence between specific clusters, the post-hoc comparisons by means of the Bonferroni test (equal variances assumed) indicated that all three clusters were statistically significantly different from one another, which is confirmed by the descriptive statistics results in Table 6.8b below.

Table 6.8b: Three-cluster: Bonferroni post-hoc test descriptive statistics

Cluster		Mean Difference	Std. Error	Sig.
1	2	1145.018*	182.998	0.000*
	3	1775.053*	199.561	0.000*
2	1	-1145.018*	182.998	0.000*
	3	630.035*	91.332	0.000*
3	1	-1775.053*	199.561	0.000*
	2	-630.035*	91.332	0.000*

* The mean difference is significant at the 0.05 level
Source: Compiled by author from SPSS (2017) results

Nevertheless, it was important to assess whether the factors included in each of the clusters formed a logical grouping, as it could enable the identification of similarities between production years.

Table 6.9: Two-Step Cluster analysis – Three-cluster analysis dominant monthly cluster

Year	August	September	October	November	December	January	February	March	April	May	June	July
2002/2003	3	3	3	3	3	3	3	3	3	3	3	3
2003/2004	3	3	3	3	3	3	3	3	3	3	3	3
2004/2005	3	3	3	3	3	3	3	3	3	3	3	3
2005/2006	3	3	3	3	3	3	3	3	3	3	3	3
2006/2007	3	3	3	3	3	3	2	2	3	3	3	3
2007/2008	3	3	3	2	2	2	2	2	2	2	2	2
2008/2009	2	2	2	2	2	2	2	2	2	2	3	3
2009/2010	3	3	3	3	3	3	3	3	2	2	3	3
2010/2011	2	2	2	2	2	2	2	2	2	2	2	2
2011/2012	2	2	2	2	2	2	2	2	2	2	2	2
2012/2013	2	2	2	2	2	2	2	2	2	2	2	2
2013/2014	2	2	2	2	1	1	1	1	1	2	2	2
2014/2015	2	2	2	2	2	2	1	1	1	1	1	1
2015/2016	1	1	1	1	1	1	1	1	1	1	1	1
2016/2017	1	1	1	1	1	1	1	1	1	1	2	2
2017/2018	2	2	2	2	2	2	2	2	2	2	2	2

Source: Compiled by author from SPSS (2017) results

The result that provides the means to compare the clustering analysis result to the percentile rank grouping analysis result is the manner in which the SPSS model identifies which cluster was dominant in each month over the period of analysis, which is reported in Table 6.9 above. This result is discussed in detail below but to ensure the reader's understanding of the SPSS result, it is important to explain the results contained in Figure 6.8. The number of clusters identified and the calculated cluster size are included in the pie chart in Figure 6.8. The specific factors included in each cluster are indicated in the bar chart and matched by colour, with the relevance or importance of the factor indicated via the predictor performance as calculated by SPSS (2017). In this instance, cluster one is made up of import parity (IP), export parity (EP), and the white maize continuous price (WM-C). Although cluster one has the smallest size, the factors may be seen as most relevant due to the high predictor performance of the factors included. Cluster two is made up of the CBOT continuous price (CBOT-C), the USD/ZAR currency pair and demand, whereas cluster three includes SOI, days' stock, ending stock, and supply.

This result means that IPR and EPR were disregarded in the result of the analysis although all 12 factors were included. One reason may be that the factor values of EPR and IPR were comparatively smaller than any of the other factor values included. The probable result of this was that the distance measures were too small to ensure that the data points were included in any of the linkage criteria, even though the first stage of the cluster analysis process allows for an expansion of the threshold linkage criterion to include more data points in existing clusters (Zhang *et al*., 1996:106).

Still, it was possible to compare the three clusters based on the factors in the clusters to the values determined by the percentile rank grouping analysis to evaluate whether the cluster results supported or confirmed the logical progression formed by the percentile rank grouping values and their relative meaning at a specific point in time. In order to facilitate this comparison, the cluster analysis results were summarised in Table 6.9. Each number in Table 6.9 represents the specific cluster perceived as more relevant at that specific point in time.

The logical approach in this instance was to evaluate if the factors in the clusters, identified at a specific point in time, coincided with instances where the factor values were relatively high or relatively low. As a result, one would expect the cluster to include import parity (IP) as a factor when IP in itself was relatively low or high, or that the cluster would include export parity (EP) as a factor when EP in itself was relatively high or low. It is in this regard specifically that the initial three-cluster analysis did not provide a logical progression, since both IP and EP were grouped together in cluster one. A comparison with the IP (Table 6.3a) and EP (Table 6.4a) percentile rank grouping values confirms that cluster one became relevant when IP was high from the end of the 2014/2015 production year up to the end of the 2016/2017 production year. This was, however, due to the high value of IP and WM-C (Table 6.2) and not necessarily due to the value of EP, since prices were far from EP, although EP in itself was relatively high during the 2015/2016 production year as well. The reason for the high percentile rank grouping value in IP and EP during this period may furthermore be ascribed specifically to the relatively high USD/ZAR (Table 6.5b), which was not included as factor in cluster one. The USD/ZAR did however form part of the factors included in cluster two, which only became significant after prices moved away from IP towards EP in the 2017/2018 production year. This interpretation shows that the inclusion of both IP and EP in cluster one made it difficult to establish a logical link between production years. Still, there were instances where the three-cluster analysis result provided logical results such as the 2008/2009 production year, when prices were actually closer to EP, according to the low EPR ratio in Table 6.4b, but both CBOT-C (Table 6.5a) and USD/ZAR (Table 6.5b) were high. Results in Table 6.9 above confirm that cluster two, which included both CBOT-C and USD/ZAR, was relevant during the 2008/2009 production year. Consequently, additional cluster analysis combination results were considered in order to derive the most plausible and logical cluster analysis result of all the alternatives evaluated.

The evaluation of alternative cluster analysis results included a reduction in the number of factors included. The reduced number of factors also included several combinations of the 12 original factors in order to evaluate if the result showed a logical alternative cluster progression and comparison to the earlier reported percentile ranking grouping analysis results. Another alternative was to adjust the number of clusters required to a specific, fixed number to determine whether the resulting cluster analysis result provided a logical comparison to the percentile rank grouping analysis results. It was through this iterative analysis and applicability evaluation of the different combinations that a specific five-cluster analysis result provided the most relevant alternative.

The results for this specific five-cluster analysis are shown in Figure 6.9 and Table 6.11 below. Similar to the three-cluster analysis result above, the number of clusters identified and the calculated cluster size are included in the pie chart in Figure 6.9. The specific factors included in each cluster are indicated in the bar chart and matched by means of colour, with the relevance or importance of the factor indicated by means of the predictor performance, as calculated by SPSS (2017). The silhouette coefficient was calculated at 0.4, indicating a fair fit. In this analysis result, the first and most relevant cluster consisted of the single factor, namely IP. The second cluster included EP and USD/ZAR, and the third cluster was made up of CBOT-C, WM-C and demand. The fourth cluster included days' stock and ending stock, with the fifth cluster being made up of SOI and supply.

As with the three-cluster analysis, a one-way analysis of variance (ANOVA) was conducted to explore the impact of the five clusters on the July white maize futures contract price. There was a statistically significant difference at the $p < 0.05$ in the July price for white maize between the different clusters:

$F\ (4{,}206) = 40.199,\ p < 0.05.$

The descriptive statistics of the analysis is provided in Table 6.10a below. The main result of the analysis in this regard was that the five clusters were significantly different from one another.

Table 6.10a: Five-cluster ANOVA descriptive statistics

Cluster	N	Mean	Std. Deviation
1	33	3036.727	1035.387
2	63	1879.730	313.145
3	22	1971.2733	132.243
4	55	1199.673	357.083
5	38	1341.789	1207.815
	df	F-ratio	Sig.
Between Groups	4	40.199	0.000*
Within Groups	206		

*The mean difference is significant at the 0.05 level.

Source: Compiled by author from SPSS (2017) results

In order to confirm the statistically significant independence between specific clusters, the post-hoc comparisons made using the Games-Howell test (unequal variances assumed) indicated that most of the five cluster comparisons were statistically significant from one another (Table 6.10b below). The similarities or rather mutual influences between specific clusters could however be logically explained.

Table 6.10b: Five-cluster: Games-Howell post-hoc test descriptive statistics

Cluster		Mean Difference	Std. Error	Sig.
1	2	1156.997*	184.505	0.000*
	3	1065.455*	182.429	0.000*
	4	1837.05455*	186.558	0.000*
	5	1694.938*	266.225	0.000*
2	1	-1156.997*	184.505	0.000*
	3	-91.543	48.491	0.332
	4	680.057*	62.248	0.000*
	5	537.941**	199.866	0.073**
3	1	-1065.455*	182.429	0.000*
	2	91.543	48.491	0.332
	4	771.600*	55.797	0.000*
	5	629.483*	197.952	0.023*
4	1	-1837.055*	186.558	0.000*
	2	-680.057*	62.248	0.000*
	3	-771.600*	55.797	0.000*
	5	-142.117	201.763	0.954
5	1	-1694.938*	266.225	0.000*
	2	-537.941**	199.866	0.073**
	3	-629.483*	197.952	0.023*
	4	142.117	201.763	0.954

* The mean difference is significant at the 0.05 level.
** The mean difference is significant at the 0.1 level.
Source: Compiled by author from SPSS (2017) results

The specific clusters that were not significantly different from each other at either the five per cent or ten per cent confidence levels were cluster two and cluster three, as well as cluster four and cluster five. The link between cluster two and cluster three may be attributed to the fact that the CBOT-C price (cluster three) forms part of the calculation of parity prices, especially EP (cluster two) (Chapter 5, Section 5.2.1.2, Table 5.1). Also, the link between cluster four and cluster five may be attributed to the fact that supply, which forms part of cluster five, forms part of the calculations for both ending stock and days' stock in cluster four (Chapter 5, Section 5.2.1.4). Yet the dependencies between these clusters did not influence or diminish the logical result obtained from the five-cluster analysis; this confirms the ANOVA result that the five clusters were significantly different when comparing their impact on the July white maize futures contract price.

The applicability of and intuitive link between the factors included in the specific clusters containing more than one factor becomes apparent when considering the influence of the USD/ZAR on EP in cluster two, since the USD/ZAR is an important determinant of the EP calculation (Auret & Schmitt, 2008:108, Geyser, 2013:16). Also, the pairing of CBOT-C, WM-C, and demand in cluster three may also be linked to the finding by Van Wyk (2012:67-68) that there is a spill-over from the US contract price formation to price formation on the South African market. This price formation in the South African market furthermore occurs in the spot or WM-C contract, which is predominantly demand-driven, since stock availability is more certain in cash contract months than in futures months. As a result, role-players react to the current and expected future availability of white maize in the cash months to ensure procurement if stock levels are or may become low. This action results in an increase in demand, which is reflected in the WM-C with the resulting consequence that price formation in the futures contract months respond accordingly (McCullough, 2010:120). The linkage in cluster four is also clear, since both ending stock and days' stock provides a measure of stock availability at a specific point in time. Lastly, cluster five also has a logical linkage, since the state of SOI does have an influence on expected production as explained in Chapter 5 (Section 5.2.1.5).

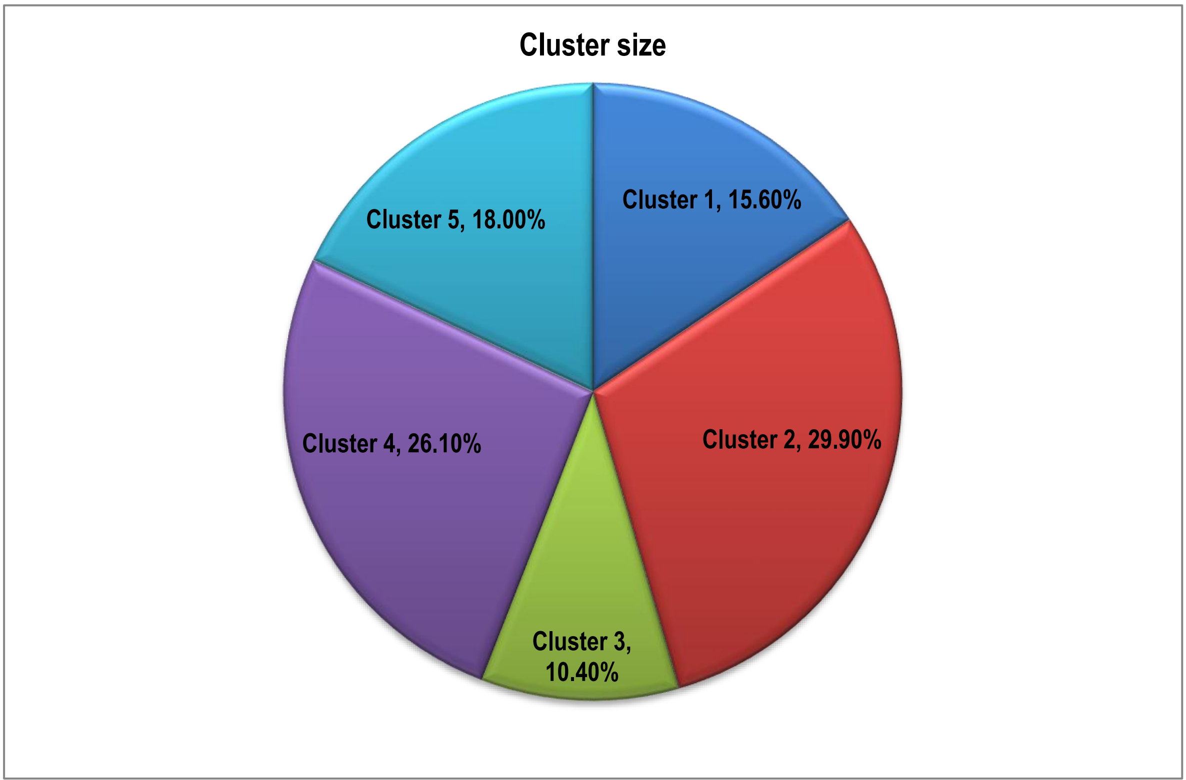


Figure 6.9: Two-Step Cluster analysis – five clusters
Source: Compiled by author from SPSS (2017) results

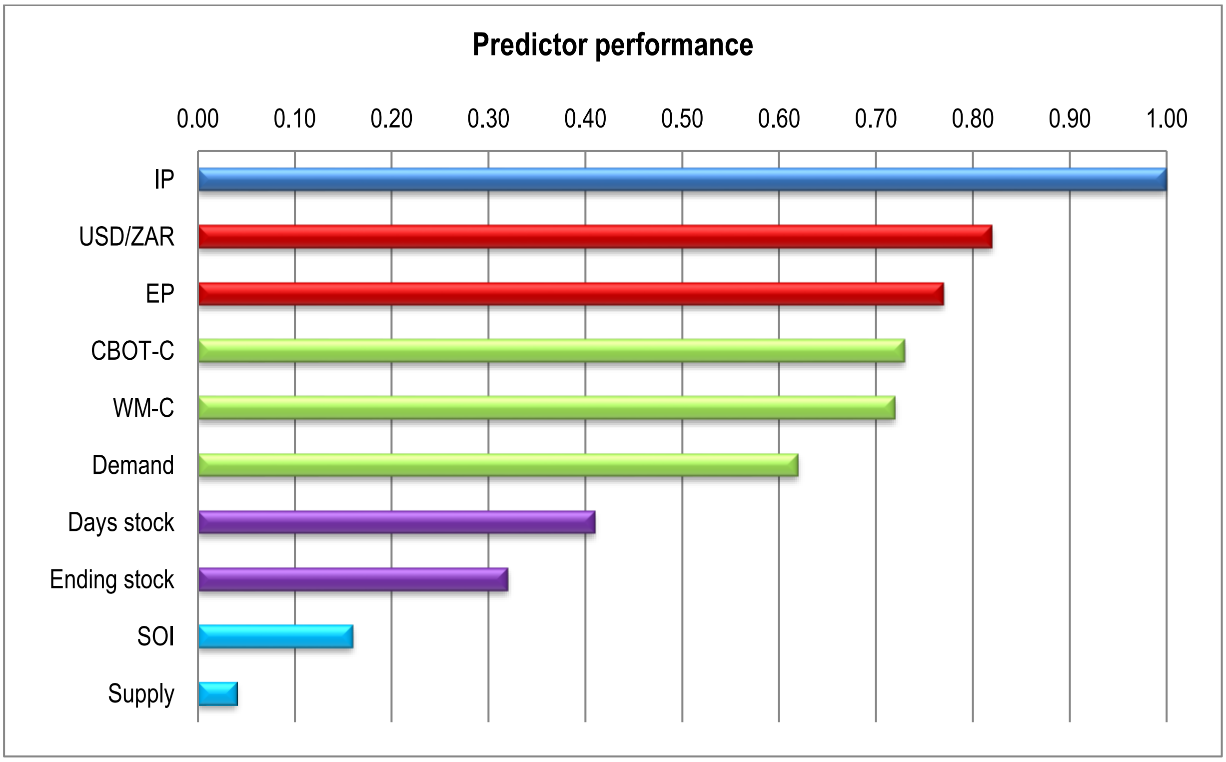


Figure 6.9: Two-Step Cluster analysis – five clusters (continued)
Source: Compiled by author from SPSS (2017) results

All of the factors in the dominant cluster at a specific point in time (Table 6.11) could furthermore be logically linked to the percentile rank grouping values of the relevant factors for the same time period. Cluster one, which includes IP as a factor, was dominant from the end of the 2014/2015 production year up to the end of the 2016/2017 production year. A comparison of Table 6.3a – which includes the percentile rank grouping values of IP – with Table 6.11 below does show that import parity (IP) in itself was high from the end of the 2014/2015 production year up to the end of the 2016/2017 production year.

Table 6.11: Two-Step Cluster analysis – Five-cluster analysis dominant monthly cluster

Year	August	September	October	November	December	January	February	March	April	May	June	July
2002/2003	4	4	4	4	4	5	5	5	5	5	4	4
2003/2004	4	4	4	4	4	4	5	5	5	5	4	4
2004/2005	4	4	4	4	4	4	4	5	5	5	4	4
2005/2006	4	4	4	4	4	4	4	5	5	5	5	4
2006/2007	4	4	4	4	4	5	2	2	5	2	4	4
2007/2008	4	4	5	2	2	2	2	2	2	2	2	2
2008/2009	2	2	2	2	2	2	2	2	5	2	4	4
2009/2010	4	4	4	4	4	4	5	5	5	2	4	4
2010/2011	2	2	2	2	2	2	2	2	2	2	2	2
2011/2012	2	2	2	2	2	2	2	2	2	2	2	2
2012/2013	2	2	2	2	2	2	2	2	2	2	2	2
2013/2014	2	2	2	2	1	1	1	1	1	3	3	3
2014/2015	3	3	3	3	3	3	1	1	1	1	1	1
2015/2016	1	1	1	1	1	1	1	1	1	1	1	1
2016/2017	1	1	1	1	1	1	1	1	1	1	3	3
2017/2018	3	3	3	3	3	3	3	3	3	3	3	3

Source: Compiled by author from SPSS (2017) results.

The percentile rank grouping values for IP actually remained high for longer than cluster one remained dominant, since cluster three became dominant from the end of the 2016/2017 production year, while IP remained high. The relevance of the change from cluster one to cluster three at the end of 2016/2017 is a logical progression, since cash market prices in the form of WM-C (Table 6.2) percentile rank grouping values moved from high levels to low levels during the second half of the 2016/2017 production year and cash prices remained low for the remainder of the 2017/2018 production year. CBOT-C (Table 6.5a), also in cluster three, was already at relatively low levels and remained at these levels throughout the 2017/2018 production year. The interaction between the factors in cluster three became more evident with demand (Table 6.6b) at relatively high levels from the end of the 2016/2017 production year throughout the 2017/2018 production year when market prices remained relatively low. The same progression between cluster one and cluster three was present at the end of 2013/2014. During this period, both CBOT-C and WM-C showed low percentile rank grouping values, while demand was high due to low market prices at the time. This result already shows that the factors in a cluster conforms with the percentile rank grouping values at either high or low values for the specific factors that form part of the cluster.

This initial finding becomes more relevant when considering the 2007/2008, 2010/2011, 2011/2012 and 2012/2013 production years when cluster two was dominant. In all of these production years and at other relevant time periods when cluster two was dominant, the percentile rank grouping values of EP (Table 6.4a) in particular was high. This could be explained by the high percentile rank grouping values for the USD/ZAR (Table 6.5b) in the corresponding years. This comparative result, based on cluster two and cluster three, shows that EP as a factor only becomes dominant when the percentile rank grouping values become high and not necessarily when market prices are trading closer to export parity (EP). Therefore, years with high EP percentile rank grouping values could be linked on the basis of this factor as well as the factors that influence EP, such as USD/ZAR. Consequently, production years during which prices tend to be closer to EP could be linked based on low CBOT-C and WM-C percentile rank grouping values coupled with relatively high levels of demand. The analysis and comparison based on the first three clusters as a result confirm that factors at either high or low levels tend to form the basis for the dominance of specific elements at a specific point in time.

The dominance of cluster four and cluster five (Table 6.11), which continued from the beginning of the 2002/2003 production year up to the second half of the 2006/2007 production year, may also be based on the high or low percentile rank grouping values of the factors in the clusters. Throughout the production years during which cluster four was dominant, both ending stock (Table 6.6c) and days' stock (Table 6.6d) started the production year at relatively high levels, but remained on these relatively higher levels for a longer period compared to other production years. However, each time cluster four was replaced by cluster five as dominant cluster at the end of these production years, ending stock began to decrease while supply (Table 6.6a) began to increase during the harvest window. The one factor that could not necessarily be linked to the percentile rank grouping values by means of cluster analysis, was SOI (Table 6.7). The reason may be that SOI generally acts as predictive measure of seasonal supply expectations (pre-seasonal factor); hence, the market would have already begun to respond to the anticipated impact of SOI on other fundamental aspects, such as ending stock.

Apart from this general analysis of the relevance of cluster analysis in determining the factors that tend to be more influential at specific points in time, several other conclusions may also be drawn. The most basic conclusion is the confirmation of the percentile rank grouping analysis result showing that dominant factors tend to change within a specific production year and also over time. The general cluster analysis result – reiterated in the results of the three-cluster and five-cluster analyses – further served to illustrate that specific fundamental factors such as supply, ending stock, and days' stock were elements that were included in the dominant factors in most cluster analysis alternatives, but only until the 2009/2010 production year. Thereafter, the other factors in the form of IP, EP, USD/ZAR, WM-C, CBOT-C, and demand became the dominant factors that formed part of the dominant clusters.

Several reasons may be provided for this general progression of dominant factors over time, but it seems that it may be connected to the premise of the Adaptive Market Hypothesis (AMH) (Chapter 3, Section 3.2.6). Consequently, the specific change in influential factor dominance may be attributed to the notion that the market will always seek to adapt to changing conditions in an attempt to exploit possible market opportunities, which inevitably leads to more efficient price formation (Lo, 2004:23). It is possible that, as the market mechanism developed over time, price formation became more mature and fundamental price reactions (e.g. due to expectations of over or under-supply) were reflected in other representative features in IP, EP, USD/ZAR, WM-C, CBOT-C, and demand, to suitably adjust prices. South African white maize market role-players are therefore becoming more and more experienced due to the lessons learned in past production years. As a result, it seems that role-players are no longer considering fundamental factors in isolation, but have progressed to a level of market analysis which predominantly considers the influence of other factors such as WM-C, USD/ZAR, and CBOT-C on price formation at extreme levels closer to IP and EP that inevitably incorporates supply and demand expectations.

To conclude – the cluster analysis approach provides the means to determine which factors are dominant at a specific point in time. The specific five-cluster result provided the most relevant alternative based on the logical linkage between the factors that were grouped in each of the five clusters, as well as to the percentile rank grouping analysis results obtained in Section 6.2.1. The logical connection between the cluster analysis result and percentile rank grouping results furthermore provided the required synergy between the two methods to identify similarities between production seasons in order to link different production years based on these similarities. This synergy is visually and practically illustrated by the filter model in Section 6.4 below. The essence of the synergy is in the percentile ranking approach which provides a meaningful comparison of all factors at a specific point in time in order to identify similarities between production years; the cluster analysis approach identifies the dominant factors to base the comparison on. Furthermore, each production year was characterised by specific market factors and associated trends (Section 6.2). The next step in the process is to identify the hedging strategies that performed better in each of the production years. The results obtained up to this point also showed that influential factors tend to change over the course of a production year and the interaction between these elements change over time. This conformation supports the premise that an optimal hedging strategy should be able to adjust to changing market conditions as a production year progresses (Lapan & Moschini, 1994:476).

6.3 Hedging strategy results

Each of the hedging strategies included in the results were discussed and the implementation explained in Chapter 5 (Section 5.4.2). Table 6.12 below contains a summary of the strategies and their implementation to resolve any remaining confusion about the specific strategies, since the results only refer to Strategy 1 up to Strategy 10 without further clarification. In addition, the results are presented on the basis of different comparisons to facilitate interpretation of the hedging strategy rankings.

Table 6.12: Hedging strategy summary

Strategy number	Strategy name	Short description
Strategy 1	Benchmark strategy	Sell all produce during the harvest month of July.
Strategy 2	Minimum price strategy	Buy minimum prices (put options) for all expected produce during the planting window.
Strategy 3	Minimum / Maximum price (collar) strategy	Buy a put option and sell a call option for all expected produce during the planting window.
Strategy 4	Three-segment strategy	Sell produce in three equal segments by means of short futures contracts at specific time frames throughout the production year.
Strategy 5	Twelve-segment strategy	Sell produce in 12 equal segments or three-week intervals from planting to harvest by means of short futures contracts.
Strategy 6	Actively managed put option strategy	Buy minimum prices (put options) for all expected produce during the planting window. Actively manage the minimum prices based on the strategy specifications to increase the realised hedge level and to reduce option cost.
Strategy 7	Out-of-the-money July contract actively managed synthetic minimum price strategy	Sell all produce by means of July short futures contracts during the planting window, but also purchase out-of-the-money call options against the July futures contract for every short futures contract. Based on the strategy specifications of Strategy 6, but differs in the sense that the out-of-the-money July call options are actively managed.
Strategy 8	At-the-money March contract actively managed synthetic minimum price strategy	Sell all produce by means of July short futures contracts during the planting window, but also purchase at-of-the-money call options against the March futures contract for every short futures contract. Based on the strategy specifications of Strategy 6, but differs in the sense that the at-of-the-money March call options are actively managed.
Strategy 9	Three-way options-based strategy	An extension of the minimum / maximum price option-based strategy included as Strategy 3. The strategy adds an additional short put option contract below long put option in the minimum / maximum strategy to reduce option cost even more.
Strategy 10	Hedging based on technical analysis	The sell signals generated by means of the composite indicator are used as a timing tool to hedge (sell) expected produce by means of short futures contracts.

Source: Compiled by author

The first comparison (Section 6.3.1) is based on the realised strategy prices against the average July white maize futures contract price over the same time period. These first set of comparisons enables a comparison of the strategy results against existing literature and also enables the identification of a more optimal hedging strategy over the longer term. The second set of comparisons (Section 6.3.2) are based on the performance measure ranking consensus as explained in Chapter 5 (Section 5.5.2, Table 5.14), to derive more evidence for establishing the optimal hedging strategy for each production year.

6.3.1 Hedging strategy results comparison to the average July white maize futures contract price

The first step in this analysis is to calculate the average July white maize futures contract price (average of the marked-to-market price for each trading day) for the time period from strategy implementation during the last two trading weeks in November up to the relevant trading day (day after option expiration) for the corresponding July white maize futures contract. Then, the realised strategy price is compared with the average July white maize futures contract price to evaluate if the strategy was able to at least outperform the average main hedging contract price during the production year. The realised strategy price is the final strategy SAFEX price minus the net-option cost applicable. The realised strategy price, therefore, provides the means to compare all the strategies on the same basis after hedging costs, since some strategies include option cost while others apply no such cost.

As a result, strategies may be ranked based on the outperformance/underperformance of the average July white maize futures contract price. Table 6.13 below provides an example of this calculation for the 2015/2016 production year when market prices increased significantly (Figure 6.10), as well as the 2016/2017 production year when market prices declined significantly (Figure 6.11). (Other production year results in this regard are included as part of the Appendix in the form of Table A2). Table 6.14 below provides a summary of the results of this comparison for all 10 strategies and 16 production years.

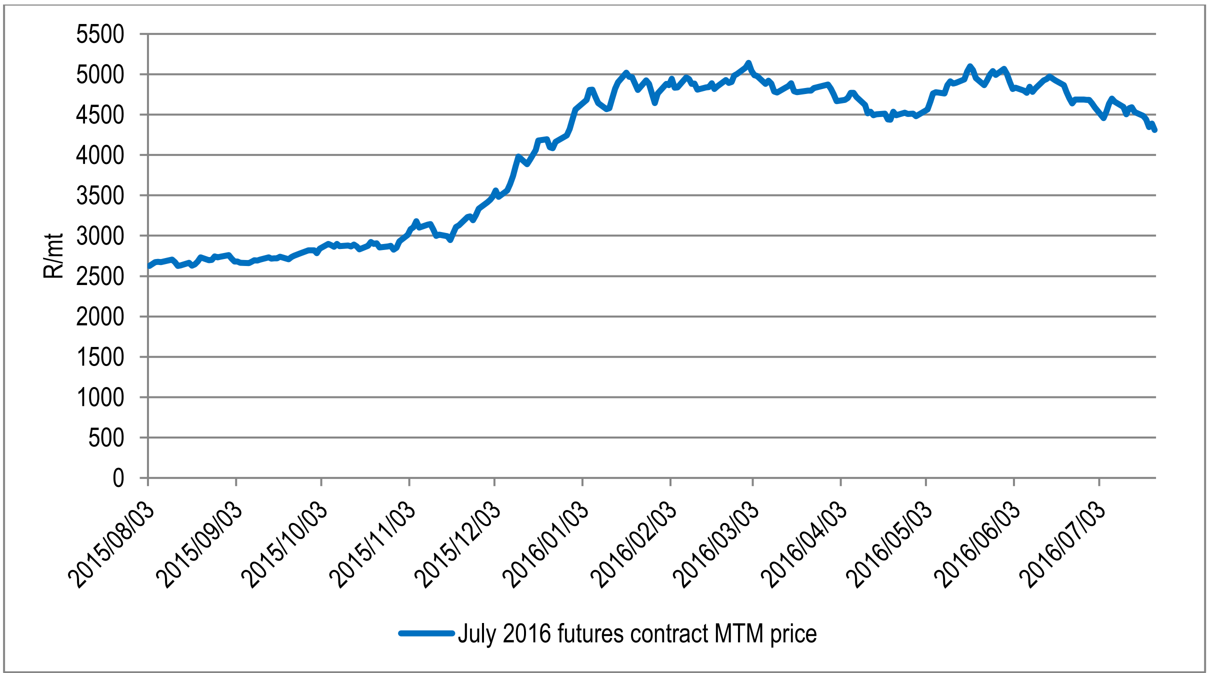


Figure 6.10: July 2016 (2015/2016 production year) futures contract price
Source: Compiled by author from Thomson Reuters Eikon for commodities data

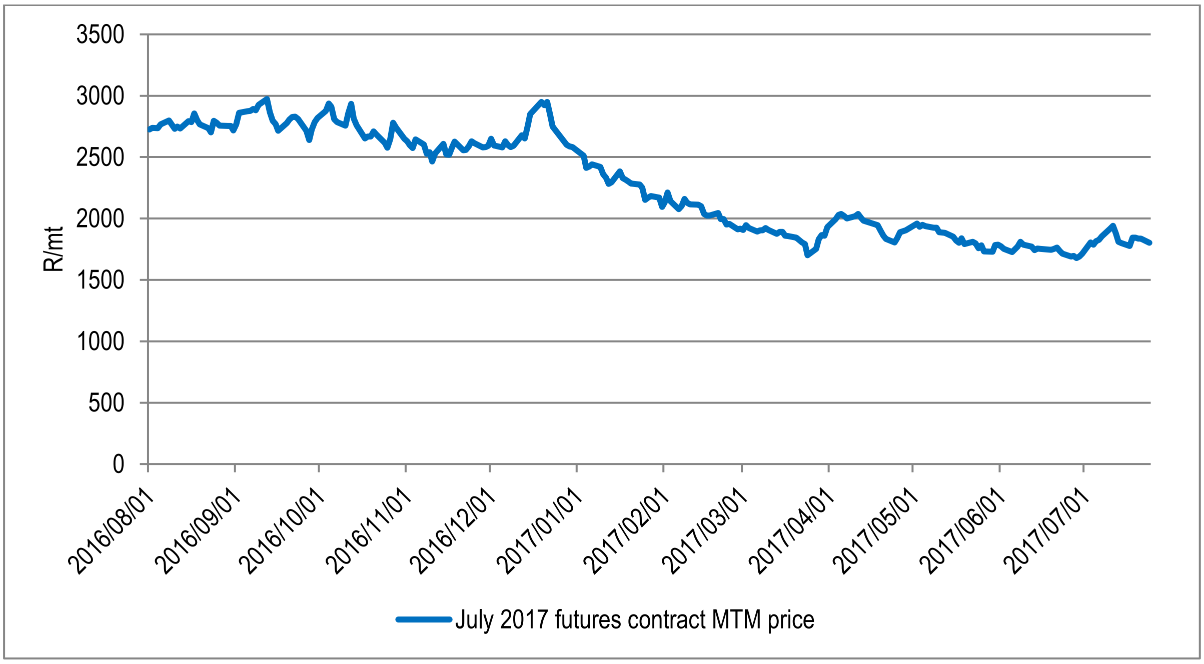


Figure 6.11: July 2017 (2016/2017 production year) futures contract price
Source: Compiled by author from Thomson Reuters Eikon for commodities data

Table 6.13: Hedging strategy results comparison to average July futures contract MTM price

2015/2016 Production year hedging strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July 2016 futures MTM price	A minus B
2016:Strategy 10	R 4 827.72	n/a	R 4 827.72	R 4 579.32	R 248.39
2016:Strategy 1	R 4 552.15	n/a	R 4 552.15	R 4 579.32	-R 27.17
2016:Strategy 5	R 4 477.38	n/a	R 4 477.38	R 4 579.32	-R 101.94
2016:Strategy 6	R 4 683.00	R 306.95	R 4 376.05	R 4 579.32	-R 203.28
2016:Strategy 2	R 4 672.75	R 322.48	R 4 350.27	R 4 579.32	-R 229.05
2016:Strategy 4	R 4 220.75	n/a	R 4 220.75	R 4 579.32	-R 358.57
2016:Strategy 8	R 3 187.20	-R 796.60	R 3 983.80	R 4 579.32	-R 595.52
2016:Strategy 7	R 3 187.20	-R 767.72	R 3 954.92	R 4 579.32	-R 624.40
2016:Strategy 9	R 3 620.00	R 18.37	R 3 601.63	R 4 579.32	-R 977.69
2016:Strategy 3	R 3 680.00	R 164.16	R 3 515.84	R 4 579.32	-R 1 063.48

2016/2017 Production year hedging strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July 2017 futures MTM price	A minus B
2017:Strategy 3	R 2 600.00	R 151.18	R 2 448.82	R 2 068.05	R 380.77
2017:Strategy 7	R 2 590.70	R 150.05	R 2 440.65	R 2 068.05	R 372.60
2017:Strategy 6	R 2 614.82	R 285.11	R 2 329.72	R 2 068.05	R 261.66
2017:Strategy 2	R 2 600.00	R 301.22	R 2 298.78	R 2 068.05	R 230.72
2017:Strategy 8	R 2 590.70	R 307.53	R 2 283.17	R 2 068.05	R 215.12
2017:Strategy 5	R 2 164.60	n/a	R 2 164.60	R 2 068.05	R 96.55
2017:Strategy 4	R 2 099.74	n/a	R 2 099.74	R 2 068.05	R 31.68
2017:Strategy 9	R 1 693.40	-R 366.96	R 2 060.36	R 2 068.05	-R 7.69
2017:Strategy 10	R 1 861.87	n/a	R 1 861.87	R 2 068.05	-R 206.18
2017:Strategy 1	R 1 801.81	n/a	R 1 801.81	R 2 068.05	-R 266.24

Source: Compiled by author

Based on the results of this specific comparison presented in Table 6.13, it is clear that Strategy 10 was able to outperform the average July 2016 futures contract price by the highest margin of R248.39/mt (Rand per metric tonne) compared to Strategy 1, which realised the second best result but underperformed in terms of the July 2016 futures contract price by R27.17/mt. Similarly, Strategy 3 was the more optimal strategy to deploy in the 2016/2017 production year, since it outperformed the average July 2017 futures price by R380.77/mt. The ranking of strategies in this manner was conducted for each production year, which enabled the compilation of a summary in Table 6.14 that shows the strategy ranking from highest (greatest outperformance of July futures contract average price) to lowest (smallest outperformance of July futures contract average price).

The results reported in Table 6.14 shows that there is not one specific strategy which could be seen as dominant over the course of the 16 production years. The result does however become clearer if the price development for the different seasons is divided into three categories. In the first category, prices gradually increased throughout the production year (upwards price movement); in the second, prices gradually decreased throughout the production year (downward price movement); in the third, prices moved a sideways. A sideways market implies that the price level at the end of the production year does not differ significantly from the price level at the beginning of the production year when hedging was implemented. The division of the July white maize futures contract price formation in this manner is shown in Figure 6.12 (upward price movement; marked with green in Table 6.14), Figure 6.13 (downward price movement; marked with yellow in Table 6.14) and Figure 6.14 (sideways price movement; marked with blue in Table 6.14).

Table 6.14: Hedging strategy rank comparison based on average July white maize futures contract price for each production year

Strategy rank	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
1	Strat 7	Strat 10	Strat 3	Strat 1	Strat 10	Strat 1	Strat 7	Strat 7	Strat 1	Strat 1	Strat 9	Strat 8	Strat 1	Strat 10	Strat 3	Strat 9
2	Strat 3	Strat 8	Strat 7	Strat 2	Strat 1	Strat 2	Strat 3	Strat 3	Strat 4	Strat 9	Strat 4	Strat 5	Strat 2	Strat 1	Strat 7	Strat 4
3	Strat 8	Strat 5	Strat 8	Strat 10	Strat 4	Strat 4	Strat 8	Strat 8	Strat 10	Strat 4	Strat 7	Strat 9	Strat 4	Strat 5	Strat 6	Strat 1
4	Strat 6	Strat 6	Strat 2	Strat 9	Strat 5	Strat 9	Strat 9	Strat 10	Strat 2	Strat 5	Strat 3	Strat 6	Strat 6	Strat 6	Strat 2	Strat 5
5	Strat 2	Strat 7	Strat 6	Strat 4	Strat 6	Strat 5	Strat 6	Strat 6	Strat 9	Strat 3	Strat 1	Strat 7	Strat 5	Strat 2	Strat 8	Strat 10
6	Strat 10	Strat 4	Strat 9	Strat 3	Strat 2	Strat 6	Strat 2	Strat 2	Strat 5	Strat 2	Strat 8	Strat 3	Strat 7	Strat 4	Strat 5	Strat 7
7	Strat 4	Strat 9	Strat 4	Strat 5	Strat 9	Strat 3	Strat 5	Strat 5	Strat 6	Strat 10	Strat 6	Strat 4	Strat 9	Strat 8	Strat 4	Strat 3
8	Strat 5	Strat 3	Strat 5	Strat 6	Strat 3	Strat 10	Strat 4	Strat 4	Strat 3	Strat 6	Strat 2	Strat 2	Strat 8	Strat 7	Strat 9	Strat 8
9	Strat 9	Strat 1	Strat 1	Strat 7	Strat 7	Strat 7	Strat 1	Strat 9	Strat 8	Strat 7	Strat 5	Strat 1	Strat 3	Strat 9	Strat 10	Strat 6
10	Strat 1	Strat 2	Strat 10	Strat 8	Strat 8	Strat 8	Strat 10	Strat 1	Strat 7	Strat 8	Strat 10	Strat 10	Strat 10	Strat 3	Strat 1	Strat 2

Source: Compiled by author

Note: “Strat” refers to Strategy.

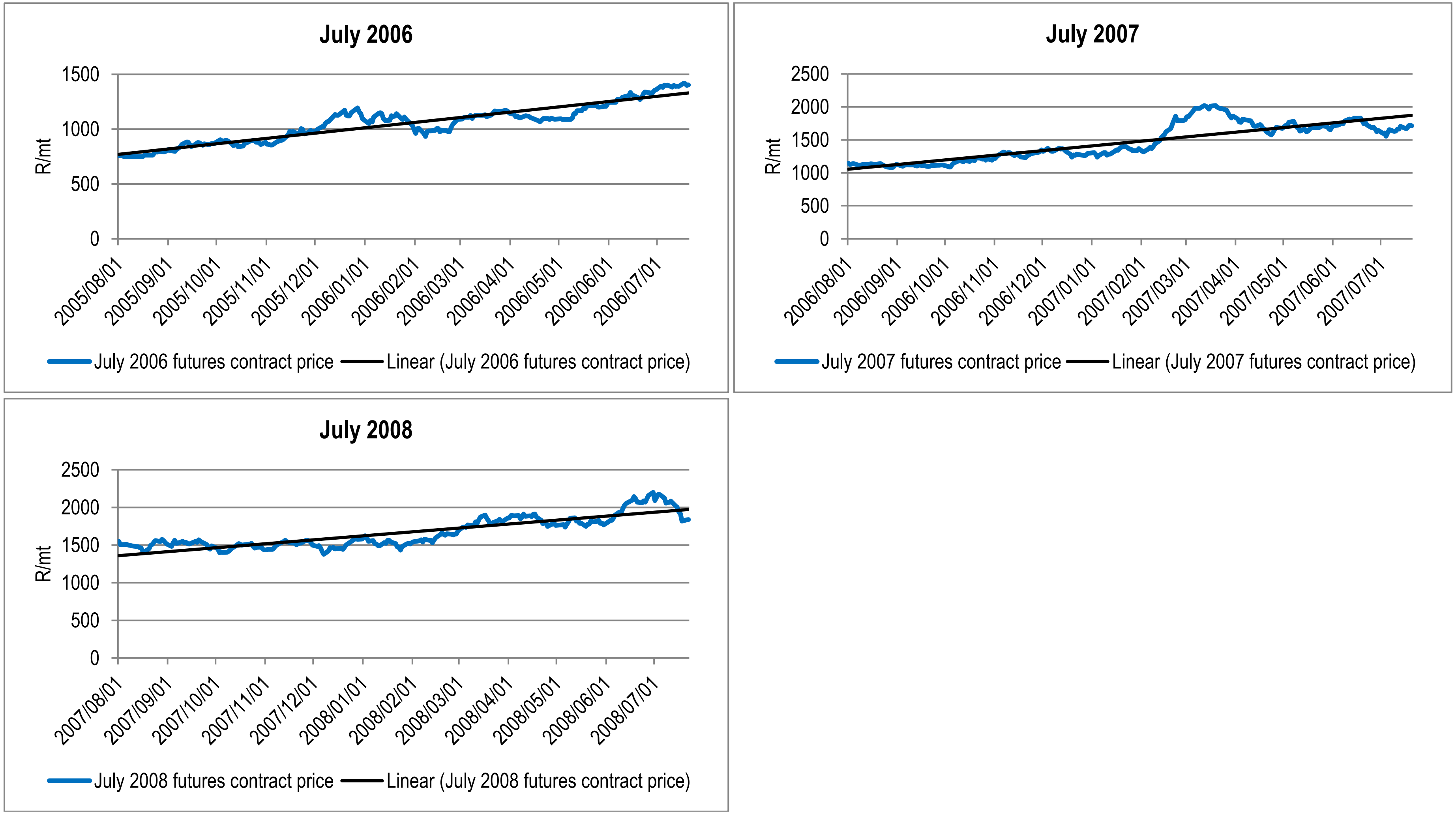


Figure 6.12: Production years when the July white maize futures contract showed an upward price movement
Source: Compiled by author from Thomson Reuters Eikon for commodities data

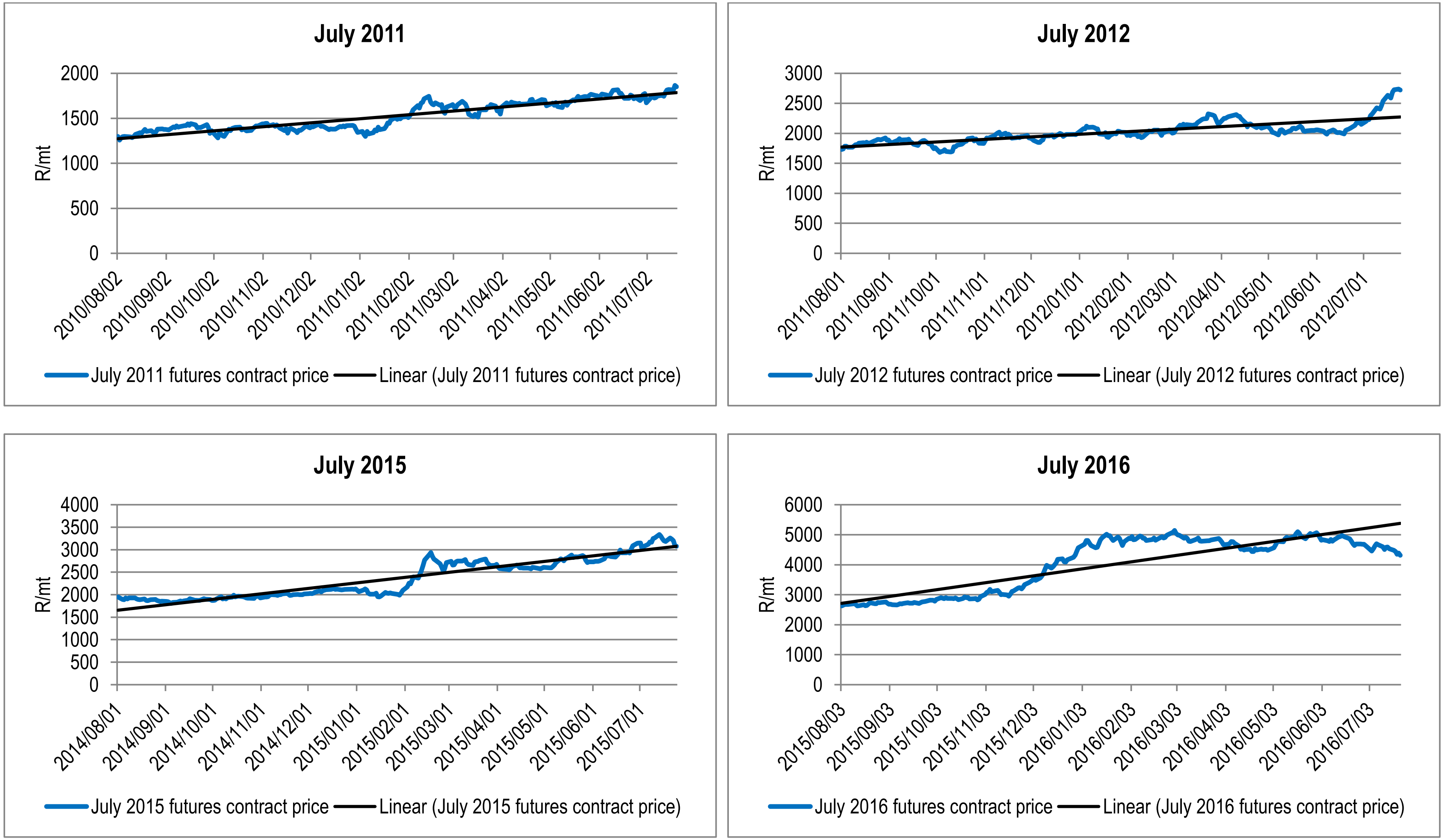


Figure 6.12 (continued): ***Production years when the July white maize futures contract showed an upward price movement***
Source: Compiled by author from Thomson Reuters Eikon for commodities data

When considering the seasons in which prices portrayed an upward price movement (2006, 2007, 2008, 2011, 2012 and 2016) (Figure 6.12), the dominant strategies are Strategy 1 and Strategy 10. The result may be interpreted as being logical, since Strategy 1 is the best option if prices increase throughout a production year and a producer is able to sell all produce when the market price is high during the harvest window without incurring any option cost. The risk of remaining un-hedged until harvest, based on the expectation that prices may increase, is not accounted for in this result, but is addressed in the explanation following Table 6.15 below. Also, given that Strategy 10 is implemented by means of three sell signals throughout a production year without incurring any option cost, and as the composite technical indicator implemented in this strategy (Chapter 5, Section 5.4.2.10) is able to account for a trending market, it is to be expected that the strategy may also yield a favourable result.

In contrast to the upward price movement result, Strategy 3, Strategy 7 and Strategy 8 reigned supreme in seasons where prices declined throughout the production year (2003, 2005, 2009, 2010, 2014, 2017) (Figure 6.13). All three of these strategies established a hedge during the planting window, but aimed to reduce option cost. As a result, a downward movement in prices is hedged by means of strategy implementation during the planting window before the crop is planted. None of the other strategies implement a hedge in this manner without incurring a greater hedging cost in the form of option cost. The only other way to improve upon these strategies is to hedge all produce during the planting window by means of short futures contracts. However, the added risk of a short futures contract is that the effect of a midsummer drought on yield potential may be so severe that a producer would not be able to deliver against the short futures contracts and, as a result, may incur costly contract buy-outs. The effect of a traditional midsummer drought becomes clear when the sudden increase in price during December to January is observed for the July contracts of 2003, 2005, 2010, 2014 and 2017 in Figure 6.13 below. In these instances, and from a risk management perspective, it would have been preferable to implement either Strategy 7 or Strategy 8, which are able to account for further unforeseen price increases. The risk of not being able to take part in a upward market price movement, as is the case with Strategy 3, becomes evident when one considers the standard deviation in the under or outperformance of the average July white maize futures contract price over time, as reported in Table 6.15.

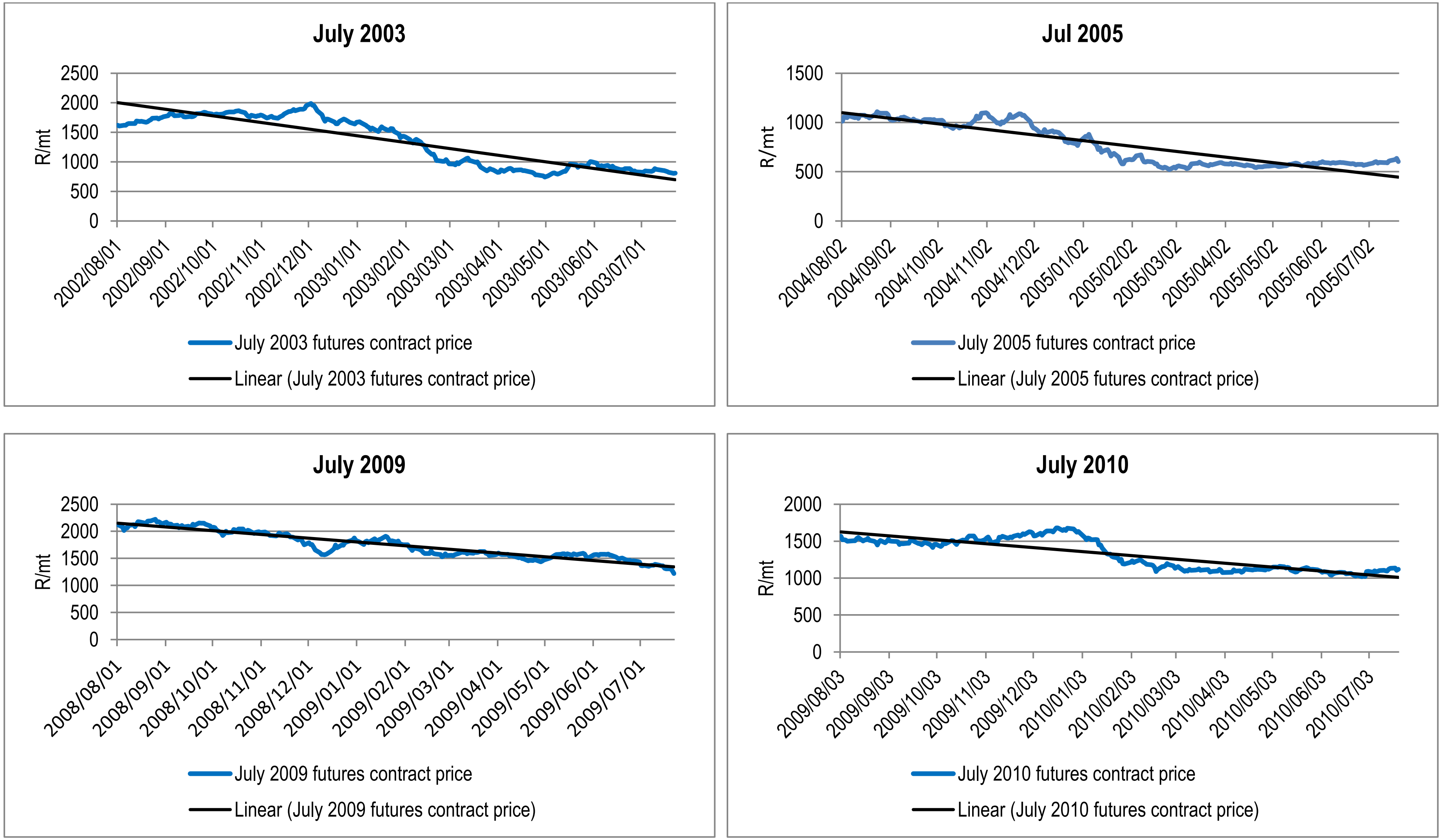
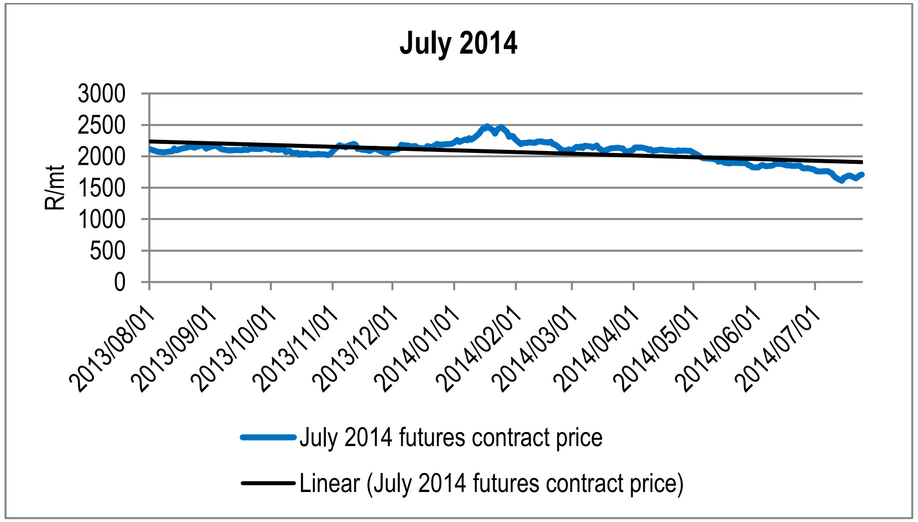


Figure 6.13: Production years when the July white maize futures contract showed a downward price movement
Source: Compiled by the author from Thomson Reuters Eikon for commodities data.



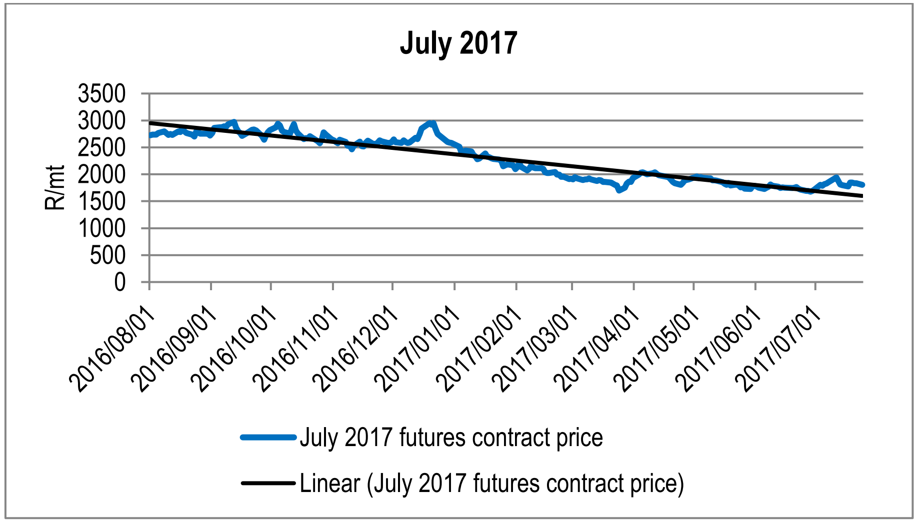
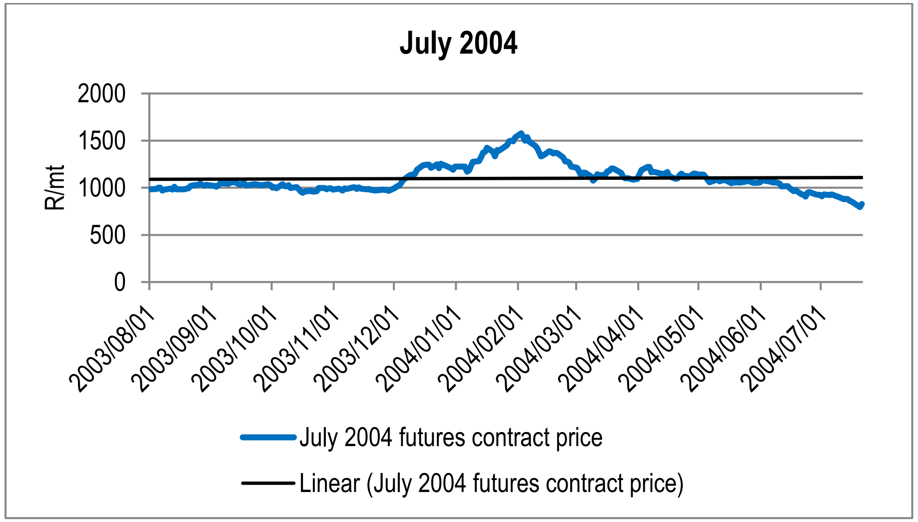
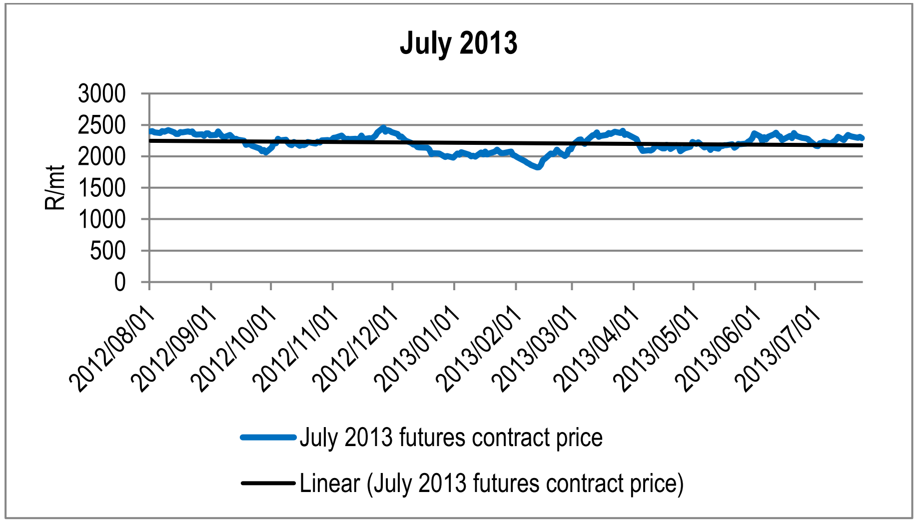


Figure 6.13 (continued): Production years when the July white maize futures contract showed a downward price movement
Source: Compiled by the author from Thomson Reuters Eikon for commodities data.

The final scenario is when prices tend to remain range bound or trade sideways for the production year, as shown in Figure 6.14 below. In these instances one would benefit most from a strategy that provides a hedge to account for unforeseen circumstances, but reduces option cost to the bare minimum. Alternatively, a strategy that is able to identify short-term price increases as hedging opportunities would be helpful. When considering the results obtained from Table 6.14 as well as the development of the 2004, 2013 and 2018 July white maize futures contract prices in Figure 6.14 below, it becomes evident that Strategy 10 and Strategy 9 would be the more optimal strategies to consider during seasons characterised by a sideways market. Yet again, the result may be seen as logical, since Strategy 10 is able to identify more optimal hedging opportunities by means of technical sell signals without incurring any option cost and Strategy 9 reduces option cost to the minimum. However, as with the more optimal strategies to be deployed during an upward or downward price movement scenario, the optimal strategies in a sideways price movement scenario do not account for the risk of deploying the same strategy over time, regardless of the type of season that materialised. The result of deploying these strategies over time, as well as a measure of risk, is reported in Table 6.15 below.





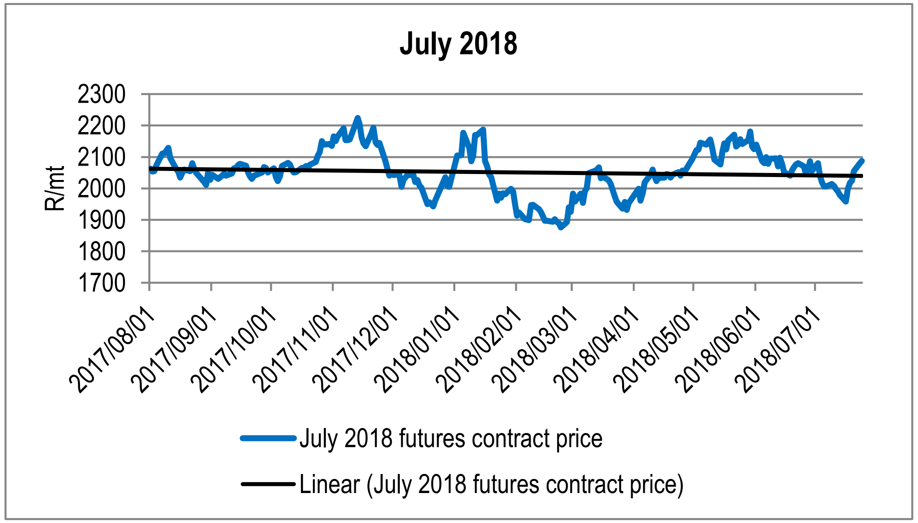


Figure 6.14: Production years when the July white maize futures contract showed a sideways price movement
Source: Compiled by the author from Thomson Reuters Eikon for commodities data.

Table 6.15: Realised strategy price comparison to average July white maize futures contract price over time

July futures contract	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2003	-R 321.38	R 544.04	R 631.17	R 81.22	R 9.58	R 550.15	R 635.44	R 621.58	-R 97.26	R 81.59
2004	-R 245.54	-R 279.74	-R 222.65	-R 136.61	R 19.40	-R 87.47	-R 135.08	R 26.30	-R 170.88	R 32.63
2005	-R 66.93	R 239.21	R 321.00	R 73.04	R 45.99	R 239.21	R 309.89	R 283.98	R 102.60	-R 76.50
2006	R 238.74	R 49.44	-R 17.27	R 14.47	-R 31.32	-R 107.47	-R 211.38	-R 236.35	R 21.78	R 42.20
2007	R 55.61	-R 104.29	-R 140.27	R 32.86	-R 30.14	-R 72.44	-R 218.13	-R 342.22	-R 105.97	R 110.99
2008	R 300.85	R 236.06	-R 80.06	R 43.21	-R 41.74	-R 66.35	-R 195.83	-R 324.28	-R 13.60	-R 113.47
2009	-R 245.94	R 62.36	R 156.28	-R 2.60	R 41.72	R 68.40	R 165.29	R 126.23	R 85.37	-R 245.94
2010	-R 151.72	R 153.60	R 244.17	R 23.79	R 57.02	R 179.98	R 246.72	R 220.70	R 19.62	R 209.49
2011	R 168.63	-R 9.22	-R 90.39	-R 8.03	-R 36.21	-R 85.26	-R 223.21	-R 219.14	-R 28.47	-R 8.99
2012	R 327.62	-R 113.91	-R 19.99	R 61.14	-R 11.48	-R 150.75	-R 244.99	-R 248.21	R 63.85	-R 141.57
2013	R 80.42	-R 9.40	R 84.56	R 120.19	-R 29.40	R 22.86	R 90.48	R 47.22	R 167.99	-R 57.34
2014	-R 334.93	-R 149.06	-R 64.80	-R 72.15	R 26.28	-R 35.99	-R 47.06	R 306.45	-R 24.66	-R 334.93
2015	R 593.07	R 347.68	-R 420.55	R 62.65	-R 134.05	-R 128.84	-R 204.15	-R 395.12	-R 362.22	-R 485.05
2016	-R 27.17	-R 229.05	-R 1 063.48	-R 358.57	-R 101.94	-R 203.28	-R 624.40	-R 595.52	-R 977.69	R 248.39
2017	-R 266.24	R 230.72	R 380.77	R 31.68	R 96.55	R 261.66	R 372.60	R 215.12	-R 7.69	-R 206.18
2018	-R 8.70	-R 128.17	-R 24.78	R 14.17	-R 9.66	-R 82.68	-R 24.69	-R 71.17	R 67.12	-R 10.73
High	R 593.07	R 544.04	R 631.17	R 120.19	R 96.55	R 550.15	R 635.44	R 621.58	R 167.99	R 248.39
Low	-R 334.93	-R 279.74	-R 1 063.48	-R 358.57	-R 134.05	-R 203.28	-R 624.40	-R 595.52	-R 977.69	-R 485.05
Average under or outperformance (A)*	R 6.02	R 52.52	-R 20.39	-R 1.22	-R 8.09	R 18.86	-R 19.28	-R 36.53	-R 78.76	-R 59.71
Standard deviation (B)**	R 268.26	R 225.42	R 376.66	R 112.98	R 58.27	R 197.51	R 307.91	R 322.18	R 270.17	R 193.74
Return per unit of risk (A/B)	2.25%	23.30%	-5.41%	-1.08%	-13.88%	9.55%	-6.26%	-11.34%	-29.15%	-30.82%

Source: Compiled by author

Note: * Refers to the average under or outperformance of the average July white maize futures contract from 2003 to 2018 for each strategy.

**Refers to the standard deviation of the under or outperformance of the average July white maize futures contract from 2003 to 2018 for each strategy.

Overall, Table 6.15 provides a summary of each strategy's under or outperformance of the average July white maize futures contract price over the corresponding strategy implementation period for each production year considered. These results make it possible to calculate the average under or outperformance, as well as the standard deviation of the under or outperformance over time.

Based on the results reported in Table 6.15 (highlighted in green), Strategy 5 realised the smallest standard deviation of R58.27/mt around the corresponding average July white maize futures contract MTM prices over time. Since this strategy is implemented by means of 12 equally spaced hedging intervals throughout the production year. The average strategy hedge level remains closest to the average July white maize futures contract MTM price and therefore logically yields the smallest standard deviation.

In terms of average under or outperformance (average returns of strategy) of the July white maize futures contract MTM price, Strategy 2 was the favourable strategy over time and realised an average outperformance of R52.52/mt over the 16 production years considered. This result confirmed the findings of Strydom *et al*. (2010:10) and Venter *et al*. (2012:9) that the implementation of a minimum price or put option strategy results in the highest mean price over time. The result is furthermore confirmed by the fact that Strategy 6, which only differs in the sense that the strategy deploys an actively managed put option strategy, realised the second highest average outperformance of R18.86/mt. None of these results however consider a measure similar to a risk-weighted return. Such a measure is included as part of Table 6.15 by dividing the average under or outperformance (i.e. average returns of the strategy) by the standard deviation of the average under or outperformance for each strategy over time.

This ratio effectively provides a measure of return per unit of risk. Based on this measure, Strategy 2 and Strategy 6 also reign supreme over time, leading to the conclusion that the deployment of a minimum price or actively managed minimum price strategy results in an outperformance of the average July white maize futures contract MTM price over time. This outperformance does however not confirm the profitability of a hedging strategy result, and more specifically does not provide a risk-adjusted performance comparison for each individual production year. It was with this potential shortcoming in mind that the study aimed to include an analysis of the returns (Chapter 5, Section 5.4.3) of each strategy for each production year by means of performance measures.

6.3.2 Hedging strategy results comparison by means of performance measures

The evaluation of hedging strategy return results by means of performance measures is one of the objectives of this study. The main reason for the inclusion of performance measure analysis as an alternative to objectively ranking hedging strategy performance was due to the fact that previous studies by Strydom *et al*. (2010) and Venter *et al*. (2012) were unable to conclusively rank hedging strategies by means of the methods they deployed. Their general end result was that a producer should decide on an appropriate hedging strategy that conforms with his/her risk profile. The evaluation of daily hedging strategy returns (daily realised strategy price minus the applicable direct input cost per production year) by means of performance measures proved to be a comprehensive task of interpreting and evaluating results to derive meaningful conclusions where relevant.

It was already stated in Chapter 4 (Section 4.1) that the application of performance measures to derivative-based hedging strategy returns may be a difficult and potentially inconclusive feat. One of the main concerns was that the performance measures included should be able to account for the presence of non-normality in order to avoid biased results (Amin & Kat, 2003:5; Van Heerden, 2015:210). These concerns were addressed by including several appropriate performance measures, since the evaluation of normality showed that returns were predominantly non-normal (Chapter 5, Section 5.2.3). The reality of non-normality in the return distribution of derivative-based option strategies (which is applicable to several of the hedging strategies deployed) was further emphasised by Mahdavi (2004:47). Results specifically showed that the returns of option-based strategies were characterised by low standard deviation, but large skewness. As a result, performance measures may overstate the performance (positive skewness) or understate the risk (negative skewness) due to the low standard deviation of the returns. Therefore, several advantages and potential shortcomings of performance measures should be evaluated and considered to reach an applicable conclusion. The results presented below aim to provide a comprehensive review as to the applicability of performance measures in this regard.

The more prominent and pertinent performance measures – as identified from literature and included in Chapter 5 (Section 5.5.2, Table 5.13) – were applied to the relevant return data for each of the 10 hedging strategies for each individual production year. A performance measure ranking consensus table was constructed for each individual production year as explained by means of Table 5.14 (Chapter 5, Section 5.5.2). An example of the results for the first three production years, which included the three types of July white maize future contract price developments (downward, sideways and upward), is presented in Table 6.16, Table 6.17 and Table 6.18 below (the rest of the results in this regard are included in the Appendix as Table A3). The results for each relevant production year are accompanied by the specific season's result in terms of strategy outperformance of the average July white maize futures contract price, as explained by Table 6.15 above.

Table 6.16: 2002/2003 Production year performance measure ranking consensus

Performance measure	2003: Strategy 1	2003: Strategy 2	2003: Strategy 3	2003: Strategy 4	2003: Strategy 5	2003: Strategy 6	2003: Strategy 7	2003: Strategy 8	2003: Strategy 9	2003: Strategy 10
Sharpe	7	4	6	10	8	1	5	2	3	9
Sortino	4	8	6	1	3	10	5	7	9	2
Calmar	9	5	3	10	8	6	2	4	7	1
Upside Potential	4	8	6	1	3	10	5	7	9	2
Kappa 3	7	4	6	10	8	1	5	2	3	9
VaR-Sharpe	4	7	5	1	3	10	6	9	8	2
CVaR-Sharpe	4	7	5	1	3	10	6	9	8	2
MVaR-Sharpe	4	7	5	1	3	10	6	8	9	2
Omega	4	8	6	1	3	10	5	7	9	2
Total ranking	47	58	48	36	42	68	45	55	65	31

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2003	-321.38	544.04	631.17	81.22	9.58	550.15	635.44	621.58	-97.26	81.59

Source: Compiled by author

Based on the results of the performance measure ranking consensus for the 2002/2003 production year presented in Table 6.15, the smallest cumulative ranking identifies Strategy 10 as the more optimal strategy from a risk-adjusted perspective. This strategy should have been deployed in the specific production year. Another way to evaluate the result may be to argue that Strategy 4 was identified as the highest ranking strategy (1st) by six out of the nine measures. But neither of the two results conform to the correct type of strategy to implement in production years when market prices decline. Neither the technical analysis strategy (Strategy 10) nor the three-segment strategy (Strategy 4) implements a minimum price or price floor (fixed price) to hedge against declining prices. Instead, they hedge as the season progresses, based on the strategy implementation procedure. Interestingly, both these strategies outperformed the average

July white maize futures contract price over the same period by nearly the same amount (see Table 6.15); but neither strategy was close to outperformance of the more optimal type of strategy to implement during a downward price movement in the form of Strategy 2, Strategy 3, Strategy 6, Strategy 7 and Strategy 8. As a result, the strategies identified by means of performance measures in this instance failed to connect to a logical conclusion. The same type of nonsensical result was found when evaluating the performance measure ranking of the 2003/2004 production year, which is reported in Table 6.17.

Table 6.17: 2003/2004 Production year performance measure ranking consensus

Performance measure	2004: Strategy 1	2004: Strategy 2	2004: Strategy 3	2004: Strategy 4	2004: Strategy 5	2004: Strategy 6	2004: Strategy 7	2004: Strategy 8	2004: Strategy 9	2004: Strategy 10
Sharpe	1	5	7	4	3	10	8	9	6	2
Sortino	3	9	8	6	5	10	1	2	7	4
Calmar	1	5	7	4	3	10	8	9	6	2
Upside Potential	3	9	8	6	5	10	1	2	7	4
Kappa 3	1	5	7	4	3	10	8	9	6	2
VaR-Sharpe	9	6	4	7	8	1	3	2	5	10
CVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
MVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
Omega	1	6	7	4	3	10	8	9	5	2
Total ranking	37	57	56	49	46	63	43	46	52	46

(Sideways July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2004	-245.54	-279.74	-222.65	-136.61	19.40	-87.47	-135.08	26.30	-170.88	32.63

Source: Compiled by author

Based on the smallest cumulative ranking value in Table 6.17 above, Strategy 1 should be the more optimal strategy to deploy in a production year when prices tend to trade sideways. But the outperformance of the average July white maize futures price results however show that Strategy 1 would have performed worse than most of the other strategies. The logical expectation would have been that Strategy 5 or Strategy 10 is more optimal in a sideways trading market, since their implementation tends to follow the market development and lead to an average hedge level closer to the average market price. Yet, when evaluating the results of the 2005/2006 production year – when the July white maize futures contract price followed an upward price movement (Table 6.18) – the result made more logical sense. Strategy 1 showed the smallest cumulative ranking and was identified as the more optimal strategy to deploy during the specific season when the July white maize futures contract price increased. The outperformance of the average July white maize futures price also confirmed that Strategy 1 performed best in terms of average outperformance (Table 6.15). However, the specific result identified in this instance was not confirmed for the rest of the production years when the July white maize futures price followed an upward price movement (see tables for upward July white maize futures contract price movement in Appendix as part of Table A3). This non-conformance of a specific, more optimal hedging strategy that could logically be linked to the July white maize futures contract price development became evident throughout all the production years considered. Table 6.21 below provides a summary of the optimal hedging strategy identified by means of the cumulative total ranking consensus for all the production years to confirm this finding. However, in order to include all considerations relevant to the result obtained in Table 6.21, it is important to first discuss the challenge that occurred in specific production years when specific performance measure values could not be meaningfully calculated.

Table 6.18: 2005/2006 Production year performance measure ranking consensus

Performance measure	2006: Strategy 1	2006: Strategy 2	2006: Strategy 3	2006: Strategy 4	2006: Strategy 5	2006: Strategy 6	2006: Strategy 7	2006: Strategy 8	2006: Strategy 9	2006: Strategy 10
Sharpe	1	5	7	4	3	10	8	9	6	2
Sortino	2	7	5	4	1	10	8	9	6	3
Calmar	1	5	7	4	3	10	8	9	6	2
Upside Potential	2	7	5	4	1	10	8	9	6	3
Kappa 3	1	5	7	4	3	10	8	9	6	2
VaR-Sharpe	9	6	4	7	8	1	3	2	5	10
CVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
MVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
Omega	1	5	7	4	3	10	8	9	6	2
Total ranking	35	52	50	45	38	63	57	60	51	44

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2006	238.74	49.44	-17.27	14.47	-31.32	-107.47	-211.38	-236.35	21.78	42.20

Source: Compiled by author

The main challenge referred to is the fact that the threshold performance measures in the form of Sortino ratio, Upside potential and the Omega ratio, could not be calculated at their respective thresholds for the 2007/2008, 2011/2012, 2012/2013, 2015/2016 and 2017/2018 production years. The applicable positive threshold for each production year was set at the company tax rate plus the prime interest rate at the time. The calculated threshold levels ranged between a low of 38.57% for the 2014/2015 production year and a high of 48.57% for the 2011/2012 production year. It was therefore necessary to determine at which constant threshold level the threshold performance measures could actually be calculated in order to compile a range of comparable estimates over time. Several threshold levels, both lower and higher than the original threshold levels, were evaluated. Results showed that all the threshold performance measures were able to calculate a value at a threshold of above 79% for all the years in question. However, this threshold level could not be substantiated or justified in any logical way, and also introduced the reality that if a threshold level is set too high, it may actually increase the risk and cause misleading results (Vilkancas, 2014:262-263). As a result, it was impossible to include the threshold performance measures as part of the cumulative ranking value for the specific years. Therefore, the summary of the cumulative ranking for all production years and strategies in Table 6.21 below only includes the cumulative ranking calculation based on the Sharpe, Calmar, Kappa 3, and the three VaR measures for the seasons for which threshold performance measures were impossible to calculate. The other production years, for which the threshold performance measure values could be calculated, includes all the measure rankings in the cumulative measure in Table 6.21.

The comparison in Table 6.21 may be disputed, since the cumulative ranking for the 2007/2008, 2011/2012, 2012/2013, 2015/2016 and 2017/2018 production years does not include the results of the threshold performance measure rankings, but the cumulative ranking for the other production years includes all the performance measure ranking values. Still, this comparison was warranted, since a comparison of the cumulative ranking with the threshold measures left out of the calculation for all production years, contributed even more to the nonsensical results. Table 6.19 below provides a summary of the cumulative ranking results if the threshold performance measure were left out of the calculation for all production years. The optimal strategy for each production year based on the smallest performance measure cumulative ranking value was assigned a light green colour. The results in Table 6.19 clearly show that the cumulative ranking identified similar optimal strategies for the 2004/2005, 2007/2008, 2008/2009, 2010/2011, and the 2014/2015 production years. Apart from the similarities in optimal ranking, the majority of production years also included similar rankings for the different hedging strategies. The inconclusiveness of this result is accentuated by the 2010/2011, as well as the 2014/2015 production years, where all the hedging strategies achieved a similar cumulative ranking.

Table 6.19: Summary of performance measure ranking consensus results (Threshold measures excluded)

July futures contract year	Strat 1	Strat 2	Strat 3	Strat 4	Strat 5	Strat 6	Strat 7	Strat 8	Strat 9	Strat 10
2003	35	34	30	33	33	38	30	34	38	25
2004	30	33	33	33	33	33	33	33	33	36
2005	30	30	33	33	33	36	33	33	33	36
2006	30	33	33	33	33	33	33	33	33	36
2007	30	33	33	33	33	33	33	33	33	36
2008	30	30	33	33	33	36	33	33	33	36
2009	35	36	31	26	36	42	24	24	35	41
2010	24	37	35	30	26	44	36	38	32	28
2011	33	33	33	33	33	33	33	33	33	33
2012	32	33	34	33	32	33	34	33	31	35
2013	32	34	32	33	35	40	22	30	34	38
2014	24	35	33	39	34	33	33	33	36	30
2015	33	33	33	33	33	33	33	33	33	33
2016	30	33	33	33	33	33	33	33	33	36
2017	22	35	36	30	28	40	36	44	31	28
2018	28	30	33	33	33	36	37	33	33	34

Source: Compiled by author
Note: "Strat" refers to Strategy.

In order to cast some light on the inconclusiveness of this result, the ranking results of the 2011/2012 production year is provided in Table 6.20 below. When considering the individual performance measure rankings assigned to Strategy 4 as an example, results show that consensus lacked. The Sharpe, Calmar, and Kappa 3 ratios assigned the highest ranking to Strategy 4, but the lowest ranking was assigned by VaR-Sharpe, CVaR-Sharpe, and MVaR-Sharpe for the same strategy. An attempt to test whether a specific measure was able to identify a logic and preferred hedging strategy proved to be inconclusive as well. Strategy 9 was identified as the more optimal strategy to implement in the upward price movement production year. The specific strategy actually performed well according to the average July white maize futures contract price comparison measure (positive value according to Table 6.15), but the strategy includes a maximum price level which means that the strategy would not have been able to take part in the upward price movement above a specific price level. The same level of unconfirmable results, which could not be linked to a logical conclusion, was found for the other production years where threshold performance measures were left out of the cumulative ranking table (See Appendix in the form of Table A3 for these results).

In order to provide a summary of the cumulative ranking approach (despite the fact that several production years did not include the ranking results of the threshold performance measures), Table 6.21 was constructed to compare the optimal strategies' as determined by the cumulative rankings to the strategies which performed better in specific production years as indicated by the under or outperformance of the July white maize futures contract price approach

Table 6.20: 2011/2012 Production year performance measure ranking consensus

Performance measure	2012: Strategy 1	2012: Strategy 2	2012: Strategy 3	2012: Strategy 4	2012: Strategy 5	2012: Strategy 6	2012: Strategy 7	2012: Strategy 8	2012: Strategy 9	2012: Strategy 10
Sharpe	4	8	6	1	3	10	5	9	7	2
Calmar	3	8	7	1	2	10	6	9	5	4
Kappa 3	4	8	6	1	3	10	5	9	7	2
VaR-Sharpe	7	3	5	10	8	1	6	2	4	9
CVaR-Sharpe	7	3	5	10	8	1	6	2	4	9
MVaR-Sharpe	7	3	5	10	8	1	6	2	4	9
Total ranking	32	33	34	33	32	33	34	33	31	35

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2012	327.62	-113.91	-19.99	61.14	-11.48	-150.75	-244.99	-248.21	63.85	-141.57

Source: Compiled by author

In order to provide a summary of the performance measure results as well as a comparison to the outperformance of the average July white maize futures price (Table 6.15), the cumulative ranking values were colour coded in Table 6.21 below. The optimal strategy for each production year based on the smallest performance measure cumulative ranking value was assigned a light green colour, whereas the optimal strategy based on the highest average July white maize futures price outperformance was assigned a light red colour. There were two production years (2005/2006 and 2008/2009) when these two measures identified a similar strategy to the more optimal strategy and these strategies were assigned a light blue colour. Based on the obvious difference in the identification of the optimal strategy for each production year, apart from the 2005/2006 and 2008/2009 production years, one may argue that the optimal strategy identified by means of the July white maize futures contract outperformance result does not include a measure of risk entailed in the implementation of each strategy. Therefore, a comparison could not be applied in this manner to determine whether the results were meaningful. Nevertheless, the literature review of hedging strategies (Chapter 4, Section 4.2.2) showed that the optimal hedge should always be time-varying or adapted to accommodate changing market conditions (Lapan & Moschini, 1994:476). This justifies a comparison of the performance measure ranking results with the strategies identified as more optimal for each production year based on their outperformance of the average July white maize futures price (Section 6.3.1).

Table 6.21: Summary of performance measure ranking consensus results

July futures contract year	Strat 1	Strat 2	Strat 3	Strat 4	Strat 5	Strat 6	Strat 7	Strat 8	Strat 9	Strat 10
2003	47	58	48	36	42	68	45	55	65	31
2004	37	57	56	49	46	63	43	46	52	46
2005	48	55	44	39	47	64	36	44	61	57
2006	35	52	50	45	38	63	57	60	51	44
2007	30	33	33	33	33	33	33	33	33	36
2008	42	57	54	36	41	66	40	51	57	51
2009	49	60	44	42	60	69	27	32	54	58
2010	27	57	58	42	32	74	54	59	55	37
2011	39	52	53	45	42	63	57	60	48	36
2012	32	33	34	33	32	33	34	33	31	35
2013	32	34	32	33	35	40	22	30	34	38
2014	27	53	54	51	43	63	57	60	51	36
2015	46	43	42	45	46	63	57	60	44	49
2016	30	33	33	33	33	33	33	33	33	36
2017	25	53	58	42	37	69	54	72	51	34
2018	37	50	50	40	43	62	48	53	58	54

Source: Compiled by author
Note: "Strat" refers to Strategy

Based on the logical results discussed in Section 6.3.1 above, when the July white maize futures price increased throughout a production year (year highlighted in green in Table 6.21), the more optimal hedging strategy to deploy should be either Strategy 1 or Strategy 10. Either one of these two strategies was confirmed by the cumulative performance measure ranking result for the 2005/2006, 2006/2007, 2010/2011, and 2015/2016 production years. This means that for four out of the six production years when prices increased, the more optimal type of strategy was confirmed by means of the cumulative performance measure ranking results. The other three production years, when the July white maize futures contract followed an upward price movement (2007/2008, 2011/2012 and 2014/2015), could not be linked to one of the strategies that outperformed the average July white maize futures contract price by the greatest margin. When considering the 2014/2015 production year in particular, the cumulative performance measure ranking result identified Strategy 3 as the more optimal strategy to deploy. Strategy 3, however, yielded the second lowest result when compared to the outperformance of the average July white maize futures price (Table 6.15). Based on the inconsistency in the results obtained from Table 6.21, as well as the nonsensical results obtained when the threshold performance measure was left out of the cumulative ranking in Table 6.19 above, it was necessary to evaluate why the application of performance measures to derivative-based hedging strategy returns may lead to results that seemed random or inconsistent.

A thorough analysis was done of the hedging strategy returns for all the production years and all of the hedging strategies, and through this evaluation a conclusion was made as follows. Performance measures, in one or the other way, include some form of variability of returns as a risk measure. This measure may be linked to the standard deviation of returns or the risk that returns may breach a specific threshold based on the variability of returns. As a result, the variability of the returns for each strategy in each of the production years are based on the variability of the hedging strategy returns. Yet when one considers how hedging strategy returns were calculated, the reality dawns that the application of a specific hedging strategy and the way a specific strategy is valued on a daily basis influences return variability and, consequently, the ranking of strategies by means of performance measures. The daily strategy valuation of all of the strategies was done by means of a simple accounting principle, whereby the strategy price was valued against the daily marked-to-market (MTM). Derivative accountants apply this valuation measure on a daily basis to account for the cash flow implications of derivative instruments. An example of this valuation may be explained by means of Strategy 2, which implements a minimum price or put option strategy based on the explanation provided in Chapter 5 (Section 5.4.2.2). A fair amount of variability may be introduced through this daily strategy valuation procedure, specifically in the case of option-based strategies such as Strategy 2.

In instances where the July white maize futures price is above the option strike price level, the put option is deemed out-of-the-money and the strategy is valued against the daily MTM price minus the relevant net option cost. The net option cost is the initial option cost when the option was purchased, minus the option premium valuation at that point in time as per the Black (1976) model provided in Chapter 5 (Section 5.4.1). However, when the July white maize futures price is below the option strike price level, the put option is deemed in-the-money and the strategy is valued against the option price minus the total option cost when the option was purchased. The reason for the valuation in this manner is that the put option cannot be sold back at a higher price than the initial purchase price when the July white maize futures price is below the option strike price level, since the gain in option value does not equate the value lost between the option strike price and the MTM price, due to the delta value[31] of the option further from expiry. As a result, this valuation around the put option strike price value immediately results in a significant change in the daily strategy price valuation and consequently contributes to the inherent variability of the returns evaluated by means of performance measures. This becomes clear when one considers the fact that Strategy 2 and Strategy 6 were identified as the more optimal strategies to implement over time in Table 6.15 above, but neither of these strategies was identified as the optimal strategy to implement by the cumulative performance measure ranking results in Table 6.21.

The reality of how the valuation of derivative-based instruments influences the variability of hedging strategy returns and consequent performance measure results becomes even more apparent when one considers the production years for which the July white maize futures contract price formation followed a downward trend or traded sideways. The more optimal strategies to implement in production years when the July white maize futures price followed a downward trend – based on the outperformance of the average July white maize futures price (Table 6.15) – were Strategy 3, Strategy 7 and Strategy 8, which established a minimum price level and significantly reduced option cost. When considering the more optimal strategy to implement during a sideways trading production year, Strategy 9 and Strategy 10 were identified as more optimal.

However, these more optimal strategies for the type of season were largely unconfirmed by the cumulative performance measure ranking results (Table 6.21). To be specific, the more optimal strategies to deploy in production years with declining July white maize futures prices were only confirmed for two (2004/2005 and 2008/2008) of the six comparative production years. In seasons

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[31] The delta of an option may be defined as the rate of change in the option value or price relative to the price change in the underlying futures price. The delta of a futures contract may be seen as 1, whereas an at-the-money option contract far from expiry would have an option contract delta of 0.5 at most. This means that an option contract with a delta of 0.5 would see a change in premium value of only 50% of the change in the underlying futures contract price (Hull, 2005: 210,302).

where prices traded sideways, none of the optimal strategies mentioned earlier were identified. In addition, the cumulative performance measure ranking results identified Strategy 1 as the more optimal strategy to deploy for three of the production years (2009/2010, 2013/2014 and 2016/2017) in which the July white futures price declined. Similarly, the cumulative performance measure ranking results (Table 6.21) for the sideways trading production years identified Strategy 1 as the more optimal strategy to deploy for two of the three sideways production years (2003/2004 and 2017/2018).

The outperformance of the average July white maize futures price (Table 6.15) does not confirm these results in any of the production years in which the July white maize futures contract declined or traded sideways. Strategy 1 was actually ranked as the last or second last strategy to implement in all of these years when the July white maize futures price trended downward or traded sideways, with the exception of the 2017/2018 production year, for which Strategy 1 was ranked third. This comparison, as a result, affirms the fact that the application of performance measures to derivative-based hedging strategy returns may lead to biased or skewed results. The confirmation lies therein that, although the final strategy price realisation achieved through Strategy 1 performed far worse than comparative strategies, the variation in daily returns were smaller, since no derivative instrument valuation influenced the return calculation. As a result, the risk (variation in daily returns) was smaller for Strategy 1 compared to the other strategies that included derivatives as hedging instruments. Hence, this strategy was identified as the more optimal strategy by means of the performance measure rankings. Apart from the fact that, according to the performance measure results (Table 6.21), the implementation of Strategy 1 could not be logically confirmed by a comparison with the average outperformance of the July white maize futures contract results (Table 6.15), literature also confirmed that Strategy 1 would not have been the more optimal strategy to deploy. Scheepers (2005:48), Strydom *et al*. (2010:6) and Venter *et al*. (2012:6) showed that the implementation of Strategy 1 would have led to a much larger variance in the mean price achieved. These results were furthermore confirmed by the fact that the standard deviation of the under or outperformance of the average July white maize futures contract in Table 6.15 was the second largest of all the strategies deployed.

The nonsensical results and the realisation that the hedging strategy return calculation may have been the cause of the skewed performance measure results, led to an alternative method for the calculation of hedging strategy returns for the performance measure evaluation process. It should, however, be added that this alternative calculation of hedging strategy returns and the evaluation by means of performance measures was not included as part of the methodological approach (Chapter 5, Section 5.5), since the results remained nonsensical. The alternative approach and basic results are nevertheless included to provide the necessary confirmation that several alternatives were considered in an attempt to reach meaningful and logical results when comparing hedging strategies by means of performance measures.

In order to explain the alternative approach to calculating hedging strategy returns, it is important to compare the initial and alternative calculation methods. The initial method entailed the calculation of daily strategy price valuations as explained for each hedging strategy in Chapter 5 (Section 5.4.2). This was followed by subtracting the relevant input cost (Chapter 5, Section 5.4.3) for each production year from the daily strategy price valuations and dividing it by the input cost to generate daily returns. The alternative method, however, follows a more general approach, which is similar to return calculations when equity based returns are calculated based on daily equity prices. For the alternative return calculation, the daily realised strategy prices were considered and the return from one day to the next was calculated by means of Formula 6.1:

$$Daily\ return = \frac{Dialy\ strategy\ valuation\ price_{(t+1)} - Dialy\ strategy\ valuation\ price_{(t)}}{Dialy\ strategy\ valuation\ price_{(t)}}. \qquad (6.1)$$

Returns were calculated for all strategies and productions seasons and the relevant normality tests (Chapter 5, Section 5.5.1) were applied to the data. Results showed that the alternative return calculation also predominantly portrayed non-normality in the return distributions, as was the case with the initial return calculations (Chapter 5, Section 5.5.1, Table 5.12). All the performance measures applied to the first set of returns based on input cost were reapplied to the alternative return data for each of the ten hedging strategies for all of the applicable production years under evaluation. The threshold, where applicable, was set to zero. The first main difference that emerged from the alternative return calculation was that all the performance measures were able to generate a performance estimate for all strategies and all production years. This was already an improvement from the previous performance measure evaluation approach, as reported in Table 6.21, where difficulties were experienced with the threshold measure, leading to the omission of some ratios (i.e. the threshold performance measures) for certain production seasons, and potentially contributing to nonsensical results obtained by means of the performance measure evaluation process.

With the alternative return calculation method, where strategy returns were estimated based on Equation 6.1, all of the performance measure results for each production year were again sorted and ranked in order to facilitate an individual production year analysis (Table 6.16, Table 6.17, Table 6.18). The same cumulative ranking comparison method (Chapter 5, Section 5.5.2, Table 5.14) applied to the initial performance measure analysis results (Table 6.21), were also applied in the alternative calculation method and is reported in Table 6.22 below. The optimal strategy for each production year based on the smallest cumulative performance measure ranking value was assigned a light green colour, whereas the optimal strategy according to the highest average July white maize futures price outperformance (Table 6.15) was assigned a light red colour. There was only one production year (2014/2015) where these two measures identified a similar strategy to the more optimal strategy, and this strategy was assigned a light blue colour.

Based on the results in Table 6.22 below, it seems that Strategy 1 and Strategy 2 were identified as the more optimal strategies to deploy for 11 of the 16 production years under evaluation. A comparison of the applicability of the optimal strategy identified by the performance measure cumulative ranking results and the application of the correct type of strategy, given the July white maize futures contract price development, was once again warranted. In the first instance, when the July white maize futures price increased throughout a production year, the more optimal strategies in terms of outperformance of the average July white maize futures contract price (Table 6.15), would have been Strategy 1 and Strategy 10. Results show that the performance measure cumulative ranking results (Table 6.22) identified Strategy 1 as the more optimal strategy for two of the seven production years (2014/2015 and 2015/2016) when the July white maize futures price increased. Strategy 1 was also identified as the more optimal strategy to deploy when the July white maize futures contract price declined in two of the six relevant production years (2013/2014 and 2016/2017). Strategy 3, Strategy 7 and Strategy 8 would have been the more optimal strategies to deploy when the July white maize futures contract price declined, but the alternative performance measure cumulative ranking results (Table 6.22) did not identify any of these strategies as more optimal for any of the production years when the July white maize futures contract price declined.

Table 6.22: Alternative return calculation method: summary of performance measure ranking consensus results

July futures contract year	Strat 1	Strat 2	Strat 3	Strat 4	Strat 5	Strat 6	Strat 7	Strat 8	Strat 9	Strat 10
2003	58	52	48	48	54	43	49	46	49	48
2004	35	47	49	52	44	58	61	55	50	44
2005	59	32	35	56	57	41	50	59	38	68
2006	47	39	46	53	53	50	56	53	42	56
2007	53	54	52	48	54	38	44	41	53	58
2008	58	28	43	54	57	37	46	55	50	67
2009	45	36	47	49	47	45	54	63	55	54
2010	46	46	47	49	47	50	56	53	45	56
2011	48	54	53	52	51	42	51	47	52	45
2012	47	46	47	51	47	50	56	53	45	53
2013	52	36	41	48	49	45	54	63	46	61
2014	41	53	55	47	47	50	56	47	49	50
2015	40	54	53	49	43	50	61	54	44	47
2016	40	44	49	46	46	56	59	53	53	49
2017	41	45	49	53	52	50	56	53	46	50
2018	62	29	40	56	57	38	47	56	39	71

Source: Compiled by author

Nevertheless, there were specific seasons when the strategy identified as more optimal by the alternative return calculation method, would not have been an altogether bad strategy. Examples include the identification of Strategy 6 in the 2002/2003 production year, Strategy 2 in the 2004/2005 production year, or Strategy 9 during the 2011/2012 production year (Table 6.22). Furthermore, one of the main confirmatory or logical results was that the alternative performance measure cumulative ranking results identified Strategy 2 (put option strategy) as the more optimal strategy to deploy irrespective of the type of production year in terms of the July white maize futures contract price development. This confirmatory result could, however, not be justified or applied in general, since there was a general lack of consensus in the results, given the aim to identify a specific type of strategy for a specific type of production year.

With the performance measure cumulative ranking results obtained from the alternative return calculation method also being unsuccessful, a final attempt was made to evaluate hedging strategies from an individual performance measure perspective. The evaluation of the individual performance measure results was based on the results obtained from the alternative return calculation method.

Based on an initial review of these results for each production year, it seemed that the Omega ratio may be a more a meaningful performance measure to consider in order to obtain logical results. An example of such a logical result is reported in Table 6.23 below, which shows the ranking results for all of the individual measures for the 2002/2003 production year. The 2002/2003 production year is characterised by a downward movement in the July white maize futures contract price. The Omega ratio identified Strategy 6, Strategy 7 and Strategy 8 as the top strategies to deploy. This result was confirmed by the positive outperformance of the average white maize futures contract price by these three strategies, as reported in Table 6.15.

Table 6.23: Alternative return calculation method: 2002/2003 production year performance measure analysis ranking results

Performance measure	2003: Strategy 1	2003: Strategy 2	2003: Strategy 3	2003: Strategy 4	2003: Strategy 5	2003: Strategy 6	2003: Strategy 7	2003: Strategy 8	2003: Strategy 9	2003: Strategy 10
Sharpe	7	3	2	9	8	4	6	5	1	10
Sortino	9	3	2	7	10	4	6	5	1	8
Calmar	10	3	2	7	9	4	6	5	1	8
Upside Potential	3	8	9	4	1	5	7	6	10	2
Kappa 3	7	3	2	9	8	4	6	5	1	10
VaR Sharpe	4	8	9	2	3	7	5	6	10	1
CVaR-Sharpe	4	8	9	2	3	7	5	6	10	1
MVaR-Sharpe	4	8	9	2	3	7	5	6	10	1
Omega	10	8	4	6	9	1	3	2	5	7
Total ranking	58	52	48	48	54	43	49	46	49	48

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2003	-321.38	544.04	631.17	81.22	9.58	550.15	635.44	621.58	-97.26	81.59

Source: Compiled by author

But the stability of the Omega ratio for identifying logical, more optimal strategies for the type of production year could not be confirmed for any of the three types of production years (upward, downward or sideways price development of the July white maize futures contract price). For instance, Table 6.24 reports the performance measure ranking results of the 2013/2014 production year, where the July white maize futures price also declined. In this example, the Omega ratio estimates identified Strategy 1 and Strategy 10 as two of the more optimal strategies to deploy when market prices declined. These strategies actually performed the worst in terms of their outperformance of the average July white maize futures contract price (Table 6.15), which greatly accentuates the nonsensical results obtained in the alternative calculation method as well. (The other individual performance measure results based on the alternative calculation method are provided in the Appendix, as Table A4).

Table 6.24: Alternative return calculation method: 2013/2014 production year performance measure analysis ranking results

Performance measure	2014: Strategy 1	2014: Strategy 2	2014: Strategy 3	2014: Strategy 4	2014: Strategy 5	2014: Strategy 6	2014: Strategy 7	2014: Strategy 8	2014: Strategy 9	2014: Strategy 10
Sharpe	1	5	8	4	3	9	10	7	6	2
Sortino	9	7	4	6	8	2	3	1	5	10
Calmar	1	7	9	4	3	8	10	5	6	2
Upside Potential	1	5	7	4	3	9	10	8	6	2
Kappa 3	1	5	9	4	3	8	10	7	6	2
VaR Sharpe	9	6	3	7	8	2	1	4	5	10
CVaR-Sharpe	9	6	3	7	8	2	1	4	5	10
MVaR-Sharpe	9	6	3	7	8	2	1	4	5	10
Omega	1	6	9	4	3	8	10	7	5	2
Total rank	41	53	55	47	47	50	56	47	49	50

Downward July WM price movement	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2014	-334.93	-149.06	-64.80	-72.15	26.28	-35.99	-47.06	306.45	-24.66	-334.93

Source: Compiled by author

Overall, several attempts were made to derive a meaningful result for establishing the optimal hedging strategy based on performance measure analyses. The results obtained were predominantly nonsensical and the main reason for this finding was attributed to the way in which a derivative-based hedging strategy influences the variability of returns through the generally applied accounting principles, which skewed the results. Thus the application of performance measures to any agricultural derivative-based strategy returns is not advised.

Yet this does not imply that the analysis of hedging strategies in this manner was meaningless. As a whole, from the basic description of the strategy results in terms of outperformance of the average July white maize futures contract price up to the ranking of hedging strategies by means of performance measures, the analysis provided the necessary foundation to evaluate different types of hedging strategies on a much higher level. This higher level evaluation involved arguing why performance measures were not able to evaluate hedging strategy returns, and, as a result, enabled the identification of more optimal strategies for the type of production year, based on what would have been a logical conclusion or expectation from the performance measure results. This logical conclusion was predominantly based on the outperformance of the average July white maize futures contract price (Table 6.15), but also considered the inherent risk involved in implementing a specific type of strategy based on the actual July white maize futures contract price development. As a result, the foundation from which to derive a meaningful conclusion as to the more optimal hedging strategy to consider for the type of production season, was the results contained in Table 6.15. However, to facilitate the interpretation of Table 6.15, it was divided according to the three types of production years based on the July white maize futures contract price development (upward, downward and sideways) and each grouping was evaluated individually, as reported in Table 6.25 to Table 6.27.

The first grouping was characterised by an increase in the July white maize futures contract price throughout the production year. Strategy 1 was identified as the more optimal strategy to deploy in terms of the outperformance of the average July white maize futures contracts for all the production years that showed an upward price progression for the July white maize futures contract price (Table 6.25). A possible objection to this result is that the inherent structure of the non-hedging alternative (Strategy 1) fails to capture the essence of price risk management. However, the decision not to hedge may be justified if one considers the inherent risk of hedging when prices are expected to increase. Futures prices are usually expected to increase as a result of production uncertainty, which is mainly associated with expectations of unfavourable weather conditions. In such instances, pre-season hedging due to a producer's uncertainty of production potential, may result in costly buy-outs of futures contracts if a producer is not able to deliver against these contracts. Based on this reality, Strategy 1 may actually be viewed as a safer strategy to implement, since producers arguably have more production certainty during the harvest window and are able to sell what has actually been harvested in the cash market.

Yet this argument in favour of Strategy 1 does not account for the uncertainty that may be experienced by a producer during a production year when prices start to react to changes in influential price determinant factors. These changes in price determinant factors may or may not be short-lived, but they may influence a possible impulsive decision to hedge based on a producer's expectation that prices may decline for the rest of the production year. As a result, it is proposed from a pure risk management perspective that a producer considers the implementation of Strategy 2, where put options are bought to hedge expected produce. This strategy immediately provides a hedge against potential price declines and also permits a producer to take part in the expected upward price movement with the added peace of mind that costly buy-outs are limited to the option premium paid for the put option in the case where physical delivery is not possible. The implementation of one or either of these two strategies, based on a producer's preference or risk sensitivity, is confirmed as the more optimal strategies to deploy when considering the outperformance of the average July white maize futures contract price over time in production years when the July white maize futures price increased (Table 6.25).

Table 6.25: Comparison of realised strategy price to average July white maize futures contract price over time: Increasing July futures contract price

July futures contract	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2006	R 238.74	R 49.44	-R 17.27	R 14.47	-R 31.32	-R 107.47	-R 211.38	-R 236.35	R 21.78	R 42.20
2007	R 55.61	-R 104.29	-R 140.27	R 32.86	-R 30.14	-R 72.44	-R 218.13	-R 342.22	-R 105.97	R 110.99
2008	R 300.85	R 236.06	-R 80.06	R 43.21	-R 41.74	-R 66.35	-R 195.83	-R 324.28	-R 13.60	-R 113.47
2011	R 168.63	-R 9.22	-R 90.39	-R 8.03	-R 36.21	-R 85.26	-R 223.21	-R 219.14	-R 28.47	-R 8.99
2012	R 327.62	-R 113.91	-R 19.99	R 61.14	-R 11.48	-R 150.75	-R 244.99	-R 248.21	R 63.85	-R 141.57
2015	R 593.07	R 347.68	-R 420.55	R 62.65	-R 134.05	-R 128.84	-R 204.15	-R 395.12	-R 362.22	-R 485.05
2016	-R 27.17	-R 229.05	-R 1 063.48	-R 358.57	-R 101.94	-R 203.28	-R 624.40	-R 595.52	-R 977.69	R 248.39
High	R 593.07	R 347.68	-R 17.27	R 62.65	-R 11.48	-R 66.35	-R 195.83	-R 219.14	R 63.85	R 248.39
Low	-R 27.17	-R 229.05	-R 1 063.48	-R 358.57	-R 134.05	-R 203.28	-R 624.40	-R 595.52	-R 977.69	-R 485.05
Average outperformance (A)	R 236.76	R 25.24	-R 261.72	-R 21.75	-R 55.27	-R 116.34	-R 274.59	-R 337.26	-R 200.33	-R 49.64
Standard deviation (B)	R 202.67	R 204.53	R 379.33	R 150.64	R 44.82	R 48.94	R 155.05	R 130.58	R 370.34	R 233.39
Return per unit of risk (A/B)	116.82%	12.34%	-68.99%	-14.44%	-123.31%	-237.74%	-177.10%	-258.28%	-54.09%	-21.27%

Source: Compiled by author

The second grouping is the instance where the July white maize futures contract price decreased throughout the production year. In this instance, the aim was to establish a hedge during the planting window and to minimise the cost of hedging without inhibiting the opportunity to take part in any potential upward price movement. Conditions may change throughout a production year and midsummer droughts have led to several price increases, even when the general trend in the July white maize futures price development showed a downward price movement (e.g. the 2009/2010 and 2013/2014 production years, Figure 6.13). The more optimal strategies to implement in these types of production years would be Strategy 6, Strategy 7 or Strategy 8 (Table 6.26), since all of these strategies establish a hedge, aim to reduce option cost, but allow a producer to take part in any unforeseen price increase if it occurs. One may argue that Strategy 3 should also be considered, but as this strategy implements a maximum price and is therefore only able to take part in a partial market price increase if it occurs, the strategy should rather be avoided. This premise is confirmed in Table 6.15, since the minimum/maximum strategy (Strategy 3) realised the greatest standard deviation in the average July white maize futures contract outperformance over time of all the strategies evaluated.

Table 6.26: Comparison of realised strategy price to average July white maize futures contract price over time: Decreasing July futures contract price

July futures contract	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2003	-R 321.38	R 544.04	R 631.17	R 81.22	R 9.58	R 550.15	R 635.44	R 621.58	-R 97.26	R 81.59
2005	-R 66.93	R 239.21	R 321.00	R 73.04	R 45.99	R 239.21	R 309.89	R 283.98	R 102.60	-R 76.50
2009	-R 245.94	R 62.36	R 156.28	-R 2.60	R 41.72	R 68.40	R 165.29	R 126.23	R 85.37	-R 245.94
2010	-R 151.72	R 153.60	R 244.17	R 23.79	R 57.02	R 179.98	R 246.72	R 220.70	R 19.62	R 209.49
2014	-R 334.93	-R 149.06	-R 64.80	-R 72.15	R 26.28	-R 35.99	-R 47.06	R 306.45	-R 24.66	-R 334.93
2017	-R 266.24	R 230.72	R 380.77	R 31.68	R 96.55	R 261.66	R 372.60	R 215.12	-R 7.69	-R 206.18
High	-R 66.93	R 544.04	R 631.17	R 81.22	R 96.55	R 550.15	R 635.44	R 621.58	R 102.60	R 209.49
Low	-R 334.93	-R 149.06	-R 64.80	-R 72.15	R 9.58	-R 35.99	-R 47.06	R 126.23	-R 97.26	-R 334.93
Average outperformance (A)	-R 231.19	R 180.14	R 278.10	R 22.50	R 46.19	R 210.57	R 280.48	R 295.68	R 13.00	-R 95.41
Standard deviation (B)	R 103.57	R 228.66	R 232.64	R 56.00	R 29.70	R 200.34	R 226.73	R 171.63	R 73.91	R 208.30
Return per unit of risk (A/B)	-223.21%	78.78%	119.54%	40.17%	155.52%	105.10%	123.71%	172.27%	17.58%	-45.80%

Source: Compiled by author

The final grouping is where the July white maize futures contract price follows a sideways price movement. This is arguably one of the more difficult types of seasons to identify beforehand, since prices usually remain under pressure closer to export parity (EP) if supply is more than ample. The identification of the more optimal type of strategy for this type of season should therefore be linked to a season where supply is expected to remain ample and the factors that influence export parity (EP) should also be at relatively low levels. The level of caution in this instance cannot be overstated, since a production year may move from a sideways price formation expectation to a constant increase in futures prices when production prospects change or when exports are favourable enough to address oversupply scenarios. As a result, strategies that are able to limit option cost to the bare minimum at these lower price levels, but also provide the means to hedge as the season progresses or to capture any potential unforeseen price increases, should be considered. The proposed strategies that adhere to these requirements are the twelve-segment hedge strategy (Strategy 5), the at-the-money March contract actively-managed synthetic minimum price strategy (Strategy 8) or Strategy 9, where hedging is carried out by means of a three-way option-based structure (Table 6.27). But caution should be taken when deploying Strategy 9, since the strategy includes a maximum price that may result in the same risks as Strategy 3; it will not be possible to take part in an upward price movement that exceeds the maximum price level. Also, from a risk-adverse perspective, the twelve-segment hedge strategy (Strategy 5) is preferable over the three-segment hedge (Strategy 4), since the standard deviation in average outperformance is smaller for Strategy 5 (Table 6.27).

Table 6.27: Comparison of realised strategy price to average July white maize futures contract price over time: Sideways July futures contract price

July futures contract	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2004	-R 245.54	-R 279.74	-R 222.65	-R 136.61	R 19.40	-R 87.47	-R 135.08	R 26.30	-R 170.88	R 32.63
2013	R 80.42	-R 9.40	R 84.56	R 120.19	-R 29.40	R 22.86	R 90.48	R 47.22	R 167.99	-R 57.34
2018	-R 8.70	-R 128.17	-R 24.78	R 14.17	-R 9.66	-R 82.68	-R 24.69	-R 71.17	R 67.12	-R 10.73
High	R 80.42	-R 9.40	R 84.56	R 120.19	R 19.40	R 22.86	R 90.48	R 47.22	R 167.99	R 32.63
Low	-R 245.54	-R 279.74	-R 222.65	-R 136.61	-R 29.40	-R 87.47	-R 135.08	-R 71.17	-R 170.88	-R 57.34
Average outperformance (A)	-R 57.94	-R 139.10	-R 54.29	-R 0.75	-R 6.56	-R 49.09	-R 23.10	R 0.78	R 21.41	-R 11.81
Standard deviation (B)	R 168.47	R 135.50	R 155.72	R 129.05	R 24.55	R 62.36	R 112.79	R 63.18	R 174.00	R 44.99
Return per unit of risk (A/B)	-34.39%	-102.66%	-34.87%	-0.58%	-26.71%	-78.72%	-20.48%	1.24%	12.30%	-26.26%

Source: Compiled by author

To conclude – Section 6.3 aimed to provide the reader with a thorough overview of the results obtained from the implementation of the proposed hedging strategies. Section 6.3.1 started off by comparing the realised strategy price of every strategy in each production season with the relevant average July white maize futures contract price to provide an initial measure of strategy performance. These initial results formed the foundation to evaluate the performance measure cumulative ranking results (Section 6.3.2). The performance measure analysis of hedging strategies however remained nonsensical but the in-depth analysis of the reasons attributing to the inability of performance measure to identify logic an applicable hedging strategies established the means to identify the correct course of price risk management action. As a result, more optimal hedging strategies were identified based on the price development in the July white maize futures contract price.

Based on the comprehensive evaluation that was followed to reach logical conclusions as to the more optimal hedging strategy to follow, as well as the percentile rank grouping (Section 6.2.1) and cluster analysis (Section 6.2.2) results, the foundation was set to reach two of the study objectives. The percentile rank grouping and cluster analysis results established the means to identify similarities between the influential price determinant factors for the different production years in order to establish a price development expectation based on the similarities between previous and upcoming production years. The objective of comparing hedging strategies by means of performance measure analysis could, however, not be reached due to the nonsensical nature of the results. The process of analysis by which to evaluate the performance measure results and consequent reasons for the nonsensical results nevertheless provided the means to determine more optimal hedging strategies based on the July white maize futures contract price development.

The ultimate objective of the study remains to combine all of these results into a meaningful decision-making tool. A filter model was constructed to address this goal and to establish a decision-making tool that would provide the means to link different production years based on percentile rank grouping and cluster analysis results; also, to propose a more optimal strategy given the seasonal price development expectation.

6.4 Filter model – a decision-making tool

The filter model was constructed based on the method explained in Chapter 5 (Section 5.3.2, Table 5.8 and Table 5.9). The purpose of the filter model as a whole was to provide an all-inclusive summary of the stance of the percentile rank grouping values and the cluster analysis results, as well as the additional factor values (Chapter 5, Section 5.2.2) at a specific point in time when a hedging decision is made. Based on the implementation methodology (Chapter 5, Section 5.4.2) of each of the hedging strategies evaluated in Section 6.3, hedging strategies were implemented during the last two weeks of November of the calendar year preceding the main July white maize futures contract hedging month. This means that a more optimal hedging strategy decision would have to be based on the production year similarities identified by means of the percentile rank grouping and cluster analysis results up to that point in time. As a result, the percentile rank grouping and cluster analysis value comparisons would be based on the values for the months of August, September and October before the following main July white maize futures contract hedging month. These months may therefore be seen as the decision months for each production year and will form the basis to determine the similarities between seasons. The comparison of the decision month's percentile rank grouping results would furthermore be based on the average stance of the percentile rank values over the three months as explained in Chapter 5 (Section 5.3.2, Table 5.9). This would enable a comparison of factors between production years in terms of the average ranking, which was grouped as either low, medium or high.

Table 6.28 should therefore be viewed as the means to provide an all-inclusive summary that functions as a filter model. The table includes the low, medium and high groupings for each factor that was subject to the percentile rank grouping analysis. The historical realisation or stance of (or characteristic associated with) the additional influential price determinant factors (Chapter 5, Section 5.2.2) also forms part of Table 6.28. The dominant factors to consider in light of the cluster analysis results for the first three months of each production year (Table 6.11) are highlighted in grey. The table also includes the optimal hedging strategy per season type, as discussed and identified in Section 6.3.2 above. The identification of the July white maize futures contract price development or movement according to colour was also included (see Section 6.3.1). Green indicates an upward price development, yellow a downward price development, and blue a sideways price development.

In order to provide a meaningful analysis based on the filter model in Table 6.28, three main filters are presented with the aim of determining whether there is any specific factor or a set of factors that could be used to characterise each of the production seasons, where the July white maize futures contract price either increased, decreased or traded sideways (reported in Table 6.29 to Table 6.31, respectively).

Table 6.28: Filter model

Production Year	Hedging Strategy	July Price Movement	Main Trend (Q4)	Stock-to-usage	Input Cost Ratio	EL Nino / La Nina
2002-2003	Strat 6, Strat 7 & Strat 8	Downwards	Downward	39%	73%	Moderate El Niño
2003-2004	Strat 5, Strat 8 & Strat 9	Sideways	Upward (Trend turn)	45%	36%	Neutral
2004-2005	Strat 6, Strat 7 & Strat 8	Downwards	Downward	37%	37%	Weak El Niño
2005-2006	Strat 1 & Strat 2	Upwards	Upward	32%	29%	Weak La Niña
2006-2007	Strat 1 & Strat 2	Upwards	Upward	11%	38%	Weak El Niño
2007-2008	Strat 1 & Strat 2	Upwards	Upward	11%	31%	Strong La Niña
2008-2009	Strat 6, Strat 7 & Strat 8	Downwards	Downward (Trend turn)	22%	38%	Weak La Niña
2009-2010	Strat 6, Strat 7 & Strat 8	Downwards	Downward	22%	32%	Moderate El Niño
2010-2011	Strat 1 & Strat 2	Upwards	Upward (Trend turn)	7%	26%	Strong La Niña
2011-2012	Strat 1 & Strat 2	Upwards	Upward	11%	31%	Moderate La Niña
2012-2013	Strat 5, Strat 8 & Strat 9	Sideways	Upward	5%	37%	Neutral
2013-2014	Strat 6, Strat 7 & Strat 8	Downwards	Upward	19%	31%	Neutral
2014-2015	Strat 1 & Strat 2	Upwards	Upward (Trend turn)	27%	27%	Weak El Niño
2015-2016	Strat 1 & Strat 2	Upwards	Upward	12%	40%	Very Strong El Niño
2016-2017	Strat 6, Strat 7 & Strat 8	Downwards	Downward	33%	37%	Weak La Niña
2017-2018	Strat 5, Strat 8 & Strat 9	Sideways	Upward (Trend turn)	23%	27%	Weak La Niña

Production Year	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	Supply	Demand	Ending Stock	Days Stock	SOI
2002-2003	High	High	Medium	High	Medium	High	Medium	Medium	Low	High	High	Low
2003-2004	Medium	Low	Medium	Low	Medium	Medium	Low	Medium	Medium	High	High	Medium
2004-2005	Medium	Low	Medium	Low	High	Low	Low	Medium	Medium	High	High	Medium
2005-2006	Low	Medium	Low	Low	High	Low	Low	Medium	Medium	High	High	High
2006-2007	Medium	High	Low	Medium	Medium	High	Medium	Medium	Medium	Medium	High	Low
2007-2008	High	High	Medium	High	High	High	Medium	Medium	Medium	Medium	Medium	High
2008-2009	High	High	Low	High	Low	High	High	Medium	High	High	Medium	High
2009-2010	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	High	High	Medium
2010-2011	Low	Medium	Low	High	Low	High	Medium	Medium	High	High	High	High
2011-2012	High	High	Medium	High	Medium	High	Medium	Medium	Medium	Medium	Medium	High
2012-2013	High	High	High	High	Low	High	High	Medium	Low	High	High	Medium
2013-2014	High	Medium	High	Medium	High	Medium	High	Medium	Low	Medium	Medium	Medium
2014-2015	Medium	Medium	Medium	Low	Medium	Low	High	Medium	High	High	Medium	Low
2015-2016	High	High	High	Medium	High	Low	High	Medium	Low	Medium	High	Low
2016-2017	High	High	High	High	Medium	Low	High	Medium	Low	Medium	Medium	Medium
2017-2018	Low	High	Low	Medium	Low	Low	Medium	Medium	High	High	High	High

Source: Compiled by author

Note: “Strat” refers to Strategy.

Table 6.29: Filter model – filter implemented to select production years where the July white maize futures contract price increased

Production Year	Hedging Strategy	July Price Movement	Main Trend (Q4)	Stock-to-usage	Input Cost Ratio	EL Nino / La Nina
2005-2006	Strat 1 & Strat 2	Upwards	Upward	32%	29%	Weak La Niña
2006-2007	Strat 1 & Strat 2	Upwards	Upward	11%	38%	Weak El Niño
2007-2008	Strat 1 & Strat 2	Upwards	Upward	11%	31%	Strong La Niña
2010-2011	Strat 1 & Strat 2	Upwards	Upward (Trend turn)	7%	26%	Strong La Niña
2011-2012	Strat 1 & Strat 2	Upwards	Upward	11%	31%	Moderate La Niña
2014-2015	Strat 1 & Strat 2	Upwards	Upward (Trend turn)	27%	27%	Weak El Niño
2015-2016	Strat 1 & Strat 2	Upwards	Upward	12%	40%	Very Strong El Niño

Production Year	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	Supply	Demand	Ending Stock	Days Stock	SOI
2005-2006	Low	Medium	Low	Low	High	Low	Low	Medium	Medium	High	High	High
2006-2007	Medium	High	Low	Medium	Medium	High	Medium	Medium	Medium	Medium	High	Low
2007-2008	High	High	Medium	High	High	High	Medium	Medium	Medium	Medium	Medium	High
2010-2011	Low	Medium	Low	High	Low	High	Medium	Medium	High	High	High	High
2011-2012	High	High	Medium	High	Medium	High	Medium	Medium	Medium	Medium	Medium	High
2014-2015	Medium	Medium	Medium	Low	Medium	Low	High	Medium	High	High	Medium	Low
2015-2016	High	High	High	Medium	High	Low	High	Medium	Low	Medium	High	Low

Source: Compiled by author

When considering the results obtained from the percentile rank grouping analysis for the decision months, as well as from the dominant factors identified by means of the cluster analysis, it seems as though none of these factors correspond or provide an indication of a specific price determinant influential factor to consider when the July white maize futures contract price follows an upward trend (Table 6.29). A specific reason (or set of reasons) supporting an increase in the July white maize futures contract price may nevertheless form part of the argument for each of the production years presented in Table 6.29.

These arguments may follow the same logical path as the percentile ranking grouping examples discussed in Section 6.2.1. For example: the beginning of the 2005/2006 production year may be characterised by low cash market prices (low WM-C), as well as low levels for the international maize price (low CBOT-C) and a relatively strong rand against the US dollar (low USD/ZAR). Furthermore, prices were closer to export parity (high EPR), and export parity (EP) in itself was relatively low (low EP). Based on the low levels of the factors that influence price formation, one could successfully argue that market prices would most probably increase since the market price is already closer to low levels.

The counter argument to such a conclusion could be that the potential of a futures price increase should be limited, since ending stock was ample with no real threat to production prospects as weather condition expectations were favourable (high SOI – high probability of wetter La Niña season). The July white maize futures contract price nevertheless increased throughout the production year and the only market factor able to support this price formation was the price trend that was present in the continuous white maize price (Chapter 5, Section 5.2.2.1). The upward continuous white maize contract price trend was established by the 100-day moving average being above the 200-day moving average during the fourth quarter of 2005. In each of the production years in Table 6.29, the July white maize futures contract followed an upward price development if the continuous white maize futures contract price trend was in an upward phase or when the trend changed to an upward trend in the fourth quarter preceding the relevant July white maize futures contract. For all of these production years when the July white maize futures contract followed an upward price movement, Strategy 1 or Strategy 2 would have been the more optimal price risk management strategies to deploy given the analysis results from Section 6.3.2.

When considering the results reported in Table 6.30, which includes the production years when the July white maize futures contract price followed a downward trend, it seems as though factors such as WM-C, CBOT and USD/ZAR were either medium or high. Also, ending stock was high at the beginning of most of these production years, which may lead to the conclusion that prices may already have been relatively high with ample ending stock and, as a result, stood a greater chance to decline. However, none of these factors took on a similar value in each production year or exhibited consistency throughout all the production years in question. This may lead to inconsistent conclusions or expectations when only considering the stance of the percentile rank grouping values during the decision months of a production year.

For example: it is possible, based on the stance of the percentile rank grouping values during the decision months, that an incorrect conclusion (arguably in hindsight) be made when evaluating the

2004/2005 production year. The stance of CBOT-C and the USD/ZAR were at low levels and the low EP value as well as the high EPR value showed that the market price was already closer to export parity. These factor values would have been ample reason for the conclusion that prices were already low and that the potential for downward market price movement was limited. The 2005 July white maize futures contract price nevertheless followed a downward price development for the production season.

The only factor that was able to identify/confirm the risk of a downward price movement in the July white maize futures contract, was the downward trend that was present in the white maize continuous price (Table 6.30). This was the case for all of the relevant production years where the July white maize futures contract price development followed a downward movement, except for the 2013/2014 production year. The reason for the only outlier in this regard could be attributed to the fact that the continuous white maize contract trend changed from an upward trend in the fourth quarter of 2013 to a strong downward trend after the first quarter of 2014.

Table 6.30: Filter model – filter implemented to select production years where the July white maize futures contract price decreased.

Production Year	Hedging Strategy	July Price Movement	Main Trend (Q4)	Stock-to-usage	Input Cost Ratio	EL Niño / La Niña
2002-2003	Strat 6, Strat 7 & Strat 8	Downwards	Downward	39%	73%	Moderate El Niño
2004-2005	Strat 6, Strat 7 & Strat 8	Downwards	Downward	37%	37%	Weak El Niño
2008-2009	Strat 6, Strat 7 & Strat 8	Downwards	Downward (Trend turn)	22%	38%	Weak La Niña
2009-2010	Strat 6, Strat 7 & Strat 8	Downwards	Downward	22%	32%	Moderate El Niño
2013-2014	Strat 6, Strat 7 & Strat 8	Downwards	Upward	19%	31%	Neutral
2016-2017	Strat 6, Strat 7 & Strat 8	Downwards	Downward	33%	37%	Weak La Niña

Production Year	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	Supply	Demand	Ending Stock	Days Stock	SOI
2002-2003	High	High	Medium	High	Medium	High	Medium	Medium	Low	High	High	Low
2004-2005	Medium	Low	Medium	Low	High	Low	Low	Medium	Medium	High	High	Medium
2008-2009	High	High	Low	High	Low	High	High	Medium	High	High	Medium	High
2009-2010	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	High	High	Medium
2013-2014	High	Medium	High	Medium	High	Medium	High	Medium	Low	Medium	Medium	Medium
2016-2017	High	High	High	High	Medium	Low	High	Medium	Low	Medium	Medium	Medium

Source: Compiled by author

This confirmation of production years during which the July white maize futures contract price formation followed a downward price progression therefore affirms the finding that a July white maize contract price development expectation may be made based on the continuous white maize contract price trend in the fourth quarter of the preceding calendar year. The trend should however be stringently monitored to anticipate a potential change in the July white maize price formation. Any change in the continuous white maize price trend would consequently lead to a change in the July white maize futures contract price development. The risk of an unexpected change in the July white maize market price development would however be accommodated in a meaningful manner by Strategy 6, Strategy 7 and Strategy 8, since they allow participation in an upward price movement despite being the more optimal strategies for a downward price development.

A review of the production seasons where the July white maize futures contract price development followed a sideways movement (Table 6.31) confirmed the difficulty of establishing such an expectation on the basis of factor characteristics during the decision months. This challenge was further highlighted by the fact that the continuous white maize contract price trend in the fourth quarter of the preceding calendar year was upwards, while the July white maize futures contract price remained in the sideways price range. This scenario nevertheless highlighted the fact that it remains important to not only base a seasonal price development expectation on the continuous white maize trend but also to evaluate the other factor values to reach a consensus decision.

A specific finding that may explain why the July white maize futures contract traded sideways (Table 6.31) while the continuous white maize contract trend was upward, is the direct link between the SOI values in the filter model and an El Niño or La Niña event. The historical realisation of an ENSO event was included as a second additional market factor to further characterise production years (Chapter 5, Section 5.2.2.3). The link lies in the possible association between a low average relative grouping value for SOI with negative SOI values, which may be seen as a potential predictor of a wetter La Niña event. The opposite event, where SOI takes on a high average relative grouping value, may be associated with positive SOI values, which may be seen as a potential predictor of a drier El Niño event. In both these instances, the filter model was able to establish this link between SOI and either an El Niño or La Niña event (Table 6.31).

The confirmed filter model link between SOI and either an El Niño or La Niña event as a result affirm the filter model's potential to identify a production year's expectation in terms of weather events. This expectation is furthermore confirmed by means of the predictive models and Sea Surface Temperatures (SST), which were explained in Chapter 5 (Section 5.2.2.3).

As a result, it was discovered that the expected price development in a production year may be characterised even further by filtering for the expectation in terms of an El Niño or La Niña event after establishing the continuous white maize price trend. The expectation in price formation may therefore be linked to the possible impact of an adverse weather event, but price formation may also be affected by the lack of any potential adverse weather conditions.

Table 6.31: Filter model – filter implemented to select production years where the July white maize futures contract price traded sideways

Production Year	Hedging Strategy	July Price Movement	Main Trend (Q4)	Stock-to-usage	Input Cost Ratio	EL Niño / La Niña
2003-2004	Strat 5, Strat 8 & Strat 9	Sideways	Upward (Trend turn)	45%	36%	Neutral
2012-2013	Strat 5, Strat 8 & Strat 9	Sideways	Upward	5%	37%	Neutral
2017-2018	Strat 5, Strat 8 & Strat 9	Sideways	Upward (Trend turn)	23%	27%	Weak La Niña

Production Year	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	Supply	Demand	Ending Stock	Days Stock	SOI
2003-2004	Medium	Low	Medium	Low	Medium	Medium	Low	Medium	Medium	High	High	Medium
2012-2013	High	High	High	High	Low	High	High	Medium	Low	High	High	Medium
2017-2018	Low	High	Low	Medium	Low	Low	Medium	Medium	High	High	High	High

Source: Compiled by author

Table 6.32: Filter model – SOI versus an El Niño or La Niña event.

Production Year	July Price Movement	Main Trend (Q4)	EL Niño / La Niña	SOI
2002-2003	Downwards	Downward	Moderate El Niño	Low
2005-2006	Upwards	Upward	Weak La Niña	High
2006-2007	Upwards	Upward	Weak El Niño	Low
2007-2008	Upwards	Upward	Strong La Niña	High
2008-2009	Downwards	Downward (Trend turn)	Weak La Niña	High
2010-2011	Upwards	Upward (Trend turn)	Strong La Niña	High
2011-2012	Upwards	Upward	Moderate La Niña	High
2014-2015	Upwards	Upward (Trend turn)	Weak El Niño	Low
2015-2016	Upwards	Upward	Very Strong El Niño	Low
2017-2018	Sideways	Upward (Trend turn)	Weak La Niña	High

Source: Compiled by author

In the light of this finding, one may argue that the reason why the 2003/2004 and 2012/2013 production years in Table 6.31 had a sideways price formation in the July white maize futures contract price, was that there was no weather-based threat to production, since the El Niño or La Niña (ENSO) classification was "Neutral". The same "Neutral" classification was present in the 2013/2014 production year, which may explain why the July white maize futures contract followed an eventual downward price development despite the fact that the continuous white maize trend was upward before the trend turned downward. The possible threat to future production prospects should always be considered when linking production years on the basis of similar seasonal characteristics. As a result, it makes sense to consider the possible impact of an adverse weather event, or even the lack thereof, when deciding between Strategy 5, Strategy 8 and Strategy 9 when the July white maize futures contract price formation expectation is sideways. In the instance where an adverse weather event is a possibility, Strategy 8 would be able to take part in an unlimited upward price movement whereas Strategy 9 would not. Alternatively, Strategy 5 or Strategy 9 would be the more optimal choices in a neutral weather expectation scenario.

Several evaluations showed that the filter model established the means to identify similarities between the other influential price determinant factors for different seasons after the two price determinant factors in the form of the continuous white maize price trend and El Niño / La Niña were established. The filter model provided the means to divide production years in different combinations in order to reach a relevant consensus for the July white maize futures contract price development (i.e. upwards, downwards or sideways). The expectation consensus also provided the necessary confirmation to derive a specific course of action in terms of the more optimal hedging strategy to deploy.

In order to provide an example of the applicability of the filter model, it was thought fitting to include an evaluation of the out-of-sample 2018/2019 production year July white maize futures contract price development expectation (which was relevant at the time of this study). All of the relevant data was acquired for the months of August, September and October 2018. The data analysis, in terms of the percentile rank grouping and cluster analysis, as well as the additional important price determinant factor results, enabled the population of the filter model to characterise the 2018/2019 production year.

The first step was to filter for the main trend in terms of the July continuous white maize contract. The 100-day moving average was above the 200-day moving average for the continuous white maize contract, which meant that the established trend in the fourth quarter of 2018 was upwards. The weather-based prediction models further reported that the Sea Surface Temperatures (SST) were positive and the ONI values (Chapter 5, Section 5.2.2.3) showed that the expectations were fairly strong for the development of a weak El Niño event. Subsequently, the second filter was set to filter for a weak El Niño event. The filter model result after the initial two filters were implemented is reported in Table 6.33 below.

Table 6.33: Filter model – evaluating the 2018/2019 production year

Production Year	Hedging Strategy	July Price Movement	Main Trend (Q4)	Stock-to-usage	Input Cost Ratio	El Niño / La Niña
2006-2007	Strat 1 & Strat 2	Upwards	Upward	11%	38%	Weak El Niño
2014-2015	Strat 1 & Strat 2	Upwards	Upward (Trend turn)	27%	27%	Weak El Niño
2018-2019	Proposed - Strat 2	Expectation - Upwards	Upward	24%	35%	Weak El Niño

Production Year	WM-C	IP	IPR	EP	EPR	CBOT-C	USD/ZAR	Supply	Demand	Ending Stock	Days Stock	SOI
2006-2007	Medium	High	Low	Medium	Medium	High	Medium	Medium	Medium	Medium	High	Low
2014-2015	Medium	Medium	Medium	Low	Medium	Low	High	Medium	High	High	Medium	Low
2018-2019	Medium	High	Low	Medium	Low	Low	High	Medium	High	High	High	Medium

Source: Compiled by author

The result obtained by means of the filter model may be interpreted as follows. The filter model established that the characteristics in terms of the main trend and El Niño / La Niña for the 2018/2019 production year corresponded with the 2006/2007 and 2014/2015 production years. As a result, the next logical step in the analysis was to identify additional similarities (in the form of other market factors) between the three production years to confirm the expectation of an upward price progression in the July 2019 white maize futures contract price. In terms of the dominant cluster analysis results (highlighted in grey) (Section 6.2.2), the dominant market factors to consider during the 2018/2019 production year decision months were the white maize continuous price (WM-C), the proxy for the international maize price (CBOT-C), and demand. A comparison between the 2018/2019 production year and the 2006/2007 and 2014/2015 production years in Table 6.33 shows that the cluster analysis results for the 2018/2019 production year corresponds with the 2014/2015 production year results.

Furthermore, the cluster analysis result for these three market factors (WM-C, CBOT-C and demand) corresponds with the similarities between the 2014/2015 and 2018/2019 production years in terms of the average percentile rank grouping result (Chapter 5, Section 5.3.2). Based on these similarities, the logical derivation was that the 2018/2019 production year should be linked to the 2014/2015 production year rather than the 2006/2007 production year. Still, an evaluation of the other factors for the 2018/2019 production year was necessary to establish further confirmation. Given the expectation of a July white maize futures price increase, a logic consideration would be to determine if market prices were high or low in terms of import (IP) and export parity (EP) (Chapter 5, Section 5.2.1.2) in order to gauge the expected price increase potential.

Prices were arguably closer to export parity (EP) due to the relatively low average export parity ratio (EPR) grouping value. Prices therefore had the potential to increase and move away from export parity if demand remained high and the relatively high ending stock levels were addressed. Export parity (EP) in itself was however on medium levels, despite the fact that prices were closer to export parity. The medium grouping level associated with EP could be attributed to the high average percentile rank grouping value for the USD/ZAR, which would support parity price levels (Chapter 5, Section 5.2.1.2). As a result, the upward price development expectation for the July 2019 white maize futures price was supported by the expectation that prices were closer to support levels in terms of export parity. The next step in the analysis was to make a decision between either Strategy 1 (hedge during harvest) or Strategy 2 (buy put options during planting window), since these strategies were identified as the more optimal hedging strategies to deploy when the expectation was for an upward price progression (Section 6.3.2) in the July white maize futures contract.

A review of Table 6.25 in Section 6.3.2 showed that Strategy 1 outperformed the average July 2015 white maize futures contract price by R593.07/mt, while Strategy 2 achieved an outperformance of R347.68/mt. However, an important consideration with regards to a hedging strategy is always the reality of production uncertainty during the planting window. Both Strategy 1 and Strategy 2 address the risk of costly contract buy-outs that may occur if a producer is not able to plant, since Strategy 1 does not hedge during the planting window and Strategy 2 limits the cost of a contract buy-out to the put option premium cost. Yet the reality remains that the July white maize futures contract price may increase during the planting window only to decrease after production certainty is achieved for the new production season. As a result, weather expectations and their possible impact on the realisation of production certainty should be considered to make the best possible price risk management decision with the available information during the decision months.

Rainfall ensures production certainty, which is why expectations of rain could be linked to SOI (Chapter 5, Section 5.2.1.5). The average percentile rank group value for SOI during the decision window was at a medium level, which does not necessarily indicate a strong probability of a drier El Niño event. This is confirmed by the ONI value (Chapter 5, Section 5.2.2.3) during the decision months, which indicated a weak El Niño event. As a result, a producer should always consider the probability of a weather-based scenario disappearing over time and the final seasonal characterisation resulting in nothing but a neutral event. Prices may as a result increase during the planting window, but stabilise once the crop has been planted. Bearing in mind this uncertainty, with the expectation of July white maize futures contract prices most probably following an upward development due to the existing upward trend in the continuous white maize contract, Strategy 2 is proposed for the 2018/2019 production year.

At the time of evaluating the proposed strategy (November 2018), the July white maize futures price had already started to increase due to warm and dry conditions, which prevented planting in the Western production regions where white maize is produced predominantly. Prices continued to increase throughout December 2018, since sufficient precipitation to enable planting had still not realised the greater central and Western white maize production regions (Figure 6.15).

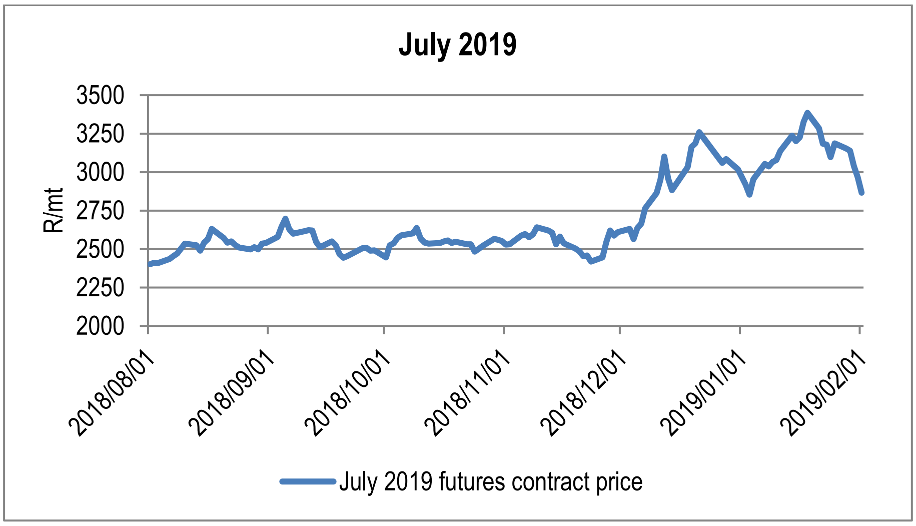

Figure 6.15: The initial July 2019 white maize futures contract price development
Source: Compiled by author from Thomson Reuters Eikon for commodities data

Much needed rain however started to fall from the beginning of January 2019, and the July 2019 white maize futures price responded to the expectation that producers would be able to plant, even though the optimal planting date had already passed (Chapter 5, Figure 5.13). This scenario nevertheless created uncertainty as to the yield potential of the crop, since optimal planting dates may be linked to optimal production potential. This uncertainty led to another price increase in January 2019, which was yet again fuelled by warm and dry conditions, as well as uncertainty about the actual hectares planted. At this point it should be stated that a producer who has established a minimum price will always have the certainty that his/her produce value will not fall below the minimum price level, and that a contract buy-out in the case of non-delivery is limited to the put option premium.

Based on the analysis and interpretation of the 2018/2019 production year factor data provided, it is clear that the filter model is a meaningful decision tool that enables the user to evaluate several alternative influential market factor value comparisons of the different production years in order to derive an informed decision. Arguably, the model also provides the means to compare each individual market factor in isolation to identify seasonal similarities. The filter model should however not be regarded as a model that provides a ready-made solution for each filter selected, but the filter model does provide the means to conduct an in-depth scenario analysis to reach a logical conclusion. It should also be borne in mind that the market remains a dynamic and ever-changing environment where changes are incorporated in the influential market factor values. It is therefore advised that new data is incorporated into the model as a new production year develops, in order to establish the means to compare the influential market factor development between similar seasons to confirm or re-evaluate the current course of action.

6.5 Chapter summary

The results included in this chapter were based on the methodological approach established in Chapter 5. The approach was based on three main steps. The first step included an evaluation of the percentile ranking and grouping results, as well as the cluster analysis results (Section 6.2). The second step (Section 6.3) provided an in-depth evaluation and comparison of the results obtained from the implementation of the 10 hedging strategies that were identified in Chapter 5 (Section 5.4.2). The third step involved the compilation of an all-inclusive filter model, with the results obtained from step one and step two combined to establish a decision-making tool (Section 6.4). The filter model decision-making tool enables the analyst to identify similarities between production years in order to arrive at an informed decision as to the more optimal hedging strategy to deploy, given the expected price development of the July white maize futures contract price. The interpretation of results throughout each step required a continuous comparative approach to evaluate the applicability of each result. This comparative approach, as a result, ensured that several additional findings were made that enabled meaningful insight into each aspect of the analysis as a whole.

The comparative approach in step one was to evaluate whether the development in the influential price determinant factor values by means of the percentile ranking and grouping analysis method showed a logical progression when compared to the progression in the applicable July white maize futures contract price values. All of the individual influential price determinant factor value progressions were considered and examples were discussed. The evaluation showed that each of the influential price determinant factors showed a logical progression when compared to the July white maize futures contract price progression. A specific confirmation was that the individual influential price determinant factor values should never be viewed or interpreted in isolation, since the progression in a specific influential price determinant factor value could also be explained by means of the specific percentile rank grouping level or progression in other influential price determinant factor values. Another important confirmation was that it became evident that it was possible to identify similarities between production years based on the similarities in the percentile rank grouping values of the influential market factors (Section 6.2.1).

The comparative analysis done to evaluate the results obtained by means of the cluster analysis method proved to be an iterative task of evaluating and considering the applicability of several cluster combinations. A specific five-cluster grouping provided the most logical result when comparing the influential price determinant factors, which were grouped together in each cluster, in addition to the linkage to the individual influential price determinant factor value results obtained by means of the percentile ranking and grouping analysis. The cluster analysis results also included a division that identified the more dominant cluster at a specific point in time and provided the means to link specific dominant influential price determinant factors to a specific month or period. Yet this ability could not necessarily provide a direct link between the different production years, but the key contribution of this analysis lay in the synergy it provided when compared to the percentile ranking and grouping analysis (Section 6.2.2).

The synergy was achieved when the percentile ranking and grouping analysis was able to identify similarities between production years, after which the dominant influential price determinant factors at a specific point in time (identified by means of the cluster analysis approach) could be used to confirm the linkage between production years based on the influential price determinant factors. Another important finding based on the cluster analysis results was that dominant influential price determinant factors changed over time. Earlier production years could generally be characterised by means of fundamental factors in the form of supply and ending stock, but the dominant market factors changed after the 2009/2010 production year to include only demand and the main price-related influential price determinant factors in the form of IP, EP, USD/ZAR, WM-C and CBOT-C (Section 6.2.2). The reason for this change over time was attributed to the premise that the market matured over time, as participants started to realise that the influence of fundamental factors would be reflected in the price levels at any point in time. In terms of the AMH theory, one could argue that the market adapted to an ever-changing market environment and that the level of market efficiency ultimately improved as market participants gained experience based on opportunities presented or lessons learned in previous production years.

The next step in the comparative analysis was to determine which hedging strategy would be more applicable, given the type of production year. The first part of this analysis was to provide a summary of the realised strategy price of each individual hedging strategy for each of the ten strategies in each production year. The results showed that the implementation of a minimum price (Strategy 2) or actively managed minimum price strategy (Strategy 6) were able to outperform the average July white maize futures contract price with the greatest average margin over time. This meant that these two strategies could be implemented in each production year, and would outperform the average July white maize futures price over time, irrespective of the seasonal price development. The results nevertheless showed that specific strategies outperformed the average July white maize futures contract price in the respective production years when the July white maize futures contract price increased, decreased or traded sideways. This result proved to be fairly logical for each production year, given the July white maize futures contract price development, and also provided the means to evaluate the applicability of the performance measure analysis approach results to rank hedging strategies.

The performance measure analysis approach, which entailed ranking hedging strategies from a risk-weighted perspective, was one of the objectives of this study. Specific and detailed results were provided in Section 6.3.2, but the simplest explanation of the results was that they were nonsensical. An alternative approach to calculating daily hedging strategy returns was also considered, but results remained inconclusive. The reality of inconclusive results in this regard warranted an explanation. After careful consideration of the specific strategies identified by means of the performance measure analysis approach – which involved a comparison with the type of hedging strategy that logically should have been a more optimal strategy to consider in each production year – the finding was that derivative-based hedging strategies tended to skew the volatility of daily hedging strategy returns.

The influence of derivative-based hedging strategies on the return volatility stemmed from the manner in which a derivative instrument is valued against the underlying July white maize futures contract marked-to-market price on a daily basis. As a result, the volatility in the returns obtained from the daily realised price of the benchmark Strategy 1 (where no derivative instrument was applied to implement a hedge) was smaller, which led to a higher ranking in terms of the performance measure approach in several instances. Still, this in-depth analysis of the performance measure analysis results and its comparison to the strategies that outperformed the average July white maize futures contract price in specific types of seasons provided the necessary foundation that enabled the identification of a more optimal hedging strategy to deploy, given the seasonal price development.

The final step in the comparative approach was to combine the results obtained in each of the steps into a single decision-making tool. The specific decision-making tool in the form of a filter model was able to combine all of these inputs in a meaningful manner and an example of the applicability of the model to link seasons based on factor similarities was provided in an *ex-ante* analysis of the 2018/2019 production year. The ability of the filter model to enable a thorough analysis of all the influential market factors in order to make an informed hedging strategy decision based on the expected price progression of the following production year proved to be meaningful.

The results presented by means of the specific steps followed in constructing the filter model may as a result be seen as the practical manner in which the study achieved two of the main objectives set out in Chapter 1: to link production years based on similarities in the influential market factors, and to identify a more optimal hedging strategy to implement, given the seasonal price formation expectation (pre-season factors) for a specific production year. The following chapter concludes the study by providing a comparison between the initial aim of the study and the goals that were set out, and the manner in which the aim and goals were achieved in order to provide an answer to the research question.

CHAPTER 7

Conclusion and Recommendations

"QED – quod erat demonstrandum."

Latin phrase, which means, "what was to be shown" or "thus it has been demonstrated".

7.1 Introduction

This study evaluated the inherently difficult decision of price risk management that white maize producers are faced with every production season. More often than not, phrases such as "I should have" or "if I only knew" form the basis of any discussion over price risk management decisions. In order to address these uncertainties, producers tend to refer to a previous production year to draw a comparison to the current production year in terms of similar seasonal characteristics. The aim of such a comparison is always to arrive at some form of conclusion regarding expected price formation for the current production year. However, these comparisons are usually based purely on similar events, such as pre-season planting difficulties or midsummer droughts, rainfall at a critical point in time, or the probable impact of frost to name but a few. The potential impact of these events is predominantly associated with scenarios that may affect supply and demand and only provide a producer with a short-term price formation expectation. Producers therefore tend to avoid making price risk management decisions due to production uncertainty. Also, the potential lack of understanding of the possible outcomes of a specific derivative-based hedging strategy often results in a bad experience that contributes to producers' reluctance to implement price risk management practices. The inevitable result of this reluctance is that producers typically end up selling their produce in the bottom third of available market prices throughout a production season, usually due to fear of further price declines.

As a result of these challenges, the **problem statement** was identified but stated as three separate subdivisions relating to the aim of the study: **Firstly, a South African maize producer without a marketing plan or hedging strategy has no means to remove or partly reduce price risk. Secondly, a South African maize producer without the necessary knowledge pertaining to white maize hedging strategy performance over time may remain reluctant to implement any form of hedging strategy with confidence. Thirdly, the optimal hedging strategy may differ from one production year to the next. By this premise, indiscriminate application of one type of marketing**

plan or hedging strategy – without due consideration of all the elements that affect price formation – may be less prudent.

Taking into account the abovementioned problem statement, the following **research questions** were formulated: **Would it be possible to identify a proposed optimal hedging strategy for different seasonal price formation expectations by linking different production years, based on specific influential price determinant factors? Additionally, would it be possible to rank, and more conclusively determine optimal white maize hedging strategies by developing a ranking measure or criteria?**

The aim of this study, which formed the basis for the individual objectives, was broken down into four specific outcomes to address the problem statement and research question in a structured manner. The structured process involved an evaluation of the influential price determinant factors from which to establish similarities between production seasons, and this formed the basis for price development expectations. In addition, several derivative-based hedging strategies were identified and implemented on historical price data to determine which type of hedging strategy would be more optimal to deploy, given previous price formation in different production seasons with similar market characteristics. The result of this analysis was the development of a decision-making model that would enable a producer to evaluate/classify different production years according to influential price determinant factors, in order to derive a more optimal course of price risk management action.

The inclusion of each part of the structured process was based on the premise that, if the reliability of expected futures market price formation could be improved, producers may become more inclined to make use of the available derivative instruments in order to deploy a more optimal hedging strategy. In order to explain how this feat was accomplished, the relevant aspects and considerations included in this study were summarised in the following subsections. Section 7.2 considers the three specific subdivisions of the problem statement as well as the breakdown of the research question. This section provides the necessary linkages between the chapters included in this study to explain how the research problems were addressed and research questions answered. Section 7.3 follows the same approach to assess how the study objectives were reached. However, in order to address the objectives, the study identified several important recommendations or considerations in the literature review and results which are included in Section 7.4. Thereafter, Section 7.5 explains how the accomplishment of the study objectives contributed to the body of knowledge in terms of literature, methodology, and practice. The chapter concludes by providing several suggestions for further study in Section 7.6. This chapter does not include a chapter overview since each of the individual literature chapters as well as the methodology and results chapters included a thorough chapter summary.

7.2 Addressing the problem statement and research question

The problem statement and research question that were revisited in the introduction to this chapter are broken down and addressed in Table 7.1 and Table 7.2, respectively. The aim of the breakdown is to ensure a thorough conclusion and identify the chapter linkages to provide an overview as to where and how the problem statement and research question were addressed.

Table 7.1: Addressing the problem statement(s)

Problem identified	Confirming and addressing the problem identified
A South African maize producer without a marketing plan or hedging strategy has no means to remove or partly reduce price risk.	The market price for South African white maize is determined on a daily basis by means of a derivative-based free market system (Chapter 2, Section 2.3). A producer may not be accustomed to the free market price setting mechanism due to changes in the market mechanism over time (Chapter 2, Section 2.2.2.4) and several other factors my influence a producer's hedging decision (Chapter 4, Section 4.2.1). The reality is that the existing SAFEX free market price setting mechanism efficiently incorporates new information (Chapter 3, Section 3.3.1), which provides the means to facilitate effective price risk management (Chapter 4, Section 4.1). As a result, even a producer who does not trust the marketing mechanism can only receive the SAFEX daily market price for his/her produce. Therefore, avoiding the market mechanism or producing white maize without a marketing plan or hedging strategy inevitably places the maize producer at a significant disadvantage in terms of removing or reducing price risk.
A South African maize producer without the necessary knowledge pertaining to white maize hedging strategy performance over time may remain reluctant to implement any form of hedging strategy with confidence.	South African white maize producers have been confronted with a changing market mechanism since deregulation (Chapter 2, Section 2.2). Producers were suddenly forced to adopt and apply derivative instruments in order to hedge their associated price risk. Derivative instruments tend to be abstract and difficult to interpret without the necessary experience and producers tend to avoid future price risk management decisions altogether if they feel that they lack the necessary knowledge about the tools available to them. The explanation of the inner workings of available derivative instruments in Chapter 2 (Section 2.3.3.2 and Section 2.3.3.3) was included to partly address the problem. Also, the literature review of applicable hedging strategies (Chapter 4, Section 4.2.2), as well as the detailed description of the hedging strategies implemented as part of this study (Chapter 5, Section 5.4.2) provided the required foundation to establish the hedging strategy evaluation result in Chapter 6 (Section 6.3). The results contained in this study should contribute positively to maize producers' understanding of derivative-based hedging strategies and, consequently, provide the reassurance needed to overcome their distrust and implement a hedging strategy.

Problem identified	Confirming and addressing the problem identified
The optimal hedging strategy may differ from one production year to the next. By this premise, indiscriminate application of one type of marketing plan or hedging strategy – without due consideration of all the elements that affect price formation – may be less prudent.	The study evaluated 10 different hedging strategies over 16 production years in order to determine which hedging strategies would have been more optimal to deploy in each of the production years. Results (Chapter 6, Section 6.3) showed that an optimal hedging strategy may differ for different production years and that specific strategies would be more optimal to deploy when the July white maize futures contract price formation was either upward, downward or sideways. In order to evaluate which type of price formation could be expected, so as to implement a more optimal hedging strategy given the expectation, several influential price determinant factors were identified in Chapter 2 (Section 2.4). These factors were specified in Chapter 5 (Section 5.2.1) and included as part of the percentile rank grouping and cluster analysis methods (Chapter 5, Section 5.3) in order to establish similarities between different production years by means of the decision-making filter model (Chapter 6, Section 6.4). The interpretation of production year similarities by means of the filter model showed that it was possible to derive a probable price formation expectation for the following July white maize futures contract hedging month and implement a more optimal course of price risk management action.

Source: Compiled by author

Table 7.2: Addressing the research question(s)

Research question	Addressing the research question
Is it possible to identify a proposed optimal hedging strategy for different seasonal price formation expectations by linking different production years, based on specific influential price determinant factors?	The results obtained from the percentile rank grouping and cluster analysis methods (Chapter 6, Section 6.2.1) enabled the compilation of the filter model (Chapter 6, Section 6.4). The filter model establishes a meaningful decision tool, which enables the user to evaluate several alternative influential market factor value comparisons of different production years in order to conduct an in-depth scenario analysis to reach a logical conclusion. This logical conclusion will provide the user with a seasonal price formation expectation for which a more optimal hedging strategy (Chapter 6, Section 6.3) may be implemented. **Based on the results, the answer to this specific part of the research question is yes, it is possible and has been proven in this study.**
Is it possible to rank, and more conclusively determine optimal white maize hedging strategies by developing a ranking measure or criteria?	The ranking measure or criteria considered as part of the methodology was the implementation of financial performance measures (Chapter 5, Section 5.5). However, results pertaining to the implementation of these measures on the daily hedging strategy returns were mainly nonsensical (Chapter 6, Section 6.3.2). Due to the nonsensical results and the realisation that the hedging strategy return calculation may have been the cause for the skewed performance measure results, an alternative method for calculating hedging strategy returns for the performance measure evaluation process was evaluated. Results nevertheless remained nonsensical. However, the analysis process as a whole, which included the basic description of the strategy results in terms of outperformance of the average July white maize futures contract price up to the ranking of hedging strategies by means of performance measures, provided the necessary foundation to evaluate different types of hedging strategies. This evaluation method established the means to identify the more optimal type of hedging strategy to deploy, based on the inherent risk involved in implementing a specific type of strategy, as well as the direction of the July white maize futures contract price development. **Hence, the answer to the specific part of the research question is yes, it is possible to rank and determine optimal white maize hedging strategies based on the July white maize futures contract price formation expectation – which can be categorised as upward, downward or sideways.**

Source: Compiled by author

7.3 Assessing the study objectives reached

The objectives of this study were addressed and reached as stipulated in Table 7.3 below.

Table 7.3: Study objectives, chapter reference, and conclusion

Objective to be satisfied	Chapter references	Assessment of objective reached
Identify the influential price determinant factors that should be included in the analysis to enable a comparison between production years based on similarities in the factors at a specific point in time.	Chapter 2, Section 2.4 Chapter 3, Section 3.3 Chapter 5, Section 5.2	The influential price determinant factors were identified from the literature in Chapter 2, and were confirmed as well as expanded on, based on the factors applied in the literature when white maize market efficiency was evaluated in Chapter 3. The individual discussion of each factor in Chapter 5 explained how the factor would be included as part of the analysis to enable a comparison between production years based on similarities in the factors at a specific point in time.
Link previous and upcoming production years by means of historical and recent factor data in order to establish an expectation of price formation for an upcoming production year.	Chapter 5, Section 5.3 Chapter 6, Section 6.2 Chapter 6, Section 6.4	Production years were linked based on the price determinant influential factor data and through the synergy achieved through the percentile rank grouping and cluster analysis, as explained in Chapter 5 and implemented in Chapter 6. Although the filter model may be seen as a means to establishing the link between production years at a specific point in time, the filter model inevitably remains an output of the results obtained through the percentile rank grouping and cluster analysis.
Identify applicable derivative-based hedging strategies from previous literature studies in order to implement 10 specific hedging strategies against the July white maize futures contract from 2003 to 2018.	Chapter 4, Section 4.2.2 Chapter 5, Section 5.4	Several hedging strategies were identified from the literature in Chapter 4. Based on this literature review, as well as applicable derivations of the hedging strategies identified, the implementation of 10 individual strategies was comprehensively explained in Chapter 5.
Determine the daily realised strategy price for each hedging strategy and production year from 2003 to 2018. The purpose thereof to calculate daily hedging strategy returns.	Chapter 5, Section 5.4.2 Chapter 6, Section 6.3.2	The daily realised hedging strategy price determination was based on a simple accounting principle: the daily strategy price would be the realised hedging level if the strategy were unbundled and valued against the mark-to-market price for the relevant July white maize futures contract. The manner in which each of the 10 strategies should be valued on a daily basis was explained in depth in Chapter 5 and the calculation results formed the basis of the performance measure analysis results presented in Chapter 6.
Compare the return results of each of the 10 implemented strategies for each of the 16 production years by means of applicable ranking measures in order to determine an optimal strategy for each production year.	Chapter 4, Section 4.3 Chapter 5, Section 5.5 Chapter 6, Section 6.3	The initial plan was to address the objective by applying financial performance measures to the hedging strategy return results. Several measures were identified as part of the literature review in Chapter 4. Furthermore, the relevant and applicable performance measures to be implemented were included in Chapter 5. However, as explained when addressing the second part of the research question above (Table 7.2), the results obtained by means of performance measures remained nonsensical, irrespective of the manner in which the hedging strategy returns were calculated (Chapter 6). Nevertheless, the objective was reached by means of the comparison provided when evaluating the under or outperformance of the average July white maize futures contract price for each strategy in each production year. Specific hedging strategies were identified as more

Objective to be satisfied	Chapter references	Assessment of objective reached
		optimal to implement given the expected direction of the July white maize futures contract price development.
Compile a decision-making model (filter model) to enable the linkage of similar production years based on similarities in the influential price determinant factors at a specific point in time.	Chapter 5, Section 5.3.2 Chapter 6, Section 6.4	The filter model was constructed based on the method explained in Chapter 5. The application of the filter model as a whole provided an all-inclusive summary of the stance of the percentile rank grouping values and the cluster analysis results, as well as the additional factor values at a specific point in time when a hedging decision is made. The filter model provided the means to divide production years in different combinations in order to reach a relevant consensus for the July white maize futures contract price development expectation (i.e. upwards, downwards or sideways). The expectation consensus also provided the necessary confirmation to derive a specific course of action in terms of the more optimal hedging strategy to deploy.

Source: Compiled by author

7.4 Important recommendations or considerations identified in the literature review and results

Throughout the course of this study, several relevant conclusions were reached and specific results obtained. It is important to revisit these findings, as they may be regarded as recommendations or considerations when similar studies are conducted in the agricultural derivatives market space in future.

- Chapter 2: Changes in the influential price determinant factors all have their own unique effects on white maize prices, depending on the impact a specific change has on current and expected supply or demand levels. The changes in these factors do not occur in isolation or on an individual basis, but create a combined effect. This combined effect may have a greater influence on expected price changes than expectations based on individual factors. The intricacy of these ever-changing factors emphasises the inherent price risk white maize producers must account for by means of derivative instruments. Nevertheless, using derivative instruments to manage their respective price risk does not exempt a producer from all market-related risks. Depending on the type of derivative instrument used by a producer to hedge, the producer is exposed to other types of risks, of which liquidity is the most prominent to account for.
- Chapter 3: The Adaptive Market Hypothesis (AMH) provided the necessary foundation to evaluate and compare white maize hedging strategies and identify the potential link between seasons based on influential market factors. This assertion corresponds with the argument that a market price development would most likely be similar for seasons that portray similar influential factor values at a specific point in time; however, it would also seek to adjust to

reflect changes in the influential price determinant factors. The changes in the influential price determinant factors throughout a season may as a result have short-term influence on price formation, since the market attempts to continuously adapt as new price implications based on changes in influential factors values enter the market information realm.

- Chapter 4: Producers are confronted with variables that are generally out of their control in terms of price formation. The harsh reality, therefore, is that a producer would still receive the market price based on the general market consensus of the impact that these variables should have on current and future price changes. However, this does not provide any reassurance that the general market consensus price would be of fair value for a specific producer. Producers should, as a result, never separate production decisions from marketing decisions in any given season. This implies that a profitable or sustainable production decision should be based on the futures price a producer is able to hedge at before or during the planting window.
- Chapter 6: Several cluster analysis combination results were considered in order to derive the most plausible and logical cluster analysis result of all the alternatives evaluated. The evaluation of alternative cluster analysis results included a reduction in the number of factors included. The reduced number of factors also included several combinations of the 12 original factors in order to evaluate if the result showed a logical alternative cluster progression and comparison to the earlier reported percentile ranking grouping analysis results. Another alternative was to adjust the number of clusters required to a specific number to determine if the resulting cluster analysis result provided a logical comparison with the percentile rank grouping analysis results. It was by means of this iterative analysis and applicability evaluation process of the different combinations that a specific five cluster analysis result provided the most relevant alternative.
- Chapter 6: The cluster analysis approach provides the means to determine which factors are dominant at a specific point in time. The logical connection between the cluster analysis result and percentile rank grouping results furthermore provides the required synergy between the two methods to identify similarities between production seasons, in order to link different production years based on these similarities.
- Chapter 6: Several attempts were made to derive a meaningful result to establish the optimal hedging strategy to be deployed according to performance measure analyses. The results obtained were generally nonsensical and the main reason for this was the way in which a derivative-based hedging strategy influences the variability of returns, which skewed the

results. Hence, the application of performance measures to any agricultural derivative-based strategy returns is not advised.

- Chapter 6: In terms of average under or outperformance (average returns of strategy) of the July white maize futures contract mark-to-market (MTM) price, the minimum price or put-option hedging strategy was the favourable strategy over time and realised the highest average outperformance of the average July white maize futures price over time. Furthermore, when considering the return per unit of risk – which is calculated by dividing the average under or outperformance (i.e. average returns of the strategy) with the standard deviation of the average under or outperformance for each strategy – results showed that the deployment of a minimum price or actively managed minimum price strategy would result in the outperformance of the average July white maize futures contract MTM price over time.
- Chapter 6: Several evaluations showed that the filter model established the means to identify similarities between the other influential price determinant factors for different seasons after the two price determinant factors in the form of the continuous white maize price trend (established by means of the 100-day and 200-day moving average stance) and El Niño / La Niña, were established. The filter model, as a result, provided the means to divide production years in different combinations in order to reach a relevant consensus for the July white maize futures contract price development (i.e. upwards, downwards or sideways). The expectation consensus also provided the necessary confirmation to derive a specific course of action in terms of the more optimal hedging strategy to deploy.
- Chapter 6: The filter model constitutes a meaningful decision tool, which enables the user to evaluate several alternative influential market factor value comparisons of the different production years in order to derive an informed decision. Arguably, the model also provides the means to compare each individual market factor in isolation to identify seasonal similarities. The filter model should however not be regarded as a model delivering a direct solution for each filter selected, but it does provide the means to conduct an in-depth scenario analysis to reach a logical conclusion. It should furthermore be taken into consideration that the market remains a dynamic and ever-changing environment where the changes are incorporated in the influential market factor values. It is therefore advised that new data be incorporated into the model as a new production year develops, in order to establish the means to compare the influential market factor development between similar seasons to confirm or re-evaluate the current course of action.

7.5 Contribution of this study

This section includes the contributions this study made. These contributions may be broken down into contributions in terms of literature, methodology, and practice.

7.5.1 Contribution to literature

The literature contribution in this study may be presented as follows:

- Chapter 2: The background to changes in market structure and agricultural policy in South Africa provided an historical overview of legislative changes. Apart from the actual policy implications on the marketing of agricultural products, this review provided meaningful insight into the actual reasons certain decisions were made over time. Furthermore, the review enhanced the reader's understanding as to why producers may not (yet) be comfortable with - or willing to - implement derivative-based hedging strategies.

- Chapter 3: Developments in market efficiency over time have arguably been dealt with by numerous studies. Discussions, however, tend to focus on arguments for and against the Efficient Market Hypothesis (EMH) after the formalisation of the concept of market efficiency. The discussion on market efficiency in this study provided the reader with an historical overview of the days before the formalisation of the EMH. This overview ensured that the reader gained the required insight into the development of specific concepts such as market anomalies, behavioural finance, technical analysis and the Adaptive Market Hypothesis (AMH), of which the reader would struggle to find a comparable compilation. Ultimately, the review reasoned that studies perceived as contradictory to the notion of market efficiency should not merely be written off or disregarded.

  Chapter 4: The literature review on hedging strategies established the means to include and evaluate several hedging strategies in detail. The identification of hedging strategies from literature was done in Chapter 4, Section 4.2.2.1 which focussed on international price risk management strategies, as well as Section 4.2.2.2 which discussed South African price risk management strategies. From the applicable literature, 10 hedging strategy concepts were identified. A thorough methodological procedure for each strategy was provided in Section 5.4.2 (subdivided into Sections 5.4.2.1 to 5.4.2.10). The implementation procedure for each strategy also included the relevant literature from which the strategy was identified or adapted. Specific reference can be made to the manner in which Strategy 6 to 8 was implemented as a contribution to literature as well a methodology. All three of these strategies establish a hedge for all tonnages during the planting window, and thereafter aimed to increase the original hedge level by reducing hedging cost and capturing upward price movement if it occurs by actively managing the options included in the strategy. The main literature in this regard, highlighting the work by Strydom *et al*. (2010) and Venter *et al*. (2012), did not include hedging strategy evaluations in this manner. Also, Strategy 3 and Strategy 9 which are option-based strategies which may be implemented by an individual producer to establish a hedge during the planting window, with a significant decrease in option cost, have not been included in previous evaluations or comparisons of white maize hedging strategies.

7.5.2 Methodological contribution

The methodological contribution of this study may be presented as follows:

- Chapter 5: This study applied percentile rank grouping and cluster analysis to the influential price determinant factors of white maize in order to identify similarities between production seasons. Based on the literature acquired and included in this study, no previous study has attempted to apply percentile rank grouping and cluster analysis in order to achieve this feat. A compareable study which leaned towards a similar notion was conducted by Auret and Schmitt (2008), who derived an explanatory model for white maize futures prices. In its simplest form, the explanatory model was a forecasting model, which incorporates the relationship of various similar influential price determinant variables in order to attempt to explain white maize future price changes. Another relevant study which aimed to identify similarities in the white maize futures market was presented by Kirk (2007). The aim of the study was to determine if there was an observable seasonal component in white maize futures prices. The study found that the white maize futures price tended to peak in the March contract and dip in the July contract of each season. A related study by Heymans (2008), also evaluated the seasonal component in the white and yellow maize contract prices traded on SAFEX. The main aim, however, was to determine if different white and yellow maize contract combinations ranging from the spot contracts to the different futures contracts moved together in order to derive a pairs trading strategy. The study found seasonal patterns for both the white and yellow maize contracts, which conformed with the expected reactions of the market to changing supply and demand conditions. As a result, the studies provided generalised results in terms of price formation and seasonality and did not provide a methodology through which different production years could be linked in order to establish a more optimal course of price risk management action.Chapter 5 and 6: The application of relevant financial performance measures to the daily realised hedging strategy returns in an attempt to more conclusively rank derivative-based hedging strategies is not an evaluation method that has been applied in previous literature. The results obtained were predominantly nonsensical and the main reason for this finding was attributed to the way in which a derivative-based hedging strategy influences the variability of returns through the general applied accounting principles, which skewed the results. This inconclusive result in itself may therefore be seen as the actual contribution in this instance, based on the conclusion that the application of performance measures to any agricultural derivative-based strategy returns is not advised.

7.5.3 Practical contribution

The practical contribution of this study may be presented as follows:

- Chapter 6: The methods of analyses before the development of the decision-making filter model only focussed on either the evaluation of hedging strategies or the comparison on production years based mainly on seasonality. When considering the applicability of the hedging strategies included in this study, Section 7.5.1 provided context as to how these strategies fit into the body of knowledge. In terms of the linkage of production years based on influential price determinant factor similarities, several applicable studies were contextualised in Section 7.5.2 above.

  However, when considering similarities between the filter model and compareable existing literature, the study by Meyer, Westhoff, Binfield and Kirsten (2006) also evauated the developments in or expectations for a South African white maize production season in relation to weather. They proposed an "econometric regime-switching model" where domestic prices in South Africa were determined by three different and specific trade and policy regimes. These three regimes depend on the current and expected stock levels of white maize in South Africa, which is greatly influenced by weather patterns. Ultimately, the model as a result only provides input from two factors and does not provide the means to compare seasons based on similarities in all of the applicable influential price determinant factors identified in this study. This becomes problematic since not all of the factors have the same constant influence or impact throughout each production season which is highlighted by Stone, *et al*. (1996) and Meyer, *et al*. (2006). They emphasised that a model which aims to predict supply and demand conditions in the market should always consider the way through which the influence of one factor may be increased by the joint influence of other factors. They also pointed out that derivations based on a specific factor value should never be done relative to a specific single value, but rather relative to values that may be linked to certain regimes, intervals or similar developments.

The filter model as a result provides the means to establish confirmation between similar seasonal developments based on consensus between the factors included in the model which may be linked to certain regimes, intervals or similar developments. The practical applicability of the filter model therefore builds on the literature and methodological contribution by combining the results of the percentile rank grouping and cluster analysis as well as the hedging strategy results. More specifically, the filter model provided the means to divide production years in different combinations in order to reach a relevant consensus for the July white maize futures contract price development (i.e. upwards, downwards or sideways). This combination to derive expectation consensus also provided the necessary confirmation to apply a specific course of action in terms of the more optimal hedging strategy to deploy.

Apart from the contextualisation of the practical applicability of the filter model within the existing literature, the development of the filter model also provides the author with a structured methodological approach based on proven results. As stated in Chapter 1, the author has been involved in the agricultural derivatives market since 2008. This involvement includes the continuous evaluation of market conditions in order to propose hedging or speculative derivative-based strategies to producers or clients.The practical contribution is not only inherent in the application of the filter model results in practice, but the fact that the individual results obtained addresses the motivation of this study. Colleagues in the agricultural derivatives market and relevant producers who were presented with results of the hedging strategy evaluation in particular, as well as the decision-making ability facilitated by the filter model, were intrigued by the applicability and simplicity of the results. There are regular requests for updates on the filter model and the accuracy of the model's suggestions for the 2018/2019 production year in terms of hedging strategy applicability, already set the stage for the improvement of an existing portfolio-based hedging product. The actual outcome of the model is that it presents market participants with the means to make an informed decision as to a more optimal hedging strategy approach, and this has notably improved their willingness to make use of the proposed strategy.

7.6 Suggestions for future study

Several recommendations for future research endeavours include the following:

- The hedging strategies included in this study provide a practical and applicable hedging basis that is applied in practice. The comparison in terms of hedging strategies proposed in this study could arguably be expanded to include an array of alternative approaches. These approaches may include variations such as:
  - Implementing the actively managed put-option strategy according to the process described in Chapter 5, but not buying put options for all of the proposed tonnages to be hedged. The tonnages not hedged by means of put options may be hedged by means of short futures contracts based on the same implementation strategy of the actively managed put option. The aim of such a study would therefore be to determine which combination of put options bought and futures contracts sold by means of the strategy implementation procedure would be the more optimal approach over time.
  - Implement a hedging strategy with the only hedging criterion a profitability measure. The aim would be to determine whether it would be possible to implement a hedging strategy, but only if the hedge level accounts for the cost of hedging as well as a profit percentage above the cost of production. The returns calculated in this study in order to implement the original performance measure evaluation, suggest that such an approach may be possible and meaningful to ensure the profitability of any hedging strategy.
- This study focussed on the development of the filter model and applicable price risk management hedging strategies for white maize. The evaluation of hedging strategies and the development of a similar filter model for other derivative-based agricultural commodities, such as sunflower seed or soybeans, can also be considered.
- This study focussed on the traditional analysis of hedging strategies and price risk management, based on the normal production season development from the planting window up to harvest in July. Yet producers are not inclined to selling produce in this manner, which means that they may consider marketing their produce from the harvest period up to the planting window, which is from July to December in each marketing year following the previous production year. The analysis approach included in this study may therefore be implemented on post-harvest derivative-based marketing strategies, as well as the expansion of the filter model to facilitate the marketing decision-making process.

- The cluster analysis results identified a general progression of dominant factors over time. The progression was attributed to the premise of the Adaptive Market Hypothesis (AMH). The timing of the definite change in dominant influential price determinant factor progression may however also be linked to the Sub-Prime financial crisis. It may be meaningful to evaluate if the change in dominant factors can be confirmed through a pre-crisis and post-crisis regression type analysis.

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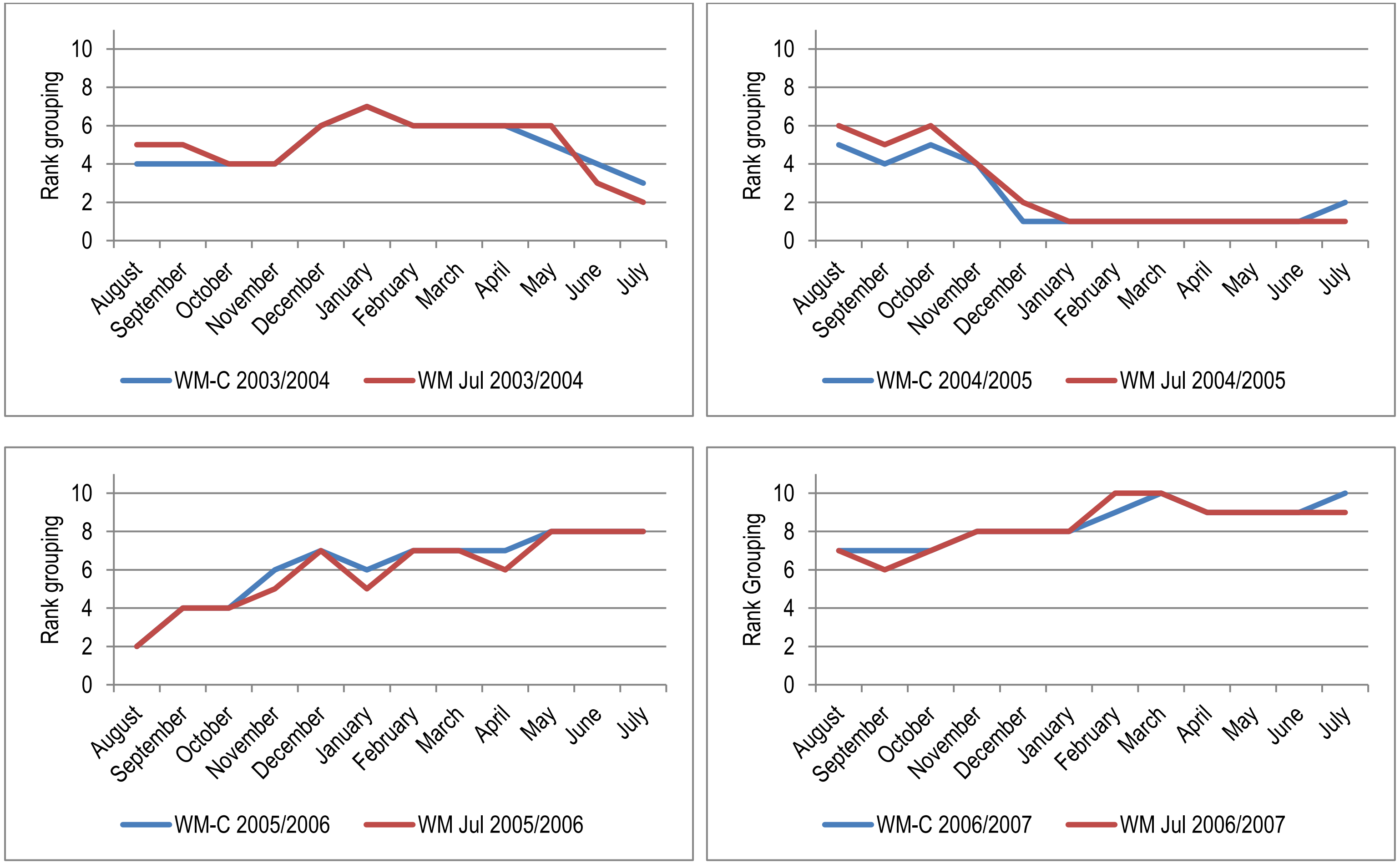
APPENDIX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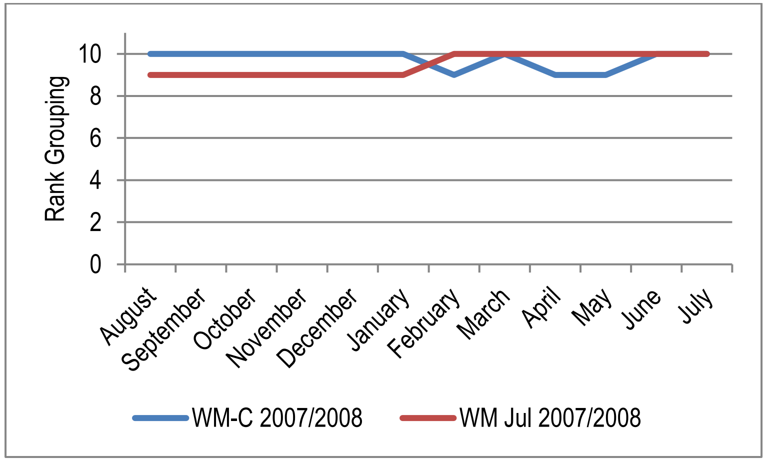
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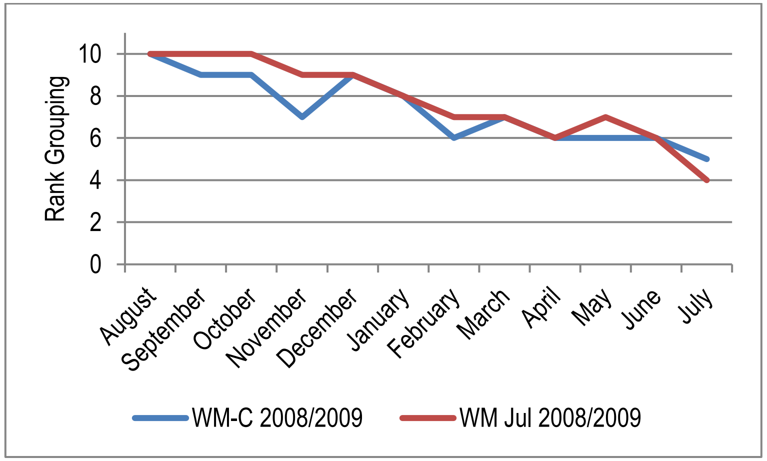
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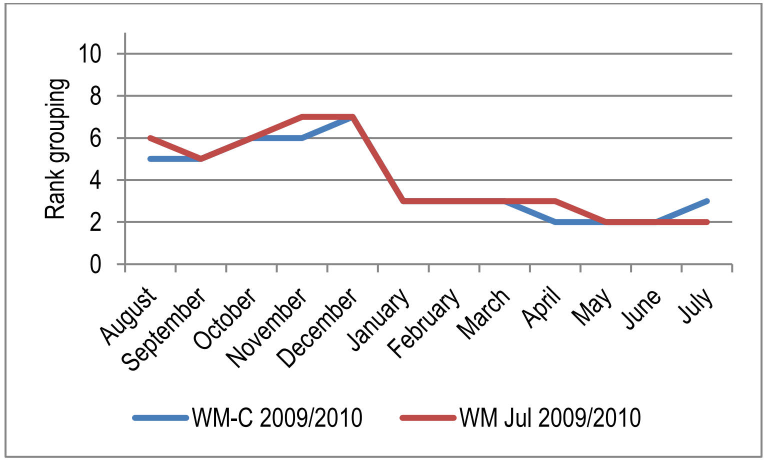
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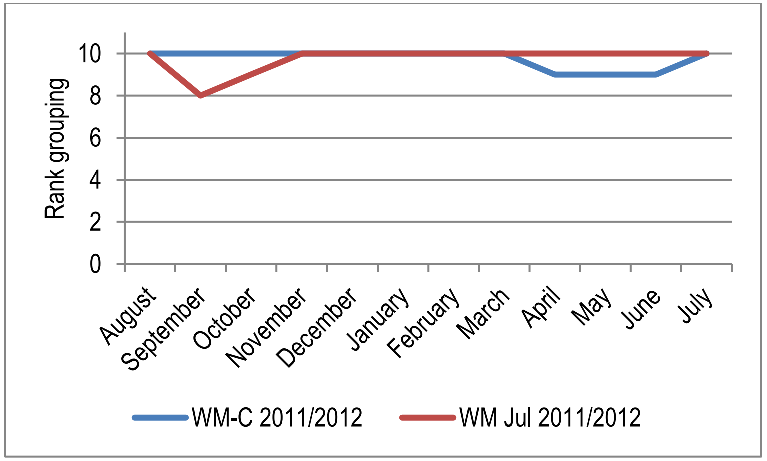
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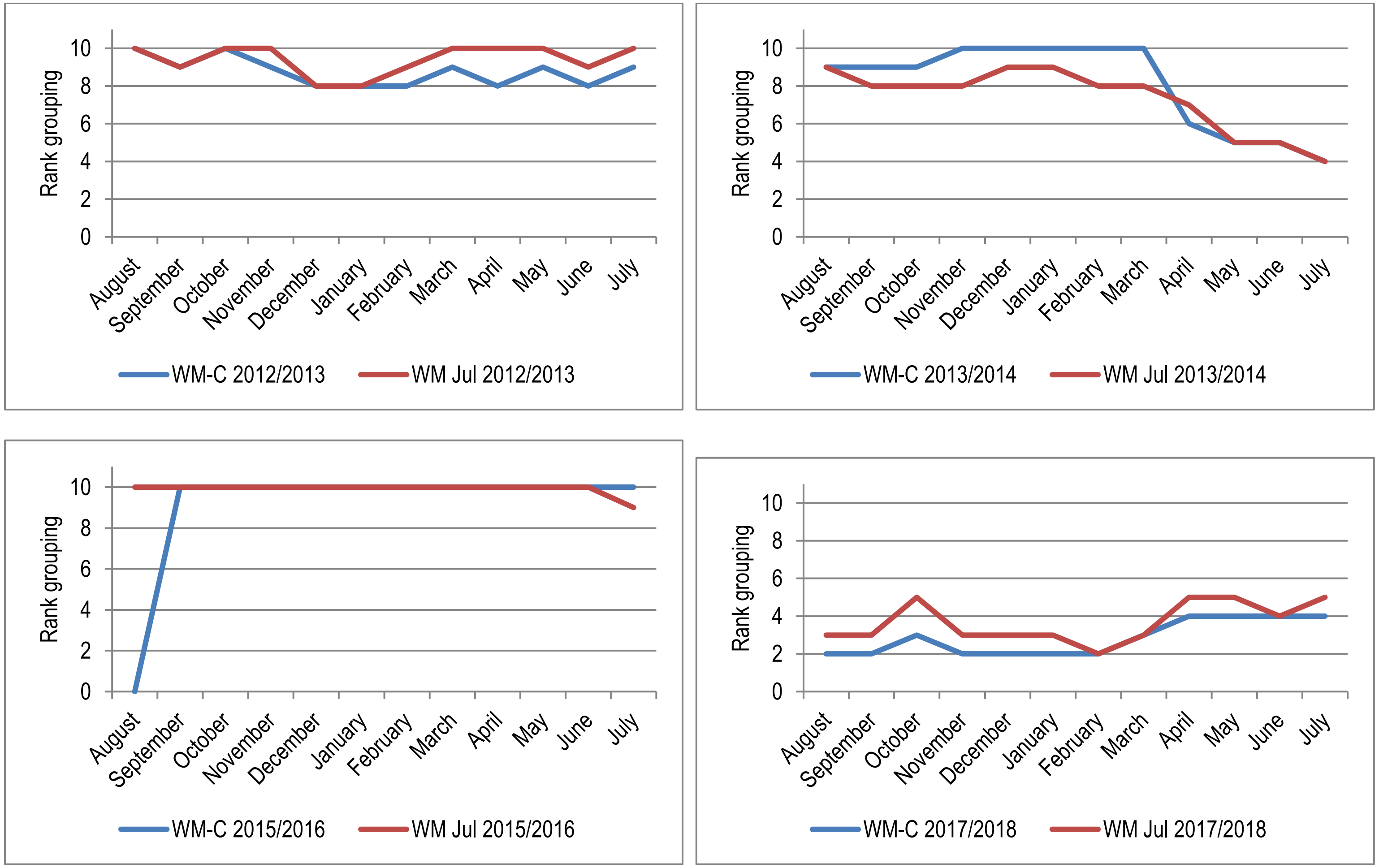

Figure A1: **Percentile rank grouping value comparison of white maize continuous (WM-C) with July white maize futures contract (WM Jul) (based on monthly values)**

Source: Compiled by author

Table A1: Methodological approach conceptualisation

Step in the methodological approach	Applicable section	Data considered (Detail included as part of Table 5.4)	Cross reference or background explanation	Reason for inclusion of the method or technique
1. Identify the relevant influential market price driving factors.	Section 5.2.1 and Section 5.2.2.	Factors taking on a monthly value: • White maize continuous price; • Import and export parity ratio; • Continuous CBOT maize price and USD/ZAR exchange rate; • Maize stock availability (Days' stock); • Southern Oscillation Index (SOI). Factors taking on an individual value or description at a specific point in time: • General price trend; • Stock-to-usage; • Sea surface temperatures (SST) and predictions; • Profitability measure: Futures price versus input cost.	All of the relevant factors were identified from literature in Chapter 2, Section 2.4. If the factor was transformed in any way to reach a comparable measure, the explanations were provided when each of the factors are discussed.	The factors taking on a monthly value forms the basis of the values applied to implement cluster analysis (Step 3), percentile rank and grouping analysis (Step 4). The factors which are based on an individual value at a specific point in time do not form part of the clustering or percentile ranking and grouping analysis, but the derived value of each of these factors will facilitate an additional linkage between similar seasons on a more holistic expectation level, which will be included in the final filter model (Step 8)
2. Introduce the data pertaining to the relevant influential market price driving factors as well as the rest of the data which will be included as part of the methodological approach.	Section 5.2.3	The statistical description of all of the influential price determinant factors which take on a monthly value as well as the as the relevant price data listed below were considered: • White maize July contract closing price (daily from 2002 to 2018); • White maize March contract closing price (daily from 2002 to 2018); • White maize July contract price option volatility (daily from 2002 to 2018); • White maize March contract price option volatility (daily from 2002 to 2018).	An explanation as to the interpretation of specifically the higher moments pertaining to the descriptive statistics is provided as part of the reporting of data characteristics in Section 5.2.3.	The relevance of including a data descriptive and higher moment analysis as part of the methodology cannot be overstated. The data applied as part of specifically the cluster analysis (Step 3) approach needs to be evaluated for normality since several methods can be applied and results may be biased if the method is not able to account for high volatility and the presence of non-normality in the data (De Silva et al., 2018:3; Banfield & Raftery, 1993:805). The cluster analysis method identified described in Step 3 will therefore be able to account for the presence of higher moments.

3. Evaluate influential price determinant factors by means of cluster analysis.	Section 5.3.1	The influential price determinant factors which take on a monthly value as well as the as the July white maize contract price data was included.	One of the main objectives of this study was to find a relevant link or specific similarities in factor and price developments for different seasons. This seasonal similarity identification must be done in an attempt to make an informed decision as to the more applicable or optimal hedging strategy to deploy (Step 5) based on the influential factor similarity found in a specific season.	Cluster analysis is included to provide an exploratory analysis of data as an alternative method that aims to order or divide raw data into meaningful groups in an attempt to identify structures or homogenous groups (Jain, 2010:651). This methodological literature review identified the SPSS Two-Step Cluster Analysis in order to find possible clusters in the factors that influence the July white maize futures price. The reason for applying the specific method stems from the method's ability to account for non-normality.
4. Evaluate influential price determinant factors by means of percentile rank and grouping analysis.	Section 5.3.2	The influential price determinant factors which take on a monthly value as well as the as the July white maize contract price data was included.		The inclusion of a percentile rank and grouping analysis approach stem from the applicability of the approach to ascertain how a specific measurement compares to the rest of the measurements in the same group (Thurstone, 1922:225). The specific factor rank grouping at a specific point in time may as a result be compared to previous rankings which showed ranking similarities to identify similarities between production years over time.
5. Evaluating hedging strategies.	Section 5.4.2	• White maize July contract closing price (daily from 2002 to 2018); • White maize March contract closing price (daily from 2002 to 2018); • White maize July contract price option volatility (daily from 2002 to 2018); • White maize March contract price option volatility (daily from 2002 to 2018).	Chapter 4, Sections 4.2.2.1 and 4.2.2.2.	Ten strategies were presented and their implementation, as well as valuation procedure, was explained. The implementation procedure included an explanation to calculate daily strategy prices in order to facilitate a return calculation as part of the performance measure analysis (Step 7).
6. Input cost calculation	Section 5.4.3	Single value data per production year obtained from Grain SA (2018b).	Section 5.4.3	Based on the daily strategy price valuation for each hedging strategy, thoroughly explained in Section 5.4.2, a return could be calculated by subtracting the relevant input cost per tonne for the applicable production year and then dividing the value by the daily strategy price. The returns for each production year could then be evaluated and compared by means of the proposed performance measures (Step 7).

7. Performance measure evaluation	Section 5.5	Return data calculated from the daily hedging strategy price results as explained in Step 6.	Performance measures: Chapter 4, Section 4.3. Evaluating normality in Section 5.2.3	The statistical characteristics in terms of skewness (S), kurtosis (K) and the consequent presence of normality was evaluated by means of the same measures included in Section 5.2.3. It was important to consider the presence of non-normality and the implications thereof to avoid biased results by giving preference to measures able to account for the presence of higher moments (Bacon, 2009:12; Wiesinger, 2010:26). The presence of normality was not seen as a prerequisite for the inclusion of certain measures, neither was it used as criteria to exclude other measures. The aim was to arrive at a consensus to rank hedging-strategy performance based on the conformation by different measures.
8. Filter model	Section 5.3.2	Includes all relevant data considered in the study. The model is however a summary of the data results calculated in Step 3, Step 4, Step 5 and Step 7.	Section 5.3.2	The purpose of the filter model as a whole was to provide an all-inclusive summary of the stance of the percentile rank grouping values and the cluster analysis results, as well as the additional factor values (Chapter 5, Section 5.2.2) at a specific point in time when a hedging decision is made. The model also includes the results of the more optimal hedging strategies to deploy in each production year. This means that a more optimal hedging strategy decision would have to be based on the production year similarities identified by means of the percentile rank grouping and cluster analysis results up to that point in time as identified by the filter model.

Source: Compiled by author

Table A2: Comparison of hedging strategy results with average July futures contract MTM price

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2003:Strategy 7	R 1 886.00	R 87.13	R 1 798.87	R 1 163.43	R 635.44
2003:Strategy 3	R 1 880.00	R 85.40	R 1 794.60	R 1 163.43	R 631.17
2003:Strategy 8	R 1 886.00	R 100.99	R 1 785.01	R 1 163.43	R 621.58
2003:Strategy 6	R 1 882.15	R 168.57	R 1 713.58	R 1 163.43	R 550.15
2003:Strategy 2	R 1 880.00	R 172.53	R 1 707.47	R 1 163.43	R 544.04
2003:Strategy 10	R 1 245.02	n/a	R 1 245.02	R 1 163.43	R 81.59
2003:Strategy 4	R 1 244.65	n/a	R 1 244.65	R 1 163.43	R 81.22
2003:Strategy 5	R 1 173.00	n/a	R 1 173.00	R 1 163.43	R 9.58
2003:Strategy 9	R 836.75	-R 229.42	R 1 066.17	R 1 163.43	-R 97.26
2003:Strategy 1	R 842.05	n/a	R 842.05	R 1 163.43	-R 321.38

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2004:Strategy 10	R 1 173.42	n/a	R 1 173.42	R 1 140.79	R 32.63
2004:Strategy 8	R 977.50	-R 189.59	R 1 167.09	R 1 140.79	R 26.30
2004:Strategy 5	R 1 160.19	n/a	R 1 160.19	R 1 140.79	R 19.40
2004:Strategy 6	R 1 150.75	R 97.43	R 1 053.32	R 1 140.79	-R 87.47
2004:Strategy 7	R 977.50	-R 28.21	R 1 005.71	R 1 140.79	-R 135.08
2004:Strategy 4	R 1 004.18	n/a	R 1 004.18	R 1 140.79	-R 136.61
2004:Strategy 9	R 980.00	R 10.09	R 969.91	R 1 140.79	-R 170.88
2004:Strategy 3	R 980.00	R 61.86	R 918.14	R 1 140.79	-R 222.65
2004:Strategy 1	R 895.25	n/a	R 895.25	R 1 140.79	-R 245.54
2004:Strategy 2	R 980.00	R 118.94	R 861.06	R 1 140.79	-R 279.74

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2005:Strategy 3	R 1 060.00	R 79.38	R 980.62	R 659.62	R 321.00
2005:Strategy 7	R 1 051.30	R 81.79	R 969.51	R 659.62	R 309.89
2005:Strategy 8	R 1 051.30	R 107.70	R 943.60	R 659.62	R 283.98
2005:Strategy 2	R 1 060.00	R 161.17	R 898.83	R 659.62	R 239.21
2005:Strategy 6	R 1 060.00	R 161.17	R 898.83	R 659.62	R 239.21
2005:Strategy 9	R 570.80	-R 191.41	R 762.21	R 659.62	R 102.60
2005:Strategy 4	R 732.66	n/a	R 732.66	R 659.62	R 73.04
2005:Strategy 5	R 705.61	n/a	R 705.61	R 659.62	R 45.99
2005:Strategy 1	R 592.68	n/a	R 592.68	R 659.62	-R 66.93
2005:Strategy 10	R 583.12	n/a	R 583.12	R 659.62	-R 76.50

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2006:Strategy 1	R 1 382.21	n/a	R 1 382.21	R 1 143.47	R 238.74
2006:Strategy 2	R 1 339.60	R 146.69	R 1 192.91	R 1 143.47	R 49.44
2006:Strategy 10	R 1 185.67	n/a	R 1 185.67	R 1 143.47	R 42.20
2006:Strategy 9	R 1 180.00	R 14.75	R 1 165.25	R 1 143.47	R 21.78
2006:Strategy 4	R 1 157.94	n/a	R 1 157.94	R 1 143.47	R 14.47
2006:Strategy 3	R 1 200.00	R 73.80	R 1 126.20	R 1 143.47	-R 17.27
2006:Strategy 5	R 1 112.15	n/a	R 1 112.15	R 1 143.47	-R 31.32
2006:Strategy 6	R 1 153.85	R 117.85	R 1 036.00	R 1 143.47	-R 107.47
2006:Strategy 7	R 976.30	R 44.21	R 932.09	R 1 143.47	-R 211.38
2006:Strategy 8	R 976.30	R 69.18	R 907.12	R 1 143.47	-R 236.35

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2007:Strategy 10	R 1 710.81	n/a	R 1 710.81	R 1 599.81	R 110.99
2007:Strategy 1	R 1 655.42	n/a	R 1 655.42	R 1 599.81	R 55.61
2007:Strategy 4	R 1 632.67	n/a	R 1 632.67	R 1 599.81	R 32.86
2007:Strategy 5	R 1 569.68	n/a	R 1 569.68	R 1 599.81	-R 30.14
2007:Strategy 6	R 1 660.90	R 133.53	R 1 527.37	R 1 599.81	-R 72.44
2007:Strategy 2	R 1 658.50	R 162.98	R 1 495.52	R 1 599.81	-R 104.29
2007:Strategy 9	R 1 500.00	R 6.15	R 1 493.85	R 1 599.81	-R 105.97
2007:Strategy 3	R 1 540.00	R 80.46	R 1 459.54	R 1 599.81	-R 140.27
2007:Strategy 7	R 1 285.70	-R 95.98	R 1 381.68	R 1 599.81	-R 218.13
2007:Strategy 8	R 1 285.70	R 28.10	R 1 257.60	R 1 599.81	-R 342.22

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2008:Strategy 1	R 2 042.65	n/a	R 2 042.65	R 1 741.80	R 300.85
2008:Strategy 2	R 2 134.50	R 156.64	R 1 977.86	R 1 741.80	R 236.06
2008:Strategy 4	R 1 785.02	n/a	R 1 785.02	R 1 741.80	R 43.21
2008:Strategy 9	R 1 740.00	R 11.80	R 1 728.20	R 1 741.80	-R 13.60
2008:Strategy 5	R 1 700.06	n/a	R 1 700.06	R 1 741.80	-R 41.74
2008:Strategy 6	R 1 804.34	R 128.89	R 1 675.45	R 1 741.80	-R 66.35
2008:Strategy 3	R 1 740.00	R 78.26	R 1 661.74	R 1 741.80	-R 80.06
2008:Strategy 10	R 1 628.33	n/a	R 1 628.33	R 1 741.80	-R 113.47
2008:Strategy 7	R 1 531.10	-R 14.88	R 1 545.98	R 1 741.80	-R 195.83
2008:Strategy 8	R 1 531.10	R 113.58	R 1 417.52	R 1 741.80	-R 324.28

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2009:Strategy 7	R 1 867.20	R 93.92	R 1 773.28	R 1 607.99	R 165.29
2009:Strategy 3	R 1 860.00	R 95.73	R 1 764.27	R 1 607.99	R 156.28
2009:Strategy 8	R 1 867.20	R 132.98	R 1 734.22	R 1 607.99	R 126.23
2009:Strategy 9	R 1 442.25	-R 251.11	R 1 693.36	R 1 607.99	R 85.37
2009:Strategy 6	R 1 860.72	R 184.34	R 1 676.39	R 1 607.99	R 68.40
2009:Strategy 2	R 1 860.00	R 189.65	R 1 670.35	R 1 607.99	R 62.36
2009:Strategy 5	R 1 649.70	n/a	R 1 649.70	R 1 607.99	R 41.72
2009:Strategy 4	R 1 605.38	n/a	R 1 605.38	R 1 607.99	-R 2.60
2009:Strategy 1	R 1 362.05	n/a	R 1 362.05	R 1 607.99	-R 245.94
2009:Strategy 10	R 1 362.05	n/a	R 1 362.05	R 1 607.99	-R 245.94

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2010:Strategy 7	R 1 576.80	R 90.57	R 1 486.23	R 1 239.51	R 246.72
2010:Strategy 3	R 1 580.00	R 96.32	R 1 483.68	R 1 239.51	R 244.17
2010:Strategy 8	R 1 576.80	R 116.59	R 1 460.21	R 1 239.51	R 220.70
2010:Strategy 10	R 1 449.00	n/a	R 1 449.00	R 1 239.51	R 209.49
2010:Strategy 6	R 1 587.66	R 168.18	R 1 419.49	R 1 239.51	R 179.98
2010:Strategy 2	R 1 580.00	R 186.89	R 1 393.11	R 1 239.51	R 153.60
2010:Strategy 5	R 1 296.53	n/a	R 1 296.53	R 1 239.51	R 57.02
2010:Strategy 4	R 1 263.30	n/a	R 1 263.30	R 1 239.51	R 23.79
2010:Strategy 9	R 1 027.50	-R 231.63	R 1 259.13	R 1 239.51	R 19.62
2010:Strategy 1	R 1 087.79	n/a	R 1 087.79	R 1 239.51	-R 151.72

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2011:Strategy 1	R 1 764.28	n/a	R 1 764.28	R 1 595.65	R 168.63
2011:Strategy 4	R 1 587.63	n/a	R 1 587.63	R 1 595.65	-R 8.03
2011:Strategy 10	R 1 586.67	n/a	R 1 586.67	R 1 595.65	-R 8.99
2011:Strategy 2	R 1 738.25	R 151.81	R 1 586.44	R 1 595.65	-R 9.22
2011:Strategy 9	R 1 580.00	R 12.82	R 1 567.18	R 1 595.65	-R 28.47
2011:Strategy 5	R 1 559.44	n/a	R 1 559.44	R 1 595.65	-R 36.21
2011:Strategy 6	R 1 629.59	R 119.20	R 1 510.39	R 1 595.65	-R 85.26
2011:Strategy 3	R 1 580.00	R 74.74	R 1 505.26	R 1 595.65	-R 90.39
2011:Strategy 8	R 1 374.00	-R 2.51	R 1 376.51	R 1 595.65	-R 219.14
2011:Strategy 7	R 1 374.00	R 1.56	R 1 372.44	R 1 595.65	-R 223.21

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2012:Strategy 1	R 2 425.52	n/a	R 2 425.52	R 2 097.91	R 327.62
2012:Strategy 9	R 2 177.25	R 15.50	R 2 161.75	R 2 097.91	R 63.85
2012:Strategy 4	R 2 159.04	n/a	R 2 159.04	R 2 097.91	R 61.14
2012:Strategy 5	R 2 086.43	n/a	R 2 086.43	R 2 097.91	-R 11.48
2012:Strategy 3	R 2 177.25	R 99.34	R 2 077.91	R 2 097.91	-R 19.99
2012:Strategy 2	R 2 177.25	R 193.26	R 1 983.99	R 2 097.91	-R 113.91
2012:Strategy 10	R 1 956.33	n/a	R 1 956.33	R 2 097.91	-R 141.57
2012:Strategy 6	R 2 084.31	R 137.16	R 1 947.15	R 2 097.91	-R 150.75
2012:Strategy 7	R 1 936.80	R 83.88	R 1 852.92	R 2 097.91	-R 244.99
2012:Strategy 8	R 1 936.80	R 87.11	R 1 849.69	R 2 097.91	-R 248.21

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2013:Strategy 9	R 2 360.00	R 11.34	R 2 348.66	R 2 180.67	R 167.99
2013:Strategy 4	R 2 300.86	n/a	R 2 300.86	R 2 180.67	R 120.19
2013:Strategy 7	R 2 365.10	R 93.95	R 2 271.15	R 2 180.67	R 90.48
2013:Strategy 3	R 2 360.00	R 94.77	R 2 265.23	R 2 180.67	R 84.56
2013:Strategy 1	R 2 261.09	n/a	R 2 261.09	R 2 180.67	R 80.42
2013:Strategy 8	R 2 365.10	R 137.22	R 2 227.88	R 2 180.67	R 47.22
2013:Strategy 6	R 2 366.87	R 163.34	R 2 203.53	R 2 180.67	R 22.86
2013:Strategy 2	R 2 360.00	R 188.73	R 2 171.27	R 2 180.67	-R 9.40
2013:Strategy 5	R 2 151.27	n/a	R 2 151.27	R 2 180.67	-R 29.40
2013:Strategy 10	R 2 123.33	n/a	R 2 123.33	R 2 180.67	-R 57.34

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2014:Strategy 8	R 2 086.00	-R 279.06	R 2 365.06	R 2 058.61	R 306.45
2014:Strategy 5	R 2 084.89	n/a	R 2 084.89	R 2 058.61	R 26.28
2014:Strategy 9	R 1 806.00	-R 227.95	R 2 033.95	R 2 058.61	-R 24.66
2014:Strategy 6	R 2 153.56	R 130.93	R 2 022.63	R 2 058.61	-R 35.99
2014:Strategy 7	R 2 086.00	R 74.44	R 2 011.56	R 2 058.61	-R 47.06
2014:Strategy 3	R 2 080.00	R 86.18	R 1 993.82	R 2 058.61	-R 64.80
2014:Strategy 4	R 1 986.46	n/a	R 1 986.46	R 2 058.61	-R 72.15
2014:Strategy 2	R 2 080.00	R 170.45	R 1 909.55	R 2 058.61	-R 149.06
2014:Strategy 1	R 1 723.68	n/a	R 1 723.68	R 2 058.61	-R 334.93
2014:Strategy 10	R 1 723.68	n/a	R 1 723.68	R 2 058.61	-R 334.93

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2015:Strategy 1	R 3 157.78	n/a	R 3 157.78	R 2 564.71	R 593.07
2015:Strategy 2	R 3 062.40	R 150.01	R 2 912.39	R 2 564.71	R 347.68
2015:Strategy 4	R 2 627.36	n/a	R 2 627.36	R 2 564.71	R 62.65
2015:Strategy 6	R 2 555.99	R 120.12	R 2 435.87	R 2 564.71	-R 128.84
2015:Strategy 5	R 2 430.67	n/a	R 2 430.67	R 2 564.71	-R 134.05
2015:Strategy 7	R 2 003.10	-R 357.46	R 2 360.56	R 2 564.71	-R 204.15
2015:Strategy 9	R 2 220.00	R 17.50	R 2 202.50	R 2 564.71	-R 362.22
2015:Strategy 8	R 2 003.10	-R 166.49	R 2 169.59	R 2 564.71	-R 395.12
2015:Strategy 3	R 2 220.00	R 75.84	R 2 144.16	R 2 564.71	-R 420.55
2015:Strategy 10	R 2 079.67	n/a	R 2 079.67	R 2 564.71	-R 485.05

Strategy rank	Strategy SAFEX price	Strategy net option cost	A: Realised strategy price	B: Average July futures MTM price	A minus B
2018:Strategy 9	R 2 120.00	R 15.09	R 2 104.91	R 2 037.79	R 67.12
2018:Strategy 4	R 2 051.97	n/a	R 2 051.97	R 2 037.79	R 14.17
2018:Strategy 1	R 2 029.10	n/a	R 2 029.10	R 2 037.79	-R 8.70
2018:Strategy 5	R 2 028.13	n/a	R 2 028.13	R 2 037.79	-R 9.66
2018:Strategy 10	R 2 027.06	n/a	R 2 027.06	R 2 037.79	-R 10.73
2018:Strategy 7	R 2 116.50	R 103.39	R 2 013.11	R 2 037.79	-R 24.69
2018:Strategy 3	R 2 120.00	R 106.99	R 2 013.01	R 2 037.79	-R 24.78
2018:Strategy 8	R 2 116.50	R 149.88	R 1 966.62	R 2 037.79	-R 71.17
2018:Strategy 6	R 2 133.77	R 178.65	R 1 955.12	R 2 037.79	-R 82.68
2018:Strategy 2	R 2 120.00	R 210.38	R 1 909.62	R 2 037.79	-R 128.17

Source: Compiled by author

Table A3: Performance measure ranking consensus – including and excluding threshold measures (where applicable) – as a single table per production year

Threshold measures included										
Performance measure	**2005: Strategy 1**	**2005: Strategy 2**	**2005: Strategy 3**	**2005: Strategy 4**	**2005: Strategy 5**	**2005: Strategy 6**	**2005: Strategy 7**	**2005: Strategy 8**	**2005: Strategy 9**	**2005: Strategy 10**
Sharpe	6	9	4	2	5	10	1	3	8	7
Sortino	6	9	3	2	4	10	1	5	8	7
Calmar	6	9	4	2	5	10	1	3	8	7
Upside Potential	6	8	4	2	5	9	1	3	10	7
Kappa 3	6	9	4	2	5	10	1	3	8	7
VaR Sharpe	4	1	7	9	6	2	10	8	3	5
CVaR-Sharpe	4	1	7	9	6	2	10	8	3	5
MVaR-Sharpe	4	1	7	9	6	2	10	8	3	5
Omega	6	8	4	2	5	9	1	3	10	7
Total rank	48	55	44	39	47	64	36	44	61	57
Threshold measures excluded										
Performance measure	**2005: Strategy 1**	**2005: Strategy 2**	**2005: Strategy 3**	**2005: Strategy 4**	**2005: Strategy 5**	**2005: Strategy 6**	**2005: Strategy 7**	**2005: Strategy 8**	**2005: Strategy 9**	**2005: Strategy 10**
Sharpe	6	9	4	2	5	10	1	3	8	7
Calmar	6	9	4	2	5	10	1	3	8	7
Kappa 3	6	9	4	2	5	10	1	3	8	7
VaR Sharpe	4	1	7	9	6	2	10	8	3	5
CVaR-Sharpe	4	1	7	9	6	2	10	8	3	5
MVaR-Sharpe	4	1	7	9	6	2	10	8	3	5
Total rank	30	30	33	33	33	36	33	33	33	36

(Downward July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2005	-66.93	239.21	321.00	73.04	45.99	239.21	309.89	283.98	102.60	-76.50

Threshold measures included										
Performance measure	**2007: Strategy 1**	**2007: Strategy 2**	**2007: Strategy 3**	**2007: Strategy 4**	**2007: Strategy 5**	**2007: Strategy 6**	**2007: Strategy 7**	**2007: Strategy 8**	**2007: Strategy 9**	**2007: Strategy 10**
Sharpe	1	5	7	4	3	10	8	9	6	2
Sortino	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Calmar	1	5	7	4	3	10	8	9	6	2
Upside Potential	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Kappa 3	1	5	7	4	3	10	8	9	6	2
VaR Sharpe	9	6	4	7	8	1	3	2	5	10
CVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
MVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
Omega	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Total rank	30	33	33	33	33	33	33	33	33	36
Threshold measures excluded										
Performance measure	**2007: Strategy 1**	**2007: Strategy 2**	**2007: Strategy 3**	**2007: Strategy 4**	**2007: Strategy 5**	**2007: Strategy 6**	**2007: Strategy 7**	**2007: Strategy 8**	**2007: Strategy 9**	**2007: Strategy 10**
Sharpe	1	5	7	4	3	10	8	9	6	2
Calmar	1	5	7	4	3	10	8	9	6	2
Kappa 3	1	5	7	4	3	10	8	9	6	2
VaR Sharpe	9	6	4	7	8	1	3	2	5	10
CVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
MVaR-Sharpe	9	6	4	7	8	1	3	2	5	10
Total rank	30	33	33	33	33	33	33	33	33	36

(Upward July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2007	55.61	-104.29	-140.27	32.86	-30.14	-72.44	-218.13	-342.22	-105.97	110.99

Threshold measures included										
Performance measure	2008: Strategy 1	2008: Strategy 2	2008: Strategy 3	2008: Strategy 4	2008: Strategy 5	2008: Strategy 6	2008: Strategy 7	2008: Strategy 8	2008: Strategy 9	2008: Strategy 10
Sharpe	4	9	7	1	2	10	3	6	8	5
Sortino	4	9	7	1	3	10	2	6	8	5
Calmar	4	9	7	1	2	10	3	6	8	5
Upside Potential	4	9	7	1	3	10	2	6	8	5
Kappa 3	4	9	7	1	2	10	3	6	8	5
VaR Sharpe	6	1	4	10	9	2	8	5	3	7
CVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
MVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
Omega	4	9	7	1	2	10	3	6	8	5
Total rank	42	57	54	36	41	66	40	51	57	51
Threshold measures excluded										
Performance measure	2008: Strategy 1	2008: Strategy 2	2008: Strategy 3	2008: Strategy 4	2008: Strategy 5	2008: Strategy 6	2008: Strategy 7	2008: Strategy 8	2008: Strategy 9	2008: Strategy 10
Sharpe	4	9	7	1	2	10	3	6	8	5
Calmar	4	9	7	1	2	10	3	6	8	5
Kappa 3	4	9	7	1	2	10	3	6	8	5
VaR Sharpe	6	1	4	10	9	2	8	5	3	7
CVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
MVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
Total rank	30	30	33	33	33	36	33	33	33	36

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2008	300.85	236.06	-80.06	43.21	-41.74	-66.35	-195.83	-324.28	-13.60	-113.47

Threshold measures included										
Performance measure	**2009: Strategy 1**	**2009: Strategy 2**	**2009: Strategy 3**	**2009: Strategy 4**	**2009: Strategy 5**	**2009: Strategy 6**	**2009: Strategy 7**	**2009: Strategy 8**	**2009: Strategy 9**	**2009: Strategy 10**
Sharpe	6	1	4	9	5	2	10	8	3	7
Sortino	2	9	5	6	8	10	1	4	7	3
Calmar	9	7	3	4	6	8	1	2	5	10
Upside Potential	3	8	5	6	10	9	1	2	7	4
Kappa 3	8	1	4	7	6	2	10	5	3	9
VaR Sharpe	4	9	7	2	6	10	1	3	8	5
CVaR-Sharpe	4	9	7	2	6	10	1	3	8	5
MVaR-Sharpe	4	9	6	2	7	10	1	3	8	5
Omega	9	7	3	4	6	8	1	2	5	10
Total rank	49	60	44	42	60	69	27	32	54	58
Threshold measures excluded										
Performance measure	**2009: Strategy 1**	**2009: Strategy 2**	**2009: Strategy 3**	**2009: Strategy 4**	**2009: Strategy 5**	**2009: Strategy 6**	**2009: Strategy 7**	**2009: Strategy 8**	**2009: Strategy 9**	**2009: Strategy 10**
Sharpe	6	1	4	9	5	2	10	8	3	7
Calmar	9	7	3	4	6	8	1	2	5	10
Kappa 3	8	1	4	7	6	2	10	5	3	9
VaR Sharpe	4	9	7	2	6	10	1	3	8	5
CVaR-Sharpe	4	9	7	2	6	10	1	3	8	5
MVaR-Sharpe	4	9	6	2	7	10	1	3	8	5
Total rank	35	36	31	26	36	42	24	24	35	41

(Downward July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2009	-245.94	62.36	156.28	-2.60	41.72	68.40	165.29	126.23	85.37	-245.94

Threshold measures included										
Performance measure	**2010: Strategy 1**	**2010: Strategy 2**	**2010: Strategy 3**	**2010: Strategy 4**	**2010: Strategy 5**	**2010: Strategy 6**	**2010: Strategy 7**	**2010: Strategy 8**	**2010: Strategy 9**	**2010: Strategy 10**
Sharpe	10	5	4	7	9	1	3	2	6	8
Sortino	1	7	8	4	2	10	5	6	9	3
Calmar	1	9	6	4	2	10	7	8	5	3
Upside Potential	1	7	8	4	2	10	5	6	9	3
Kappa 3	10	5	4	7	9	3	2	1	6	8
VaR Sharpe	1	6	7	4	2	10	8	9	5	3
CVaR-Sharpe	1	6	7	4	2	10	8	9	5	3
MVaR-Sharpe	1	6	7	4	2	10	8	9	5	3
Omega	1	6	7	4	2	10	8	9	5	3
Total rank	27	57	58	42	32	74	54	59	55	37
Threshold measures excluded										
Performance measure	**2010: Strategy 1**	**2010: Strategy 2**	**2010: Strategy 3**	**2010: Strategy 4**	**2010: Strategy 5**	**2010: Strategy 6**	**2010: Strategy 7**	**2010: Strategy 8**	**2010: Strategy 9**	**2010: Strategy 10**
Sharpe	10	5	4	7	9	1	3	2	6	8
Calmar	1	9	6	4	2	10	7	8	5	3
Kappa 3	10	5	4	7	9	3	2	1	6	8
VaR Sharpe	1	6	7	4	2	10	8	9	5	3
CVaR-Sharpe	1	6	7	4	2	10	8	9	5	3
MVaR-Sharpe	1	6	7	4	2	10	8	9	5	3
Total rank	24	37	35	30	26	44	36	38	32	28

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2010	-151.72	153.60	244.17	23.79	57.02	179.98	246.72	220.70	19.62	209.49

Threshold measures included										
Performance measure	2011: Strategy 1	2011: Strategy 2	2011: Strategy 3	2011: Strategy 4	2011: Strategy 5	2011: Strategy 6	2011: Strategy 7	2011: Strategy 8	2011: Strategy 9	2011: Strategy 10
Sharpe	2	6	7	4	3	10	8	9	5	1
Sortino	2	6	7	4	3	10	8	9	5	1
Calmar	2	6	7	4	3	10	8	9	5	1
Upside Potential	2	7	6	4	3	10	8	9	5	1
Kappa 3	2	6	7	4	3	10	8	9	5	1
VaR Sharpe	9	5	4	7	8	1	3	2	6	10
CVaR-Sharpe	9	5	4	7	8	1	3	2	6	10
MVaR-Sharpe	9	5	4	7	8	1	3	2	6	10
Omega	2	6	7	4	3	10	8	9	5	1
Total rank	39	52	53	45	42	63	57	60	48	36
Threshold measures excluded										
Performance measure	2011: Strategy 1	2011: Strategy 2	2011: Strategy 3	2011: Strategy 4	2011: Strategy 5	2011: Strategy 6	2011: Strategy 7	2011: Strategy 8	2011: Strategy 9	2011: Strategy 10
Sharpe	2	6	7	4	3	10	8	9	5	1
Calmar	2	6	7	4	3	10	8	9	5	1
Kappa 3	2	6	7	4	3	10	8	9	5	1
VaR Sharpe	9	5	4	7	8	1	3	2	6	10
CVaR-Sharpe	9	5	4	7	8	1	3	2	6	10
MVaR-Sharpe	9	5	4	7	8	1	3	2	6	10
Total rank	33	33	33	33	33	33	33	33	33	33

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2011	168.63	-9.22	-90.39	-8.03	-36.21	-85.26	-223.21	-219.14	-28.47	-8.99

Threshold measures included										
Performance measure	**2013: Strategy 1**	**2013: Strategy 2**	**2013: Strategy 3**	**2013: Strategy 4**	**2013: Strategy 5**	**2013: Strategy 6**	**2013: Strategy 7**	**2013: Strategy 8**	**2013: Strategy 9**	**2013: Strategy 10**
Sharpe	6	1	4	10	8	2	9	5	3	7
Sortino	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Calmar	7	5	3	10	9	6	1	2	4	8
Upside Potential	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Kappa 3	7	1	4	10	9	2	6	5	3	8
VaR Sharpe	4	9	7	1	3	10	2	6	8	5
CVaR-Sharpe	4	9	7	1	3	10	2	6	8	5
MVaR-Sharpe	4	9	7	1	3	10	2	6	8	5
Omega	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Total rank	32	34	32	33	35	40	22	30	34	38
Threshold measures excluded										
Performance measure	**2013: Strategy 1**	**2013: Strategy 2**	**2013: Strategy 3**	**2013: Strategy 4**	**2013: Strategy 5**	**2013: Strategy 6**	**2013: Strategy 7**	**2013: Strategy 8**	**2013: Strategy 9**	**2013: Strategy 10**
Sharpe	6	1	4	10	8	2	9	5	3	7
Calmar	7	5	3	10	9	6	1	2	4	8
Kappa 3	7	1	4	10	9	2	6	5	3	8
VaR Sharpe	4	9	7	1	3	10	2	6	8	5
CVaR-Sharpe	4	9	7	1	3	10	2	6	8	5
MVaR-Sharpe	4	9	7	1	3	10	2	6	8	5
Total rank	32	34	32	33	35	40	22	30	34	38

(Sideways July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2013	80.42	-9.40	84.56	120.19	-29.40	22.86	90.48	47.22	167.99	-57.34

Threshold measures included										
Performance measure	**2014: Strategy 1**	**2014: Strategy 2**	**2014: Strategy 3**	**2014: Strategy 4**	**2014: Strategy 5**	**2014: Strategy 6**	**2014: Strategy 7**	**2014: Strategy 8**	**2014: Strategy 9**	**2014: Strategy 10**
Sharpe	3	6	7	1	2	10	8	9	5	4
Sortino	1	6	7	4	3	10	8	9	5	2
Calmar	1	6	7	4	3	10	8	9	5	2
Upside Potential	1	6	7	4	3	10	8	9	5	2
Kappa 3	1	6	7	4	3	10	8	9	5	2
VaR Sharpe	7	5	4	10	9	1	3	2	6	8
CVaR-Sharpe	7	5	4	10	9	1	3	2	6	8
MVaR-Sharpe	5	7	4	10	8	1	3	2	9	6
Omega	1	6	7	4	3	10	8	9	5	2
Total rank	27	53	54	51	43	63	57	60	51	36

Threshold measures excluded										
Performance measure	**2014: Strategy 1**	**2014: Strategy 2**	**2014: Strategy 3**	**2014: Strategy 4**	**2014: Strategy 5**	**2014: Strategy 6**	**2014: Strategy 7**	**2014: Strategy 8**	**2014: Strategy 9**	**2014: Strategy 10**
Sharpe	3	6	7	1	2	10	8	9	5	4
Calmar	1	6	7	4	3	10	8	9	5	2
Kappa 3	1	6	7	4	3	10	8	9	5	2
VaR Sharpe	7	5	4	10	9	1	3	2	6	8
CVaR-Sharpe	7	5	4	10	9	1	3	2	6	8
MVaR-Sharpe	5	7	4	10	8	1	3	2	9	6
Total rank	24	35	33	39	34	33	33	33	36	30

(Downward July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2014	-334.93	-149.06	-64.80	-72.15	26.28	-35.99	-47.06	306.45	-24.66	-334.93

Threshold measures included										
Performance measure	**2015: Strategy 1**	**2015: Strategy 2**	**2015: Strategy 3**	**2015: Strategy 4**	**2015: Strategy 5**	**2015: Strategy 6**	**2015: Strategy 7**	**2015: Strategy 8**	**2015: Strategy 9**	**2015: Strategy 10**
Sharpe	1	6	7	4	2	10	8	9	5	3
Sortino	6	2	1	4	5	10	8	9	3	7
Calmar	1	6	7	4	2	10	8	9	5	3
Upside Potential	6	2	1	4	5	10	8	9	3	7
Kappa 3	1	6	7	4	2	10	8	9	5	3
VaR Sharpe	10	5	4	7	9	1	3	2	6	8
CVaR-Sharpe	10	5	4	7	9	1	3	2	6	8
MVaR-Sharpe	10	5	4	7	9	1	3	2	6	8
Omega	1	6	7	4	3	10	8	9	5	2
Total rank	46	43	42	45	46	63	57	60	44	49

Threshold measures excluded										
Performance measure	**2015: Strategy 1**	**2015: Strategy 2**	**2015: Strategy 3**	**2015: Strategy 4**	**2015: Strategy 5**	**2015: Strategy 6**	**2015: Strategy 7**	**2015: Strategy 8**	**2015: Strategy 9**	**2015: Strategy 10**
Sharpe	1	6	7	4	2	10	8	9	5	3
Calmar	1	6	7	4	2	10	8	9	5	3
Kappa 3	1	6	7	4	2	10	8	9	5	3
VaR Sharpe	10	5	4	7	9	1	3	2	6	8
CVaR-Sharpe	10	5	4	7	9	1	3	2	6	8
MVaR-Sharpe	10	5	4	7	9	1	3	2	6	8
Total rank	33	33	33	33	33	33	33	33	33	33

(Upward July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2015	593.07	347.68	-420.55	62.65	-134.05	-128.84	-204.15	-395.12	-362.22	-485.05

Threshold measures included										
Performance measure	2016: Strategy 1	2016: Strategy 2	2016: Strategy 3	2016: Strategy 4	2016: Strategy 5	2016: Strategy 6	2016: Strategy 7	2016: Strategy 8	2016: Strategy 9	2016: Strategy 10
Sharpe	1	4	7	5	3	10	8	9	6	2
Sortino	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Calmar	1	4	7	5	3	10	8	9	6	2
Upside Potential	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Kappa 3	1	4	7	5	3	10	8	9	6	2
VaR Sharpe	9	7	4	6	8	1	3	2	5	10
CVaR-Sharpe	9	7	4	6	8	1	3	2	5	10
MVaR-Sharpe	9	7	4	6	8	1	3	2	5	10
Omega	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Total rank	30	33	33	33	33	33	33	33	33	36
Threshold measures excluded										
Performance measure	**2016: Strategy 1**	**2016: Strategy 2**	**2016: Strategy 3**	**2016: Strategy 4**	**2016: Strategy 5**	**2016: Strategy 6**	**2016: Strategy 7**	**2016: Strategy 8**	**2016: Strategy 9**	**2016: Strategy 10**
Sharpe	1	4	7	5	3	10	8	9	6	2
Calmar	1	4	7	5	3	10	8	9	6	2
Kappa 3	1	4	7	5	3	10	8	9	6	2
VaR Sharpe	9	7	4	6	8	1	3	2	5	10
CVaR-Sharpe	9	7	4	6	8	1	3	2	5	10
MVaR-Sharpe	9	7	4	6	8	1	3	2	5	10
Total rank	30	33	33	33	33	33	33	33	33	36

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2016	-27.17	-229.05	-1063.48	-358.57	-101.94	-203.28	-624.40	-595.52	-977.69	248.39

Threshold measures included										
Performance measure	2017: Strategy 1	2017: Strategy 2	2017: Strategy 3	2017: Strategy 4	2017: Strategy 5	2017: Strategy 6	2017: Strategy 7	2017: Strategy 8	2017: Strategy 9	2017: Strategy 10
Sharpe	9	5	4	7	8	2	3	1	6	10
Sortino	1	6	8	4	3	10	5	9	7	2
Calmar	1	6	7	4	3	9	8	10	5	2
Upside Potential	1	6	7	4	3	10	5	9	8	2
Kappa 3	9	6	4	7	8	2	1	3	5	10
VaR Sharpe	1	6	7	4	3	9	8	10	5	2
CVaR-Sharpe	1	6	7	4	3	9	8	10	5	2
MVaR-Sharpe	1	6	7	4	3	9	8	10	5	2
Omega	1	6	7	4	3	9	8	10	5	2
Total rank	25	53	58	42	37	69	54	72	51	34
Threshold measures excluded										
Performance measure	2017: Strategy 1	2017: Strategy 2	2017: Strategy 3	2017: Strategy 4	2017: Strategy 5	2017: Strategy 6	2017: Strategy 7	2017: Strategy 8	2017: Strategy 9	2017: Strategy 10
Sharpe	9	5	4	7	8	2	3	1	6	10
Calmar	1	6	7	4	3	9	8	10	5	2
Kappa 3	9	6	4	7	8	2	1	3	5	10
VaR Sharpe	1	6	7	4	3	9	8	10	5	2
CVaR-Sharpe	1	6	7	4	3	9	8	10	5	2
MVaR-Sharpe	1	6	7	4	3	9	8	10	5	2
Total rank	22	35	36	30	28	40	36	44	31	28

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2017	-266.24	230.72	380.77	31.68	96.55	261.66	372.60	215.12	-7.69	-206.18

Threshold measures included										
Performance measure	**2018: Strategy 1**	**2018: Strategy 2**	**2018: Strategy 3**	**2018: Strategy 4**	**2018: Strategy 5**	**2018: Strategy 6**	**2018: Strategy 7**	**2018: Strategy 8**	**2018: Strategy 9**	**2018: Strategy 10**
Sharpe	4	9	7	1	2	10	3	6	8	5
Sortino	4	9	7	1	2	10	3	6	8	5
Calmar	3	9	7	1	2	10	5	6	8	4
Upside Potential	4	9	7	2	3	10	1	6	8	5
Kappa 3	3	9	7	1	2	10	5	6	8	4
VaR Sharpe	6	1	4	10	9	2	8	5	3	7
CVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
MVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
Omega	1	2	3	4	5	6	7	8	9	10
Total rank	37	50	50	40	43	62	48	53	58	54
Threshold measures excluded										
Performance measure	**2018: Strategy 1**	**2018: Strategy 2**	**2018: Strategy 3**	**2018: Strategy 4**	**2018: Strategy 5**	**2018: Strategy 6**	**2018: Strategy 7**	**2018: Strategy 8**	**2018: Strategy 9**	**2018: Strategy 10**
Sharpe	4	9	7	1	2	10	3	6	8	5
Calmar	3	9	7	1	2	10	5	6	8	4
Kappa 3	3	9	7	1	2	10	5	6	8	4
VaR Sharpe	6	1	4	10	9	2	8	5	3	7
CVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
MVaR-Sharpe	6	1	4	10	9	2	8	5	3	7
Total rank	28	30	33	33	33	36	37	33	33	34

(Sideways July WM price movement)	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**	**Strategy 5**	**Strategy 6**	**Strategy 7**	**Strategy 8**	**Strategy 9**	**Strategy 10**
2018	-8.70	-128.17	-24.78	14.17	-9.66	-82.68	-24.69	-71.17	67.12	-10.73

Source: Compiled by author

Table A4: Alternative return calculation method: performance measure analysis ranking results

Performance measure	2004: Strategy 1	2004: Strategy 2	2004: Strategy 3	2004: Strategy 4	2004: Strategy 5	2004: Strategy 6	2004: Strategy 7	2004: Strategy 8	2004: Strategy 9	2004: Strategy 10
Sharpe	3	6	1	7	5	9	10	8	2	4
Sortino	3	6	2	7	5	9	10	8	1	4
Calmar	3	6	1	7	5	9	10	8	2	4
Upside Potential	1	4	9	5	3	7	8	6	10	2
Kappa 3	3	6	1	7	5	9	10	8	2	4
VaR Sharpe	7	5	10	4	6	2	1	3	9	8
CVaR-Sharpe	7	5	10	4	6	2	1	3	9	8
MVaR-Sharpe	7	5	10	4	6	2	1	3	9	8
Omega	1	4	5	7	3	9	10	8	6	2
Total rank	35	47	49	52	44	58	61	55	50	44

(Sideways July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2004	-245.54	-279.74	-222.65	-136.61	19.40	-87.47	-135.08	26.30	-170.88	32.63

Performance measure	2005: Strategy 1	2005: Strategy 2	2005: Strategy 3	2005: Strategy 4	2005: Strategy 5	2005: Strategy 6	2005: Strategy 7	2005: Strategy 8	2005: Strategy 9	2005: Strategy 10
Sharpe	2	7	5	6	4	8	9	10	1	3
Sortino	7	3	2	10	9	4	5	6	1	8
Calmar	9	3	2	7	8	4	5	6	1	10
Upside Potential	5	7	4	1	2	8	9	10	3	6
Kappa 3	3	6	2	10	5	7	8	9	1	4
VaR Sharpe	8	1	6	5	7	2	3	4	10	9
CVaR-Sharpe	8	1	6	5	7	2	3	4	10	9
MVaR-Sharpe	8	1	6	5	7	2	3	4	10	9
Omega	9	3	2	7	8	4	5	6	1	10
Total rank	59	32	35	56	57	41	50	59	38	68

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2005	-66.93	239.21	321.00	73.04	45.99	239.21	309.89	283.98	102.60	-76.50

Performance measure	2006: Strategy 1	2006: Strategy 2	2006: Strategy 3	2006: Strategy 4	2006: Strategy 5	2006: Strategy 6	2006: Strategy 7	2006: Strategy 8	2006: Strategy 9	2006: Strategy 10
Sharpe	4	1	3	7	6	8	10	9	2	5
Sortino	4	1	3	7	6	8	10	9	2	5
Calmar	4	1	3	7	6	8	10	9	2	5
Upside Potential	9	4	7	6	8	1	3	2	5	10
Kappa 3	4	1	3	7	6	8	10	9	2	5
VaR Sharpe	6	10	8	4	5	3	1	2	9	7
CVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
MVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
Omega	4	1	3	7	6	8	10	9	2	5
Total rank	47	39	46	53	53	50	56	53	42	56

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2006	238.74	49.44	-17.27	14.47	-31.32	-107.47	-211.38	-236.35	21.78	42.20

Performance measure	2007: Strategy 1	2007: Strategy 2	2007: Strategy 3	2007: Strategy 4	2007: Strategy 5	2007: Strategy 6	2007: Strategy 7	2007: Strategy 8	2007: Strategy 9	2007: Strategy 10
Sharpe	5	1	3	7	6	8	10	9	2	4
Sortino	4	1	3	10	9	6	8	7	2	5
Calmar	9	1	3	7	8	4	6	5	2	10
Upside Potential	6	10	8	1	5	2	4	3	9	7
Kappa 3	4	1	3	7	6	8	10	9	2	5
VaR Sharpe	6	10	8	4	5	3	1	2	9	7
CVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
MVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
Omega	7	10	8	4	5	1	3	2	9	6
Total rank	53	54	52	48	54	38	44	41	53	58

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2007	55.61	-104.29	-140.27	32.86	-30.14	-72.44	-218.13	-342.22	-105.97	110.99

Performance measure	2008: Strategy 1	2008: Strategy 2	2008: Strategy 3	2008: Strategy 4	2008: Strategy 5	2008: Strategy 6	2008: Strategy 7	2008: Strategy 8	2008: Strategy 9	2008: Strategy 10
Sharpe	1	7	5	4	3	8	9	10	6	2
Sortino	2	6	1	10	5	7	8	9	4	3
Calmar	9	2	1	7	8	3	4	5	6	10
Upside Potential	9	2	8	1	6	3	4	5	7	10
Kappa 3	1	7	5	4	3	8	9	10	6	2
VaR Sharpe	9	1	6	7	8	2	3	4	5	10
CVaR-Sharpe	9	1	6	7	8	2	3	4	5	10
MVaR-Sharpe	9	1	6	7	8	2	3	4	5	10
Omega	9	1	5	7	8	2	3	4	6	10
Total rank	58	28	43	54	57	37	46	55	50	67

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2008	300.85	236.06	-80.06	43.21	-41.74	-66.35	-195.83	-324.28	-13.60	-113.47

Performance measure	2009: Strategy 1	2009: Strategy 2	2009: Strategy 3	2009: Strategy 4	2009: Strategy 5	2009: Strategy 6	2009: Strategy 7	2009: Strategy 8	2009: Strategy 9	2009: Strategy 10
Sharpe	1	7	6	4	3	8	9	10	5	2
Sortino	6	2	8	10	9	3	4	5	1	7
Calmar	1	6	5	4	3	7	8	9	10	2
Upside Potential	8	4	3	1	2	5	6	7	10	9
Kappa 3	1	7	6	4	3	8	9	10	5	2
VaR Sharpe	9	1	5	7	8	2	3	4	6	10
CVaR-Sharpe	9	1	5	7	8	2	3	4	6	10
MVaR-Sharpe	9	1	5	7	8	2	3	4	6	10
Omega	1	7	4	5	3	8	9	10	6	2
Total rank	45	36	47	49	47	45	54	63	55	54

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2009	-245.94	62.36	156.28	-2.60	41.72	68.40	165.29	126.23	85.37	-245.94

Performance measure	2010: Strategy 1	2010: Strategy 2	2010: Strategy 3	2010: Strategy 4	2010: Strategy 5	2010: Strategy 6	2010: Strategy 7	2010: Strategy 8	2010: Strategy 9	2010: Strategy 10
Sharpe	4	1	3	7	5	8	10	9	2	6
Sortino	7	1	3	9	8	4	6	5	2	10
Calmar	4	1	3	6	5	8	10	9	2	7
Upside Potential	2	10	8	3	1	5	7	6	9	4
Kappa 3	4	1	3	6	5	8	10	9	2	7
VaR Sharpe	7	10	8	4	6	3	1	2	9	5
CVaR-Sharpe	7	10	8	4	6	3	1	2	9	5
MVaR-Sharpe	7	10	8	4	6	3	1	2	9	5
Omega	4	2	3	6	5	8	10	9	1	7
Total rank	46	46	47	49	47	50	56	53	45	56

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2010	-151.72	153.60	244.17	23.79	57.02	179.98	246.72	220.70	19.62	209.49

Performance measure	2011: Strategy 1	2011: Strategy 2	2011: Strategy 3	2011: Strategy 4	2011: Strategy 5	2011: Strategy 6	2011: Strategy 7	2011: Strategy 8	2011: Strategy 9	2011: Strategy 10
Sharpe	4	1	3	7	5	8	10	9	2	6
Sortino	8	1	3	7	10	4	6	5	2	9
Calmar	4	1	3	8	6	7	10	9	2	5
Upside Potential	3	10	8	4	1	5	7	6	9	2
Kappa 3	4	1	3	7	5	8	10	9	2	6
VaR Sharpe	7	10	8	4	6	3	1	2	9	5
CVaR-Sharpe	7	10	8	4	6	3	1	2	9	5
MVaR-Sharpe	7	10	8	4	6	3	1	2	9	5
Omega	4	10	9	7	6	1	5	3	8	2
Total rank	48	54	53	52	51	42	51	47	52	45

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2011	168.63	-9.22	-90.39	-8.03	-36.21	-85.26	-223.21	-219.14	-28.47	-8.99

Performance measure	2012: Strategy 1	2012: Strategy 2	2012: Strategy 3	2012: Strategy 4	2012: Strategy 5	2012: Strategy 6	2012: Strategy 7	2012: Strategy 8	2012: Strategy 9	2012: Strategy 10
Sharpe	4	1	3	6	5	8	10	9	2	7
Sortino	7	1	3	10	8	4	6	5	2	9
Calmar	4	1	3	6	5	8	10	9	2	7
Upside Potential	3	10	8	2	1	5	7	6	9	4
Kappa 3	4	1	3	6	5	8	10	9	2	7
VaR Sharpe	7	10	8	5	6	3	1	2	9	4
CVaR-Sharpe	7	10	8	5	6	3	1	2	9	4
MVaR-Sharpe	7	10	8	5	6	3	1	2	9	4
Omega	4	2	3	6	5	8	10	9	1	7
Total rank	47	46	47	51	47	50	56	53	45	53

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2012	327.62	-113.91	-19.99	61.14	-11.48	-150.75	-244.99	-248.21	63.85	-141.57

Performance measure	2013: Strategy 1	2013: Strategy 2	2013: Strategy 3	2013: Strategy 4	2013: Strategy 5	2013: Strategy 6	2013: Strategy 7	2013: Strategy 8	2013: Strategy 9	2013: Strategy 10
Sharpe	8	3	1	7	10	4	5	6	2	9
Sortino	8	3	2	7	10	4	5	6	1	9
Calmar	9	3	1	7	8	4	5	6	2	10
Upside Potential	3	6	5	1	2	7	8	9	10	4
Kappa 3	9	3	1	7	8	4	5	6	2	10
VaR Sharpe	2	5	10	4	1	6	7	8	9	3
CVaR-Sharpe	2	5	10	4	1	6	7	8	9	3
MVaR-Sharpe	2	5	10	4	1	6	7	8	9	3
Omega	9	3	1	7	8	4	5	6	2	10
Total rank	52	36	41	48	49	45	54	63	46	61

(Sideways July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2013	80.42	-9.40	84.56	120.19	-29.40	22.86	90.48	47.22	167.99	-57.34

Performance measure	2015: Strategy 1	2015: Strategy 2	2015: Strategy 3	2015: Strategy 4	2015: Strategy 5	2015: Strategy 6	2015: Strategy 7	2015: Strategy 8	2015: Strategy 9	2015: Strategy 10
Sharpe	1	5	7	4	2	8	10	9	6	3
Sortino	5	10	2	7	6	3	9	4	1	8
Calmar	1	6	7	4	2	8	10	9	5	3
Upside Potential	1	4	10	5	2	7	9	8	6	3
Kappa 3	1	5	7	4	2	8	10	9	6	3
VaR Sharpe	10	6	4	7	9	3	1	2	5	8
CVaR-Sharpe	10	6	4	7	9	3	1	2	5	8
MVaR-Sharpe	10	6	4	7	9	3	1	2	5	8
Omega	1	6	8	4	2	7	10	9	5	3
Total rank	40	54	53	49	43	50	61	54	44	47

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2015	593.07	347.68	-420.55	62.65	-134.05	-128.84	-204.15	-395.12	-362.22	-485.05

Performance measure	2015: Strategy 1	2015: Strategy 2	2015: Strategy 3	2015: Strategy 4	2015: Strategy 5	2015: Strategy 6	2015: Strategy 7	2015: Strategy 8	2015: Strategy 9	2015: Strategy 10
Sharpe	3	6	2	7	5	9	10	8	1	4
Sortino	1	5	6	7	3	9	10	8	4	2
Calmar	3	6	2	7	5	9	10	8	1	4
Upside Potential	8	2	3	1	7	5	6	4	10	9
Kappa 3	3	6	2	7	5	9	10	8	1	4
VaR Sharpe	7	5	9	4	6	2	1	3	10	8
CVaR-Sharpe	7	5	9	4	6	2	1	3	10	8
MVaR-Sharpe	7	5	9	4	6	2	1	3	10	8
Omega	1	4	7	5	3	9	10	8	6	2
Total rank	40	44	49	46	46	56	59	53	53	49

(Upward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2016	-27.17	-229.05	-1063.48	-358.57	-101.94	-203.28	-624.40	-595.52	-977.69	248.39

Performance measure	2017: Strategy 1	2017: Strategy 2	2017: Strategy 3	2017: Strategy 4	2017: Strategy 5	2017: Strategy 6	2017: Strategy 7	2017: Strategy 8	2017: Strategy 9	2017: Strategy 10
Sharpe	4	1	3	7	6	8	10	9	2	5
Sortino	7	1	3	9	10	4	6	5	2	8
Calmar	4	1	3	7	6	8	10	9	2	5
Upside Potential	1	10	8	4	3	5	7	6	9	2
Kappa 3	4	1	3	7	6	8	10	9	2	5
VaR Sharpe	6	10	8	4	5	3	1	2	9	7
CVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
MVaR-Sharpe	6	10	8	4	5	3	1	2	9	7
Omega	3	1	5	7	6	8	10	9	2	4
Total rank	41	45	49	53	52	50	56	53	46	50

(Downward July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2017	-266.24	230.72	380.77	31.68	96.55	261.66	372.60	215.12	-7.69	-206.18

Performance measure	2018: Strategy 1	2018: Strategy 2	2018: Strategy 3	2018: Strategy 4	2018: Strategy 5	2018: Strategy 6	2018: Strategy 7	2018: Strategy 8	2018: Strategy 9	2018: Strategy 10
Sharpe	1	7	4	5	3	8	9	10	6	2
Sortino	7	3	1	10	9	4	5	6	2	8
Calmar	9	3	1	7	8	4	5	6	2	10
Upside Potential	8	3	10	1	2	4	5	6	7	9
Kappa 3	1	7	4	6	3	8	9	10	5	2
VaR Sharpe	9	1	6	7	8	2	3	4	5	10
CVaR-Sharpe	9	1	6	7	8	2	3	4	5	10
MVaR-Sharpe	9	1	7	6	8	2	3	4	5	10
Omega	9	3	1	7	8	4	5	6	2	10
Total rank	62	29	40	56	57	38	47	56	39	71

(Sideways July WM price movement)	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Strategy 7	Strategy 8	Strategy 9	Strategy 10
2018	-8.70	-128.17	-24.78	14.17	-9.66	-82.68	-24.69	-71.17	67.12	-10.73

Source: Compiled by author

DECLARATION OF LANGUAGE EDITING

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DECLARATION OF LANGUAGE EDITING

I, Ina-Lize Venter, hereby declare that I edited the research study entitled:

Analysing white maize hedging strategies in South Africa

for **FA Dreyer**

for the purpose of submission as a postgraduate study. Changes were indicated in track changes and implementation was left to the author.

Regards,

I Venter

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