Timing a hedge decision: The development of a composite technical indicator for white maize

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It all starts here ™

Dedication

To my parents

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Abstract

The South African white maize market is considered to be significantly more volatile than any other agricultural product traded on the South African Futures Exchange (SAFEX). This accentuates the need to effectively manage price risk, by means of hedging, to ensure a more profitable and sustainable maize production sector (Geyser, 2013:39; Jordaan, Grové, Jooste, A. & Jooste, Z.G., 2007:320). However, hedging at lower price levels might result in significant variation margins or costly buy–outs in order to fulfil the contract obligations. This challenge is addressed in this study by making use of technical analysis, focusing on the development of a practical and applicable composite technical indicator with the purpose of improving the timing of price risk management decisions identified by individual technical indicators. This may ultimately assist a producer in achieving a higher average hedge level compared to popular individual technical indicators.

The process of constructing a composite indicator was commenced by examining the prevailing tendency of the market. By making use of the Directional Movement Index (DMI), as identified in the literature study, the market was found to continually shift between trending prices (prices moving either upwards or downwards) and prices trading sideways. Consequently, implementing only a leading (statistically more suitable for trading markets) or lagging (statistically more suitable for trending markets) technical indicator may generate false sell signals, as demonstrated by the application of these technical indicators in the white maize market. This substantiated the motivation for compiling a composite indicator that takes both leading and lagging indicators into account to more accurately identify hedging opportunities. The composite indicator made use of the Relative Strength Index (RSI) and Stochastic oscillator as leading indicators, and the Exponential Moving Average (EMA) and Moving Average Convergence Divergence (MACD) as lagging indicators. The results validated the applicability of such a composite indicator, as the composite indicator outperformed the individual technical indicators in the white maize market. The composite indicator achieved the highest average hedge level, the lowest average sell signals generated over the entire period, as well as the highest average hedge level as a percentage of the maximum price over the entire period. Hence, the composite indicator recognised hedging opportunities more

accurately compared to individual technical indicators, which ultimately led to higher achieved hedging levels.

KEYWORDS: Agricultural commodity market; efficient market; composite indicator; hedging; technical analysis; trading market; trending market; SAFEX; white maize.

Opsomming

Die Suid–Afrikaanse witmieliemark word beskou as aansienlik meer wisselvallig in vergelyking met enige ander kommoditeit wat op die Suid–Afrikaanse Termynbeurs (SAFEX) verhandel word. Dit beklemtoon die noodsaaklikheid om prysrisiko te bestuur, deur middel van verskansing, om ŉ meer winsgewende en volhoubare produksiesektor te verseker (Geyser, 2013:39; Jordaan *et al*., 2007:320). Maar verskansing teen 'n laer prysvlak kan lei tot beduidende hoë variasie marges of duur uitkoopkostes ten einde die kontrak verpligtinge na te kom. Hierdie uitdaging word in dié studie aangespreek deur gebruik te maak van tegniese analise, met die fokus op die ontwikkeling van n praktiese en toepaslike saamgestelde tegniese aanwyser. Die doel van die saamgestelde aanwyser is om die tydsberekening van individuele tegniese aanwysers se prysrisikobestuur besluite te verbeter, ten einde ŉ produsent se gemiddelde verskansingsvlak te verbeter.

Die bouproses van 'n saamgestelde aanwyser vereis aanvanklik die bestudering van die heersende tendens van die mark. Deur gebruik te maak van die Rigting Bewegings Indeks (DMI), soos geïdentifiseer in die literatuur, is daar bevind dat die mark deurlopend verander van neigende prystendense (pryse beweeg hetsy opwaarts of afwaarts) na ŉ sywaartse verhandeling in markpryse. Gevolglik kan vals verkoop seine ontstaan wanneer slegs ŉ leidende (statistiese meer geskik vir markte wat sywaarts verhandel) of sloerende (statistiese meer geskik vir markte wat in ŉ rigting neig) tegniese aanwyser geïmplementeer word, soos gedemonstreer deur die toepassing van hierdie tegniese aanwyser in die witmieliemark. Dit staaf die ontwikkeling van 'n saamgestelde aanwyser wat beide leidende en sloerende tegniese aanwysers in ag neem, ten einde verskansingsgeleenthede meer akkuraat te identifiseer. Die saamgestelde aanwyser maak dus gebruik van die Relatiewe Sterkte Indeks (RSI) en Stogastiese Ossilleerder as leidende aanwysers en die Eksponensiële Bewegende Gemiddeld (EMA) en Bewegende Gemiddeld Konvergensie Divergensie (MACD) as sloerende aanwysers. Die resultate van die studie bevestig die toepaslikheid van so 'n saamgestelde aanwyser, aangesien die saamgestelde aanwyser beter gevaar het in die witmieliemark as die individuele tegniese indikatore. Die saamgestelde aanwyser het die hoogste gemiddelde verskansingsvlak, die laagste gemiddelde aantal verkoop seine oor die hele tydperk, asook die hoogste gemiddelde verskansingsvlak as 'n persentasie van die maksimum prys oor die hele tydperk behaal. Uit die resultate is dit duidelik dat die saamgestelde aanwyser verskansingsgeleenthede meer akkuraat geïdentifiseer het in vergelyking met individuele tegniese aanwysers, wat uiteindelik gelei het tot hoër verskansingsvlakke.

SLEUTELWOORDE: Landbou kommoditeite mark; effektiewe mark; saamgestelde aanwyser; verskansing; tegniese analise; sywaartse mark; neigende mark; SAFEX; witmieliemark.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

"Now is always the most difficult time to invest"

~ Charles Welles Buek (1959)

1.1 Introduction

Risk has always been an inherent component in the agricultural market, due to factors such as uncertainty surrounding weather, intricate biological processes, the seasonality of production, price transmission, the domestic and international political economics of food, and globalisation of commodity chains (Geyser, 2013:35; Stockil & Ortmann, 1997:139). The agricultural environment has also been very volatile in the past few years which increased the overall risk associated with the agricultural market; more specifically the risk associated with volatile price movements (Geyser, 2013:35–40**;** Goodwin & Schroeder, 1994:936).

Price risk in the white maize market has shown to be significantly higher compared to any other agricultural commodity traded on the South African Futures Exchange (SAFEX) (Geyser, 2013:39; Jordaan *et al.*, 2007:320). This is due to the price inelasticity of the white maize market caused by the small amount of substitutes available for white maize (Bown *et al.*, 1999:277–278; Van Zyl, 1986:53–54). Another explanation is that the increased price volatility was caused by the deregulation of the agricultural commodities market in the mid–1990s (Groenewald, Gudeta, Fraser, Jari, Jooste, Jordaan, Kambewa, Klopper, Magingxa, Obi, Pote, Stroebel, van Tilburg & van Schalkwyk*,* 2003; Monk*, Jordaan & Grové*, 2010:1).

As mentioned above, all these factors affect a maize producer's price risk management decisions significantly, which ultimately affects a maize producer's profitability and the sustainability of maize production. Also, determining the correct timing of implementing a price risk management decision throughout a production season, mainly through derivative instruments, is a difficult task for maize producers. This is evident from the unwillingness of South African maize producers to hedge their produce by means of derivative instruments. This statement may be substantiated by a study done by Dorfman and Karali (2008:1), who found that South African grain producers considers the use of derivative instruments complex and are therefore unwilling or hesitant to hedge their produce optimally. This supports the necessity for developing a less complicated price risk management decision tool for South African grain producers.

1.2 Background

Prior to deregulation, the Maize Board controlled maize price setting, and was the sole buyer and seller of maize in South Africa, which led to a market that was considered as being free from price risk (Krugel, 2003:52; Vink, 2012:558). Consequently, since no price fluctuations were present, market participants had no concern about price risk management and were only interested in minimising the possible consequences of other risks, such as adverse weather conditions (Chabane, 2002:1; Monk *et al*., 2010:447). Therefore, since the abolition of the Maize Board, agricultural market participants have been individually responsible for the marketing of their maize, as well as managing their price risk (Bown *et al.*, 1999:276; Chabane, 2002:1; Krugel, 2003:52).

SAFEX facilitates these price risk management responsibilities by enabling market participants, including producers, buyers and speculators, to come together on one exchange traded platform. SAFEX, a division of the Johannesburg Stock Exchange (JSE), created the Agricultural Products Division (APD), previously known as the Agricultural Markets Division (AMD), for the purpose of marketing and trading agricultural derivatives (JSE, 2013a:1). The derivatives market is focused primarily on providing an effective marketing mechanism to market participants, essentially by means of the futures market, due to its efficient role in transparent price determination (JSE, 2013a:1–2; Krugel, 2003:4; Monk *et al.*, 2010:447).

In order to establish transparent price formulation, it is essential that an efficient agricultural market exists (Wiseman, Darroch & Ortmann, 1999:322). This fact is still questioned by maize producers in the South African maize market, and although the majority of previous studies[1] suggested that the white maize market is at least weak

[1] See studies conducted by McCullough (2010:131), Moholwa (2005:21), Scheepers (2005:61), Viljoen (2003:206), and Wiseman *et al.* (1999:332-333).

form efficient[2], the South African white maize market's efficiency has not yet been extensively researched (Jordaan & Grové, 2007:562). Wiseman *et al.* (1999:332–333)[3] indicated that the white maize market was relatively inefficient in the first few years after the deregulation of the Maize Board in 1997, but became more efficient as market participants gained more experience, knowledge and understanding of the derivatives market over time. However, later studies contradict this statement, and suggest that there is no evidence to support a change in market efficiency and that the white maize market in South Africa will continue to be weak form efficient (see for example Moholwa (2005:21)).This was corroborated by McCullough's (2010:131) findings of a weak form efficient white maize market for the period 1996 to 2009.

Weak form efficient implies that all security market information is already incorporated into the current price, including rates of return and historical trends of prices (Brown & Reilly, 2009:153). It also implies that no correlation between past rates of return and future rates of return exist (Brown & Reilly, 2009:153). In spite of this, all public information is not always reflected in the current price in a weak form efficient market, where some market participants have monopolistic access to private information (Brown & Reilly, 2009:153; Fama, 1970:414). This implies that some market participants have the ability of making abnormal profits by means of superior analytical methods.

Two main analytical methods used by market participants are fundamental analysis[4] and technical analysis. Technical analysis refers to the study of market behaviour, which is quantified in graphs, in an attempt to predict future price movements, based on the assumption that past trends will repeat in the future, and so will reveal buy or sell signals (Achelis, 2001:2; Reuters, 1999:8–9). The ability to capture and analyse market behaviour, including the psychological factors that influence market behaviour, is one of the main advantages technical analysis has over fundamental

[2] All security market information is already incorporated into the current price, including rates of return and historical trends of prices (Brown & Reilly, 2009:153; Fama, 1970:414).

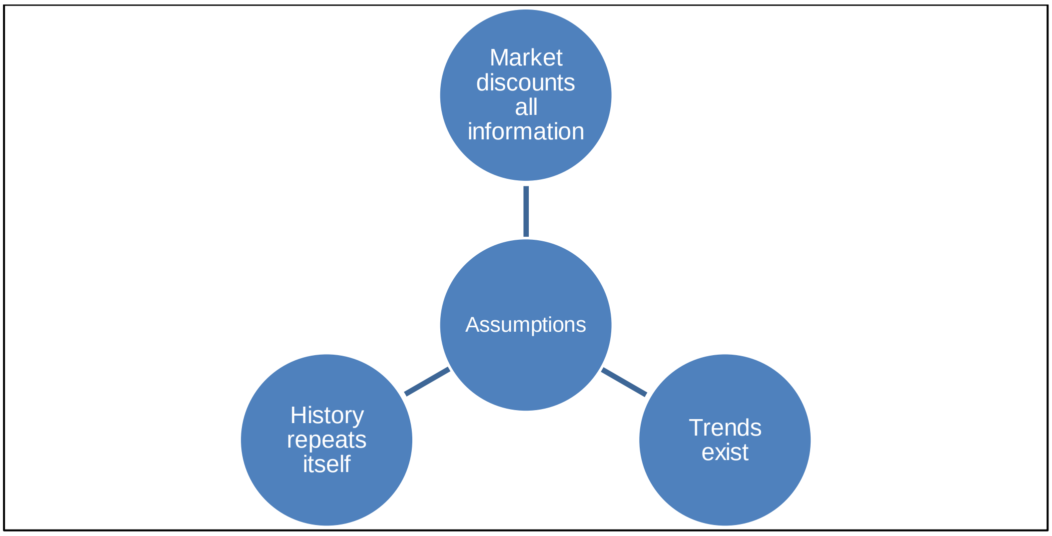
[3] This was one of the first studies done on market efficiency after the deregulation of the Maize Board in 1997.

[4] Fundamental analysis can be defined as a method of evaluating and forecasting price movements by means of a detailed macroeconomic, industry and company examination (Marx *et al.*, 2010:75; Reuters, 1999:8).

analysis (Brown & Reilly, 2009:519–520). The reason behind this is that fundamental analysis depends heavily on stock supply and demand balance sheets, which do not capture human psychology, whereas the price incorporates all these psychological factors which are then graphically represented by the graphs technical analysts use to analyse the market. Another major advantage of technical analysis is that technicians are able to experience ideal timing regarding when to invest (Brown & Reilly, 2009:520). However, psychological factors do play a significant role in technical analysis' decision–making process and can be considered a disadvantage of technical analysis. An example of this is where market participants are encouraged to implement a trading rule that have shown to be highly successful in the past, and in spite of this still be subjective when applying the trading rule (Brown & Reilly, 2009:521).

In line with the advantages and disadvantages, technical analysis relies on three fundamental assumptions as graphically illustrated in Figure 1.1 (Reuters, 1999:9). The first assumption states that the market discounts all information, specifically that all underlying factors affecting the price are reflected in the price (Krugel, 2003:47; Reuters, 1999:9). The second assumption reasons that prices move in trends or patterns and have a tendency to recur in the future (Geyser, 2013:20; Reuters, 1999:9). Lastly, technical analysis assumes that history repeats itself, which implies that human behaviour stayed relatively constant over time (Colby, 2003:6; Reuters, 1999:9).

Figure 1.1: Fundamental assumptions of technical analysis



Source: Compiled by the author.

Notwithstanding the three assumptions, accurate technical analysis still depends on determining if prices are moving in a trend or if markets are trading (Achelis, 2001:35–36). Trending markets' prices move either upwards or downwards, whereas trading markets' prices move sideways (Achelis, 2001:35–36). Specific indicators[5] were developed to help identify the type of market. However, these indicators do not indicate whether a market is primarily trending (trading) or secondarily trading (trending). This concept can be explained further by means of Figure 1.2, where prices that are primarily in a trending market (line A) may move into a secondarily trading market (box B and box C), before continuing with the initial trend (Marx, Mpofu, De Beer, Nortjé & Van De Venter , 2010:190–192). It is important to distinguish between the correct type of market, since applying the wrong combination of technical indicators in a trending or trading market may indicate false buy or sell signals, which in turn may result in a loss.

[5] These include Aroon, Chande Momentum Oscillator, Commodity Selection Index, Random Walk Index, and Directional Movement Index (DMI) to name but a few (Achelis, 2001:36; Murphy, 1986:468).

Figure 1.2: Primary and secondary trends

Source: Compiled by the author; Credit Suisse (2012:8).

To enhance the understanding of applying the correct technical indicators it is important to know the different categories available, which entail leading and lagging indicators (Achelis, 2001:33–35). Leading indicators include – but are not limited to – the Relative Strength Index (RSI) and Stochastic oscillator, which indicate buy or sell signals (Achelis, 2001:35, 297, 321). Alternatively, lagging indicators include – but are not limited to – the Moving Average (MA) and Moving Average Convergence Divergence (MACD), which identifies late buy or sell signals (Achelis, 2001:33, 199, 203). The proposed approach is to use leading indicators in a trading market and lagging indicators in a trending market for effective and accurate technical analysis (Achelis, 2001:33).

In light of the above, it may be difficult to distinguish between trending and trading markets, even with the assistance of specific indicators. Technical analysis may then generate false selling signals since the right indicator is used in the wrong type of market. Thus, constructing a composite indicator that includes both trending and trading markets' indicators, and assigning more weight to the indicators that are more applicable in the given type of market, may assist in generating more accurate buy and sell signals.

1.3 Motivation and research aim

From the abovementioned background it is clear that the South African white maize market is considered to be weak–form efficient[6]. This inherently means that prices are slow to adjust to new fundamental information entering the market and it may be possible for a superior analyst to generate abnormal returns by applying technical analysis (Brown & Reilly, 2009:546). Additionally, market anomalies exist that may decrease a market's efficiency even further (Viljoen, 2003:210–211). These market anomalies include the January effect[7], low book value[8], the size effect[9], and the weekend effect[10] to name but a few (Keim, 2006:3; Latif, Arshad, Fatima & Farooq, 2011:3–4). It is essentially in times that market anomalies occur that human mass psychology[11] plays an integral role in price determination, specifically due to the emotional nature of humans (Viljoen, 2003:201–211; Wouters, 2006:18, 25).

Consider the weekend effect for instance, where prices tend to be higher on a Friday than on the subsequent Monday and where negative returns in prices were experienced from the close of trading on a Friday to the opening of trading on a Monday (Rogalski, 1984:1613). This is the result of investor fears that information released over the weekend may adversely affect their holdings' price which prompts investors to clear their portfolios of these holdings (Thaler, 1987:175).

The weekend effect thus specifically encompasses the human emotion of fear. This is only one of the many emotions that market role-players experience in different market conditions and adverse market movements. Human emotions play an intrinsic role in the decision-making process. The basic rule of "buy low, sell high" is set aside as emotional reactions tend to overpower logic (Geyser, 2013:20). The

[6] See studies conducted by McCullough (2010:131), Moholwa (2005:21), Scheepers (2006:61) and Viljoen (2003:206).

[7] A general increase in stock prices within the first two to three weeks of January.

[8] Stocks with a below-average price-to-book ratio tend to generate abnormal returns.

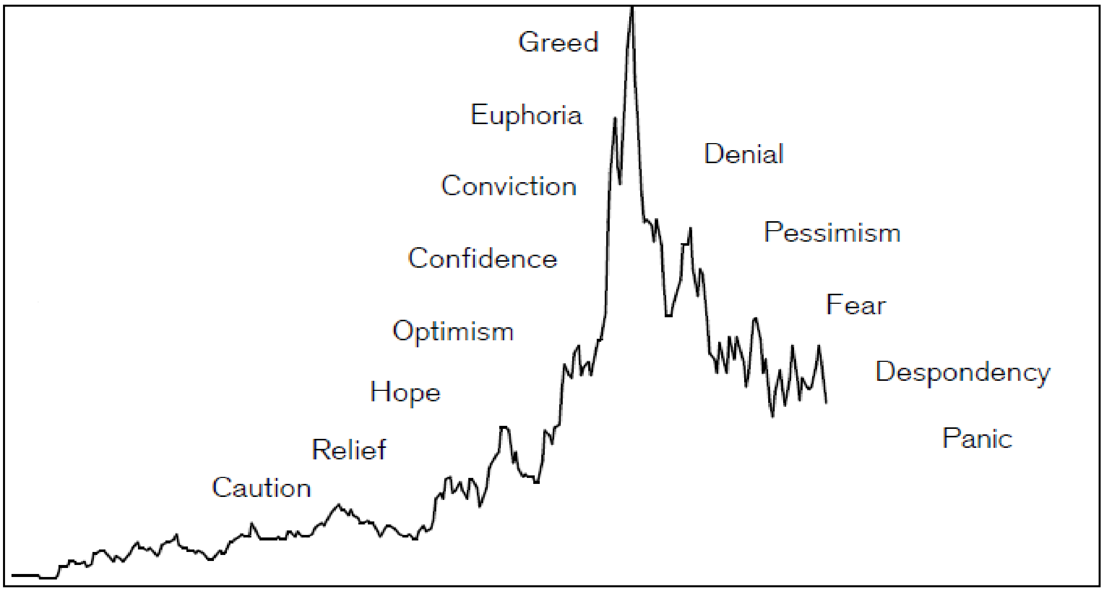
[9] Small-cap companies tend to outperform large-cap companies.

[10] Stock prices tend to be lower on a Monday than on the previous Friday.

[11] A group's emotional and behavioural characteristics and attitudes (Dictionary.com Unabridged, 2013:1)

influence of certain price formations on human emotions can be graphically illustrated by Figure 1.3.

Figure 1.3: Cycle of market emotions



Source: Credit Suisse (2012:1).

From Figure 1.3 it is clear that market role-players may react in the same manner during different stages of a market movement, thus individuals tend not to act as individuals, but as a group. This concept also applies to hedgers using technical analysis, since everyone sees the same graphs, applies the same technical analysis with the same findings, but they do not act against the general view of the market, mainly as a result of fear.

Fear is also a dominant decision–making emotion that white maize producers struggle with. Maize producers are unwilling, hesitant or fearful to adopt price risk management instruments due to a “lack of capacity”, “distrust of the market”, and “bad experiences” (Jordaan & Grové, 2007:561). Their main fears with regard to price risk are hedging at the wrong time, or not having hedged enough when the time was indeed right (Jordaan & Grové, 2007:561). Another fear may include hedging expected produce at the right time, but not being able to fulfil the delivery contract due to the standardised nature of futures contracts (Bernstein, 2000:42–43; Jordaan & Grové, 2007:561). This would then force a maize producer to be a buyer of maize, potentially at a price higher than an initial hedging contract's price, to fulfil the contract's delivery.

This study will specifically focus on the development of a practical and applicable composite technical indicator with the purpose of improving the timing aspect of price risk management decisions that maize producers struggle with. If the trends and daily grain price predictions can be improved, maize producers will be less hesitant and fearful to adopt derivative instruments as a price risk management tool (Ueckermann, Blignaut, Gupta & Raubenheimer, 2008:235). The development of a composite indicator may improve a maize producer's willingness to adopt derivative price risk management instruments, which in turn can result in maize producers hedging more optimally.

1.4 Problem statement and research question

In light of the issues mentioned above, a problem can be formulated as follows. To ensure sustainable and profitable maize production, it is necessary for South African maize producers to hedge their expected harvest at the highest possible price. Producers who hedge their produce at lower levels may be subject to substantial variation margin requirements in order to sustain their futures position in the market. Additionally, potential costly buy–outs of futures contracts at higher price levels may occur, when a producer cannot fulfil his/her contract delivery obligations.

Given this problem, a research question may be formulated. **Would it be possible to improve maize producers' hedging ability by constructing a composite indicator, which will take different market types and technical indicators into account, thus improving the timing and selling levels identified by popular individual technical indicators?**

1.5 Research objectives

The primary objective of this study was to construct a composite indictor compiled from several individual technical indicators, with the possible ability to generate better selling signals that would ultimately assist in effectively hedging against adverse price movements. In achieving this primary objective, the following secondary objectives were also determined:

i. identifying different indicators to evaluate if the white maize market is currently trending or trading;
ii. determining the most popular and basic technical indicators to use in constructing the composite indicator by means of a literature and empirical study; and
iii. determining the average hedge level achieved by means of individual indicators (This needed to be done for both types of indicators individually in different seasons in order to compare each individual indicator's achieved hedge level to the composite indicator's average achieved hedge level).

It is, however, important to take note that this study was/is not aimed at:

i. challenging or disproving the Efficient Market Hypothesis (EMH); or
ii. constructing a composite indicator in the hope of outperforming the market or to benchmark price level.

1.6 Literature review

A comprehensive literature review will be included in this study in order to achieve the research objectives, as stated above. This literature study will include a summary of the following:

i. background study of the South African agricultural market, with particular reference to the white maize market in order to understand the reasons for market participants to gain knowledge of derivative instruments (Chapter 2);
ii. the EMH, as well as the efficiency of the white maize market in South Africa, to ensure that technical analysis can be performed on the white maize market (Chapter 2);
iii. market anomalies as a link to human mass psychology and the applicability of technical analysis (Chapter 2);
iv. technical analysis, which includes the assumptions that technical analysis rely on, to provide a background to the functioning of technical indicators (Chapter 3);
v. leading and lagging indicators to determine which indicators to include in constructing a composite indicator (Chapter 3); and

vi. trending and trading markets to provide a background on the accuracy of leading and lagging indicators (Chapter 3).

1.7 Methodology

In order to improve the readers understanding of the methodology it proved meaningful to divide the section. Firstly, the proposed data and software used is explained and secondly a basic description of the method to be applied in the development of the composite indicator is provided.

1.7.1 Data and software

The empirical study is of a quantitative nature, and made use of seasonal contract data, more specifically the daily closing prices for every season, for the July white maize futures contract for the period 2001 to 2013. Technical analysis was applied to this data by means of using Metastock 11 software, created by Equis International and a product of Thomson Reuters. The data was extracted from the Thomson Reuters database via Metastock 11. The researcher made use of Microsoft Excel 2010 in order to determine the different hedging levels achieved by the different individual indicators, as well as to construct and implement the proposed composite indicator.

1.7.2 Method

A basic description of the various indicators identified in the literature review as well as the interpretation of each indicator, in order to identify selling levels, will be included in the methodology. Furthermore, a description of the methodology behind the calculation of the assigned value and weight of each individual indicator included in the proposed composite indicator was essential.

Table 1.1 is a simplified illustration of the calculations surrounding the construction of the composite indicator. As seen in Table 1.1, the indicator value for each indicator was bounded between 0 and 100. The reason for this is to ensure the accuracy of the composite indicator, given that lagging indicators are not bound between 0 and 100, whereas leading indicators are. After examining the type of market by means of specific indicators, and for example determining that the market is primarily trending, the application of lagging indicators are more accurate in identifying selling levels. It was therefore sensible to assign a greater weight to the lagging indicators and less weight to the leading indicators in the construction of the composite indicator. Accordingly, a weight value was calculated by multiplying the assigned indicator value and the calculated weight. Adding all the indicators' weighted values provided a new composite indicator value, which was interpreted accordingly to identify buy and sell signals.

Table 1.1: Calculation of composite indicator in a trending market

Type of Market		Trending Market		
		Indicator Value	Indicator Weight	Weight Value (Value x Weight)
Indicators	Trading Indicator 1	0–100	0–1	x
	Trading Indicator 2	0–100	0–1	y
	Trending Indicator 1	0–100	0–1	z
	Trending Indicator 2	0–100	0–1	α
				Composite Indicator Value

Source: Compiled by the author.

1.8 Chapter layout

Following the introduction to the study, Chapter 2 entails the history of the South African white maize market, as well as the background on SAFEX, so as to better understand the reasoning behind some producers' hesitancy or difficulty to hedge. Also, as mentioned before, one of the most significant reasons for producers' hesitancy towards hedging is their distrust of market efficiency in the white maize market. Thus, Chapter 2 will also examine the EMH, focusing specifically on previous studies done on the efficiency of the South African white maize market.

Chapter 3 is also a literature study, and the use of technical analysis as an analytical method is elaborated on. The background of technical analysis will be provided, including the Dow Theory, as well as the assumptions of technical analysis. Details regarding the tendency of market price movements are provided, whereafter the indicators aimed at determining the current trend of the market are examined in an attempt to determine the best possible indicator to apply in this study. Thereafter, the best indicators to apply in the construction of the composite indicator will be examined.

The methodology and empirical results of this study is provided in Chapter 4. Firstly, the primary tendency of the market will be determined, whereafter the composite indicator is constructed and compared to the results of the individual indicators, so as to determine if a more effective hedging level can be established through the appropriate use of technical indicators. The results validate the construction of the composite technical indicator, which proved to outperform the other individual indicators.

Lastly, conclusions regarding the findings and results of constructing a composite indicator in the South African white maize market are provided in Chapter 5. Recommendations for further research are also provided.

Chapter 2

Agricultural Commodities

"Farming looks mighty easy when your plow is a pencil, and you're a thousand miles from the corn field."

~President Dwight D. Eisenhower (1956)

2.1 Introduction

The South African agricultural market was a highly government regulated market for decades, with the main objective of minimising the negative effects of volatile prices (Larson, Anderson & Varangis, 2004:199; Ueckermann *et al.*, 2008:222). It was found, however, that regulating markets were unsuccessful, unsustainable and hindering growth. Consequently, due to international and domestic pressure, the South African agricultural market was deregulated in 1996 (Larson, 2004:199; Chabane, 2002:1). Since deregulation, prices have been volatile and producers were faced with the necessity to hedge against adverse price movements (Chabane, 2002:1; Krugel, 2003:52).

Since their introduction in South Africa in 1996, futures contracts have been increasingly popular as a price risk hedging instrument (Mahalik, Acharya & Babu, 2009:1). Managing price risk in the agricultural market is essential, especially since price variations play an integral role in profit variations (Goodwin & Schroeder, 1994:936). Despite the necessity to hedge, producers are hesitant, reluctant or fearful to adopt derivative instruments as a price risk management tool. This is due to several reasons, including bad experiences in the past, lack of capacity to make use of risk management instruments, and a general distrust of the market's efficiency (Jordaan & Grové, 2007:561).

In order to better understand some of the reasons behind most producers' hesitancy or difficulty to hedge, Section 2.2 commences with a summary of the history of the white maize market in South Africa, whereafter an overview of SAFEX follows in Section 2.3. Also, one of the more significant reasons for producers' hesitancy towards hedging, as mentioned, is their distrust or disbelief of market efficiency in the agricultural market. Since it is of significant importance that the market functions efficiently so as to enable a producer to apply a hedging strategy effectively, the first part of Section 2.4 provides a detailed description of the EMH, as well as an overview of the previous studies done on the efficiency of the South African white maize market in particular. The last part of Section 2.4 will provide an analysis of some market anomalies that can decrease a market's efficiency, making it possible for some market participants to benefit from market movements by means of superior analytical methods, which is discussed in Chapter 3. Lastly, Section 2.5 concludes this chapter.

2.2 The history of the maize market in South Africa

Agriculture was a highly government regulated market in South Africa since the 1930s as a result of low, unsustainable prices in the commodities market (Cass, 2009:25). These prices were a result of a recession in the 1920s up to the early 1930s, which followed high prices and inflation caused by the Anglo–Boer War of 1899 to 1902 and the First World War of 1914 to 1918. The recession led to decreasing prices while financing ceased, which ultimately led to several farmers declaring bankruptcy. Fluctuating national prices followed shortly thereafter, mainly due to the lack of marketing resources and speculation by traders (De Swardt, 1983:4–5).

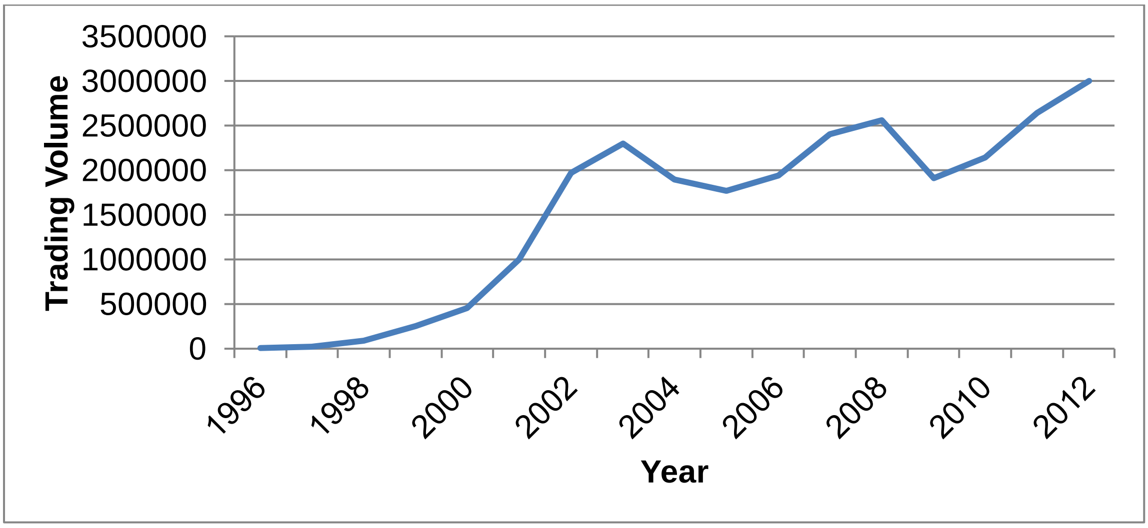
With the main purpose of limiting this price volatility, commodity control boards were established by the Marketing Act of 1937 (Groenewald, 2000:376). Furthermore, to limit volatility, a single channel, fixed price marketing system was implemented, where government control boards determined a price for the selected commodity and from the 1980s hedged this fixed price by trading on the Chicago Board of Trade (CBOT) (Bown *et al.,* 1999:276; Cass, 2000:25). Buyers and sellers could only participate in the market through the selected control board, which ensured a risk–free environment for both buyers and sellers (Bown *et al.*, 1999:276; Krugel, 2003:51–52). This risk–free market ensured that producers were paid a predetermined price, calculated as an average of production costs along with a profit margin (De Swardt, 1983:4; Vink, 2012:558). However, due to the domestic price on average being significantly higher than the world price, which encouraged producers to overproduce, all surpluses were exported at a deficit (Vink, 2011:560). The deficit was covered by a stabilisation fund set up by the Maize Board, but due to continuously increasing maize prices in South Africa, a bail–out by the government was required during the late 1980s (Vink, 2011:560).

During this time, domestic and international pressure to deregulate the market intensified, and since the Marketing of Agricultural Products Act in 1996, market participants were able to trade in a free market environment (Geyser, 2013:3). However, the deregulated market was not without challenges, as producers were consequently responsible for the marketing of maize (Bown *et al.*, 1999:276). Furthermore, since government intervention no longer existed, prices were allowed to fluctuate, which resulted in the necessity for producers to manage price risk (Chabane, 2002:1; Krugel, 2003:52). With guidance provided by SAFEX's Agricultural Markets Division (AMD), producers were able to market their produce on an exchange traded platform (SAFEX), as well as manage their price risk primarily by means of the derivative instruments offered by SAFEX (Geyser, 2013:3; JSE, 2013a:1). The following section provides more background on SAFEX.

2.3 The South African Futures Exchange (SAFEX)

The first futures contracts to be listed on SAFEX's AMD were beef and potatoes in 1995, but due to inactivity both contracts were delisted in 1996 (Geyser, 2013:3). White and yellow maize were the next futures contracts to be listed on SAFEX in 1996, where wheat, sunflower seed and soybean contracts followed in 1997, 1999, and 2002, respectively (Geyser, 2013:3; JSE, 2013a:1). In 2001, SAFEX's members accepted a buyout from the Johannesburg Stock Exchange (JSE), becoming a separate division within the JSE (Geyser, 2013:3; JSE, 2013a:1). This also brought about a change of name from SAFEX's AMD to the Agricultural Products Division (APD) of SAFEX in August 2001 (Geyser, 2013:3; JSE, 2013a:1).

Figure 2.1: Total trading volumes of APD: 1996 to 2012



Source: Compiled by the author; JSE (2013b:1).

Since 2001, the APD showed significant growth in trading volumes (see Figure 2.1). In 2012 a new trading volume record was established with the total number of contracts traded just under 3 million, a significant 17% higher than the previous record in 2008 (JSE, 2013b:1). Reasons for this significant growth in the agricultural market include greater market participation, better understanding of the market and the improvement and expansion of the broad base of derivative instruments as marketing strategies (JSE, 2013a:1). The following section elaborates further on the significant growth in the agricultural market, which may be applied in marketing strategies, including the economic functions, advantages and disadvantages of the derivatives market.

2.3.1 Derivatives market

Agricultural market role players' greater market participation can be attributed to their increased reliance on derivative instruments due to an ever–increasing necessity to manage price risk (Mahalik *et al.*, 2009:1).The derivatives market offers a wide range of financial instruments[12], of which futures contracts[13] are the most favourable, with

[12] These instruments include, but are not limited to, forward contracts, future contracts, option contracts and swaps (Geyser, 2013:1).

[13] A futures contract can be defined as a standardised agreement between two parties to buy or sell an underlying asset at a specific future price and future time (Marx *et al.*, 2010:241).

the main purpose of managing adverse price movements (Geyser, 2013:4; JSE, 2013a:2; Krugel, 2003:10; Murphy, 1996:1). The futures market serves several significant economic functions, including:

i. functioning as a price risk management tool (Hasbrouck, 1995:1175);
ii. playing an active role in price discovery, price transparency, portfolio diversification and providing an effective hedging mechanism (JSE, 2013a:1; Srinivasan & Bhat, 2009:29);
iii. providing liquidity and a market for speculating (McCullough, 2010:22); and
iv. minimising volatility surrounding investments, sales and purchases (Marshall, 1989:52–54; Phukubje & Moholwa, 2006:199).

Other than these economic functions, futures contracts traded on an exchange provide additional significant functions to market participants. They encourage them to trade on a formal exchange and to increasingly rely on futures contracts as a risk management tool. These functions are thoroughly covered in the following subsection.

2.3.1.1 Function (advantages) of an exchange traded futures contracts

A formal exchange provides an efficient platform for buyers and sellers to trade futures contracts in an organised manner (Krugel, 2003:27). Furthermore, the futures contracts offered on an exchange serve several functions to market participants, all of which can be regarded as advantages as well. These functions can be set out as follows (Bernstein, 2000:53):

i. Price discovery

The futures exchange is only a mechanism or platform for buyers and sellers to discover the prices of a futures contract and not a system that sets prices (Krugel, 2003:27). This function of price discovery[14] is considered as one of the most important functions of an exchange traded futures market (Fedderke & Joao, 2001:1; Mahalik *et al.,* 2009:3; Srinivasan & Bhat, 2009:29). Effective price discovery is of particular importance in the agricultural market, more specifically the white maize

[14] The manner in which prices respond to new information entering the market, more specifically the influence and result of supply and demand on prices (Hasbrouck, 1995:1175).

market, since producers plant white maize in December with the risk of the price decreasing up to harvest time in July (McCullough, 2010:23; Van Der Wath, 2011:2)

The price risk associated with the white maize market can also be assigned to several fundamental factors. These factors include the domestic supply, the demand and stock levels; the Rand–Dollar exchange rate; the CBOT corn price, which reflects international supply and demand; the domestic prime interest rate; and weather conditions, to name but a few (Cass, 2009:4; Geyser & Cutts, 2007:296; Kleinman, 2002:114; Krugel, 2003:66). It is important that these factors are effectively and efficiently incorporated into the futures price so as to enable producers to estimate the future value of white maize. Also, this estimate will enable producers to make informed and profitable white maize production and hedging decisions (Geyser, 2013:5; McCullough, 2010:24).

ii. Risk transfer

In addition to price discovery, the ability to manage, transfer, or hedge price risk is also considered an important function of an exchange traded futures market (Mahalik *et al.*, 2009:3). Futures contracts allow a producer to reduce the risk of adverse price movements by shifting the risk onto another party (JSE, 2013a:2; Geyser, 2013:62; Mahalik *et al.*, 2009:3). Hedging with white maize futures contracts on an exchange holds several advantages, including no credit risk[15]; the price is known in advance which aids in the budgeting and planning process; and high liquidity ensures risk can be effectively transferred from hedgers to speculators (Bernstein, 2000:42–43,53; Geyser, 2013:67; JSE, 2013a:2; McCullough, 2010:26–27).

However, for the futures market to be effectively utilised as a risk management tool, certain factors regarding the futures market must first be acknowledged. The study by Roehner (2002:66) identified these factors as follows: high trading volumes; standardised products; availability of profit-making opportunities; product authentication by a secure and established exchange; and, products following market participants' trading behaviour, which is discussed accordingly.

[15] The risk of a loss due to a counterparty defaulting on a credit agreement (Hull, 2012:802). Also referred to as default risk.

iii. Standardised contracts

Given that white maize futures contracts are traded on a formal exchange, contracts and product specifications are standardised (Coopers & Lybrand, 1995:415–416; Geyser, 2013:4; Marx *et al.*, 2010:241). The basic features in a standardised futures contract[16] for white maize entail the following:

- contract size of 100 metric tonnes white maize;
- contract quoted in Rands per metric tonne;
- main futures contract months or expiration dates in March, May, July, September and December; and
- initial margin of R10 000 up to first notice day (initial margin requirement may vary in relation to market volatility).

These standard specifications allow a wide array of market participants, including hedgers and speculators, to make use of futures contracts (Bernstein, 2000:53). This is advantageous to the market participants, as more market participation promotes contract liquidity. Another advantage of standardisation is the possibility of closing out a futures contract at an earlier stage, before the first delivery date, as this again promotes liquidity (Bernstein, 2000:53).

iv. Liquidity

A liquid market can be defined as a market where market participants are able to buy and/or sell futures contracts with relative ease without prompting significant price changes (Pennings & Meulenburg, 1997:296). Liquidity is a market characteristic that assists white maize futures contracts to succeed in the agricultural market environment by providing a sufficient amount of tradable contracts at the current fair market price level (McCullough, 2010:27). This is of particular importance when considering the efficiency of the market, since the market efficiency significantly affects the price discovery and risk transfer functions of futures contracts (Aulton, Ennew & Rayner, 1997:422; Pennings & Meulenberg, 1997:296). These functions require the participation of a considerable amount of market participants, which in

[16] Appendix A contains a more detailed summary of the contract specifications for a white maize futures contract.

effect promotes liquidity to facilitate effective pricing actions and almost instantaneous transactions (Bernstein, 2000:53; JSE, 2013a:2; Pennings & Meulenburg, 1997:296).

2.3.1.2 Disadvantages of futures markets

Despite the functions and/or advantages of trading futures contracts on a formal exchange, certain disadvantages do exist (Coopers & Lybrand, 1995:416; Jecheche, 2011:13). These disadvantages may be set out as follows:

i. A futures contract is a legal agreement, thus bound by law to obligate the agreement. This may introduce new risks to a producer, such as not being able to deliver the exact quantity stipulated in the futures contract.
ii. The standardised nature of a futures contract is a disadvantage, specifically from a hedging perspective. Specifications such as contract size and trading months make it difficult to hedge perfectly. The reason for this is that different producers have different producing capabilities, more specifically not being able to produce the standard 100 metric tonnes required per contract. For example, producers face the risk of hedging more than their expected crop or certain parts of the crop may be left unhedged. In both cases significant losses may occur. Firstly, when a producer cannot supply all the tonnages hedged and face a contract buy–out at a higher price level than the original hedged level. Secondly, when prices drop throughout the season and unhedged produce is sold at lower prices during harvest. This validates the motivation for hedging at the highest possible price within a season, since such an accomplishment would counter the effect of both instances.
iii. Futures contracts are Marked–to–Market[17], which necessitates that variation margins need to be paid at the end of each trading day. These variation margins can cause significant cash flow problems if the market moves significantly unfavourable.

[17] The practice of adjusting the margin account at the end of each trading day according to the respective day's price movement (Brown & Reilly, 2009:766-767; Hull, 2012:27).

iv. Non–members of the clearinghouse still face default risk[18], since the clearinghouse cannot guarantee transactions of a broker or clearing agent.

2.3.1.3 Producers and derivative instruments

Despite the advantages of derivative instruments, producers do not make use of price risk management instruments on an exchange as often as would be expected, with specific reference to the use of white maize futures contracts. A study by Bown *et al.* (1999:275) confirmed an increase from 27% to 49% of white maize producers who apply price risk management tools from 1998 to 1999/2000. However, only 15% of the 49% of producers made use of exchange traded derivative instruments. One might argue that the study is outdated, though Jordaan and Grové (2007:552) found that this number has stayed relatively constant at 44% of producers who have used some form of forward pricing methods, with only 4% of producers using white maize futures contracts.

These application rates of futures contracts as risk management tools in South Africa are considerably less than would be expected, despite the fact that price risk seems to be one of the key risks producers face in the agricultural environment (Jordaan & Grové, 2007:548–549). Reasons for white maize producers' unwillingness or hesitancy to adopt price risk management instruments are labelled by Jordaan and Grové (2007:561) as a "lack of capacity", "bad experiences", and "distrust of the market". Maize producers' lack of knowledge and understanding of the white maize derivatives market consequently encourage a producer's lack of self–confidence, bad experiences and distrust of the market's efficiency (Bown *et al.*, 1999:285–286; Monk *et al.*, 2010:562; Jordaan & Grové, 2007:561–562; Ueckermann *et al.*, 2008:234). To elaborate more on the concept of market efficiency the next section provides a discussion on the EMH and its applicability to the South African agricultural market.

2.4 Efficient Market Hypothesis

Maize producers' distrust of the market function and efficiency can be ascribed to their belief that the market can be manipulated by other, more influential market

[18] Please refer to Footnote15.

participants (Jordaan & Grové, 2007:561). In order to test the validity of this belief, it was necessary to evaluate the white maize market's efficiency by means of examining previous studies conducted in this regard. However, to ensure a better understanding of these studies, it is important to provide a detailed background of EMH, as presented in this section.

2.4.1 Definition of EMH and the different forms of efficiency in markets

The concept of market efficiency is of particular importance in the agricultural market, since it provides producers with the ability to more accurately determine futures prices, as well as allowing them to manage price risk more effectively (McCullough, 2010:5). A market can be referred to as efficient when the market can provide an environment for effective risk management and price stabilisation (Aulton *et al*., 1997:1; Moholwa, 2005:3). An efficient market, better known as Fama's (1970) EMH, broadly entails that all known information is already reflected in the current market price and in effect that there is no chance of beating the market (Colby, 2003:256; Fama, 1970:383). The assumption in the EMH is that current prices are not affected by historical data and thus that increased returns are unattainable. However, this explanation of EMH is extremely restricted and can be explained in more detail by dividing the EMH into three different types, according to the market's ability to process information effectively and efficiently (Fama, 1970:414; Brown & Reilly, 2009:153).

The predominant and first EMH form in practice is the **weak form EMH** (Fama, 1970:414), which states that all security market information is already incorporated into the current price, including rates of return and historical trends of prices (Brown & Reilly, 2009:153). The hypothesis also states that no correlation between past rates of return, as well as all other historical information, and future rates of return exist (Brown & Reilly, 2009:153). In spite of this, all public information is not reflected in the current price in a weak efficient market and some market participants do have monopolistic access to private information (Brown & Reilly, 2009:153; Fama, 1970:414).

The second form, the **semi–strong form of the EMH**, states that all public information is already incorporated into the current price. Public information includes market information mentioned in the weak form EMH, as well as incorporating non–market information such as economic and political news (Brown & Reilly, 2009:153). Nonetheless, only public information is incorporated in the current price in a semi–strong efficient market and not all available information (Brown & Reilly, 2009:513; Fama, 1970:414).

The last form of EMH is considered a benchmark to which deviations from market efficiency can be compared to and is not an accurate portrayal of reality (Fama, 1970:414). The **Strong form of the EMH** assumes that all information, including all expectations of anticipated events, are already incorporated into the price and that it is impossible to make abnormal returns using any type of market analysis (Brown & Reilly, 2009:153; McCullough, 2010:21). It is also assumed that new information enters the market in an unpredictable, random fashion (Marx *et al.*, 2010:33). Furthermore, it is assumed that there is a perfect market, where all information is available to all market participants at the same time at no cost (Fama, 1970:414; Brown & Reilly, 2009:154).

An alternative definition by Teweles and Jones (1974:95) suggest that a market is efficient once a large number of profit–maximising, competitive market participants react accordingly to new information randomly entering the market. In addition, efficiency specifically within the agricultural market can be defined as futures market prices that incorporate all information effectively. This enables market participants to formulate more accurate spot prices, consequently making it impossible to generate abnormal returns using trading behaviour and/or trade analysis (Wang & Ke, 2002:2–3).

To summarise, a fully efficient market necessitates the following (Marx *et al.*, 2010:33):

i. A significant number of profit–maximising, competitive market participants;
ii. New information enters the market randomly and are available to all market participants at no cost; and
iii. All new information is rapidly and effectively incorporated into the price.

2.4.2 Testing for efficiency

Determining if a market is indeed efficient, differentiating between the different forms of efficiency, can be done by means of several statistical tests, with the most popular tests including testing for cointegration and unbiasedness (McCullough, 2010:11; Scheepers, 2005:61; Viljoen, 2003:75–76; Wiseman *et al.*, 1999:325–326)[19]. In order to elaborate more on these tests the following subsection provides the necessary background to better understand the efficiency studies mentioned in Section 2.4.3.

2.4.2.1 Cointegration tests

Cointegration tests are a way of validating the presence of a long–run relationship between two time series. This long–run relationship is the first requirement of market efficiency, since this shows that current futures prices and future spot prices converge to one another (McCullough, 2010:33–34; Wang & Ke, 2002:2–3). Popular[20] cointegration tests include the Engel–Granger (1987) approach and the Johansen (1991) approach. Thus, once the Engel–Granger (1987) and/or the Johansen (1991) test confirm a long–run relationship between the futures price and the spot price, the market may be deemed weak form efficient.

2.4.2.2 Unbiasedness

If cointegration is found to exist between the spot and futures market, it is necessary to further investigate the relationship by determining which one of the markets is an unbiased predictor of the other. This is considered the second step in testing for efficiency in a market, as these tests reveal if there is indeed effective price discovery present within the markets (McCullough, 2010:42). Popularly[21], this can be determined by estimating either an Error Correction Model (ECM), in the case where the Engel–Granger (1987) cointegration approach was implemented, or a Vector Error Correction Model (VECM), in the case where the Johansen (1991)

[19] Also refer to Beck (1994:250), McKenzie and Holt (1998:1,4-5), Santos (2009:8-10), and Wang and Ke (2002) as references to international studies.

[20] Please refer to studies by Leng (2002), McCullough (2010), Mckenzie and Holt (1998), Santos (2009), and Wang and Ke (2002).

[21] Please refer to studies by Leng (2002), McCullough (2010), Mckenzie and Holt (1998), Santos (2009), and Wang and Ke (2002).

cointegration approach was implemented (Asteriou & Hall, 2011:365; McCullough, 2010:41). Thus, if the respective variables estimated in the models are found to be statistically significant, indicating that either the spot or futures market is an unbiased predictor of the other, the market may be deemed weak form efficient.

If the tests used to determine market efficiency indicate that the market is indeed efficient, the results commonly reveal two main implications (McCullough, 2010:6):

i. Historical prices cannot be used for future price predictions. This implies that the market should be an efficient mechanism for price discovery, thus allowing expected futures prices to be more accurate.
ii. Efficient price discovery allows for an increased possibility in reducing price risk by means of different hedging strategies.

Considering these implications of an efficient market, it is evident that a South African white maize producer requires an efficient white maize market mechanism in order to manage price risk effectively. This leads to the following section in which historical studies are evaluated to determine the level of market efficiency of the South African white maize market.

2.4.3 South African white maize market efficiency

The efficiency of the South African white maize market has yet to be investigated extensively, with only a few studies focusing solely on agricultural market efficiency. This can be ascribed to the fact that the agricultural market in South Africa is relatively new when compared to international markets (see Table 2.1 for a list of established international exchanges). For example, the first maize futures contract was listed on CBOT was in 1877, where maize was only listed on the JSE in 1996 (CME, 2013:1; JSE, 2013c:1). Since CBOT is considered to be a weak form efficient market, it can be expected that the South African white maize market is weak form efficient as well, possibly even inefficient (Armah & Shanmugam, 2013:73; McKenzie & Holt, 2002:1530; Yang & Leatham, 1998:111). To accentuate this argument the following sub–sections provides an overview of historical studies that evaluated the efficiency of the white maize market in South Africa.

Table 2.1: Established international exchanges

Name of Exchange	Futures Market Established	First Futures Contract Traded	Website of Exchange
Chicago Board of Trade (CBOT)	1865	Corn, Wheat and Oats	www.cbot.com
South African Futures Exchange (SAFEX)	1995	Beef	www.safex.co.za
Kansas City Board of Trade (KCBT)	1876	Hard Red Winter Wheat	www.kcbt.com
Minneapolis Grain Exchange (MGEX)	1883	Hard Red Spring Wheat	www.mgex.com
ICE Futures US	1870	Cotton	www.theice.com
Australian Securities Exchange (ASX)	1960	Wool	www.asx.com.au
London International Financial Futures Exchange (LIFFE)	1982	Short–term Interest Rates	www.liffe.com

Source: Compiled by the author.

2.4.3.1 Wiseman, Darroch and Ortmann (1999)

The first study of its kind, after market deregulation in 1996, was done by Wiseman, Darroch and Ortmann (1999:322) who determined the level of efficiency of the white maize market between 1997 and 1998. It was determined that a long–run relationship existed between the spot and futures prices by using the Engel–Granger (1987) cointegration approach (Wiseman *et al.*, 1999:325–326). The results indicated no relationship for 1997, but did however indicate a long–run relationship for 1998, which suggests a weak form efficient white maize futures market during this specific time period (Wiseman *et al.*, 1999:332). The adjustment from an inefficient to a weak form efficient market was mainly due to better knowledge and understanding of the market by market participants but also due to the higher liquidity (Wiseman *et al.*, 1999:332–333).

2.4.3.2 Viljoen (2003)

Viljoen (2003) tested for efficiency in the white maize and yellow maize futures markets between 1996 to 2002. However, the focus of the study was not solely on the efficiency of the selected futures markets, but also more specifically on the efficiency of price discovery in the South African agricultural futures market (Viljoen, 2003:3). The long–run relationship between the spot and futures markets was examined by means of a Johansen (1991) cointegration approach and concluded in favour of the relationship in each of the selected markets. These results, therefore, confirmed that all the markets demonstrated weak form efficiency (Viljoen, 2003:75,200–201).

Furthermore, the results obtained from this study are also partially in disagreement with the results obtained by the study of Wiseman *et al.* (1999:332). Reasons for the dissimilarity are summarised as follows (Viljoen, 2003:201–202):

i. The study of Wiseman *et al.* (1999:322) was conducted over a shorter period of time.
ii. The market was still in the early stages of development when Wiseman *et al.* (1999:322) examined the futures market. Problems such as low trading volumes and liquidity, which could have negatively influenced the market's price discovery function, may have influenced the study's findings.
iii. Wiseman *et al.* (1999:326) attempted to overcome the abovementioned problem by using only the contract months that showed the highest trading volumes, so as to better determine the level of efficiency of the white maize futures market.

2.4.3.3 Nikolova (2003)

Another study was done by an Honours student in 2003 and wherein only the efficiency of the South African white maize market between 1997 and 2002 was examined. Nikolova (2003:33–36) examined the long–run relationship between the spot and futures market for the selected period by applying the Engel–Granger (1987) cointegration technique to lagged and log normal transformed data. No evidence was found in this study of a relationship between the spot and futures market, which implies that the white maize market was inefficient. However, McCullough (2010:56) criticised this study by arguing that the study examined only the long–run relationship between the spot and futures market. Furthermore, applying the selected cointegration analysis to each year separately would provide bias results and the study should have been extended to incorporate a cointegration test for the entire time period.

2.4.3.4 Moholwa (2005)

In 2005, Moholwa (2005:20) investigated the efficiency of both the white and yellow maize futures markets between 1999 and 2003. Using only the futures prices of the selected crops, the selected observations of each contract month over the selected period were pooled into a single data set (Moholwa, 2005:9–10). Despite the popularity of using cointegration methods to test for efficiency, a forecasting framework was used in this study to test the predictability of futures price changes (Moholwa, 2005:13–14). Results could not explicitly confirm the presence of weak form efficiency for both the white and yellow maize futures markets, concluding that the futures prices are only predictable to some extent and thus that market efficiency has not changed over time. Although, when trading costs and the time value of money were incorporated into the futures price calculation no evidence existed that past prices could be used to estimate future prices (Moholwa, 2005:21).

2.4.3.5 Scheepers (2005)

The study conducted by Scheepers (2005:3–4) was not primarily aimed at testing the efficiency of the white maize futures market, but intended to investigate the success of different hedging strategies in order to minimise risk faced by producers. However, for these strategies to be successful it is vital for the agricultural market to be efficient and, therefore, the study considered efficiency testing as one of the key objectives (McCullough, 2010:22; Scheepers, 2005:3–4; Wiseman *et al.*, 1999:332). The Engel–Granger (1987) cointegration test was used to determine if a long–run relationship between the spot and futures markets exists (Scheepers, 2005:61). The results not only showed a long–run relationship, indicating white maize market efficiency, but also obtained similar results as the study conducted by Wiseman *et al.* (1999:332–333). These results therefore substantiate the argument that the white maize market's efficiency will increase over time (Scheepers, 2005:61).

2.4.3.6 McCullough (2010)

The most recent study on the efficiency of the white maize futures market was done by McCullough (2010). The Engel–Granger (1987) and Johansen's (1991) cointegration tests were used to test for a long–run relationship between the spot and futures markets. A second stage efficiency test was implemented by means of deriving and interpreting an ECM model and a VECM model, which included examining the functioning of price discovery[22] (McCullough, 2010:11). The results illustrated that a long–run relationship was present between the spot and futures market and that price discovery between these two markets existed (McCullough, 2010:126). Furthermore, given the results obtained, it was concluded in this particular study that the South African white maize futures market was weak form efficient between 1996 and 2009 (McCullough, 2010:127).

2.4.3.7 Summary of South African efficiency studies

It is evident from the above-mentioned studies that the South African white maize market has generally demonstrated weak form efficiency. This implies that prices are slow to adjust to new fundamental information entering the market, allowing some market participants to benefit from the price movements using different analysis techniques (Brown & Reilly, 2009:546; Wiseman *et al*., 1999:332). Furthermore, these findings may in some way support maize producers' distrust of market efficiency, but also rules out complete market inefficiency. To conclude, from the findings discussed above the weak form efficiency of the South African white maize futures market can be ascribed to several factors:

i. The South African futures market is still relatively new when compared to other international established futures markets (Leng, 2002:2).
ii. The non–existence of a reporting system of market spot prices. Since the spot prices used in efficiency studies are derived from futures contracts, these data points do not fully reflect cash market transactions (McCullough, 2010:68).

[22] McCullough (2010:126) was the first to apply the ECM and VECM models in a South African agricultural efficiency study in order to confirm the level of efficiency of the South African white maize market.

iii. The presence of market frictions or market anomalies[23] (Frankfurter, 2007:83; Latif *et al.*, 2011:1; Srinivasan & Bhat, 2009:29; Viljoen, 2003:205).

However, despite these findings, market anomalies still exist that can decrease a futures market's efficiency over the short– to medium–run (Viljoen, 2005:205). Some market anomalies are also more frequently observed in certain markets than others. This is also true for the market anomalies associated with the white maize market, which is why market anomalies are discussed in more depth in the following section.

2.4.4 Market anomalies

A market anomaly can be defined as a distortion or divergence of price from a smooth pattern in a financial market (Latif *et al.*, 2011:1). Some of the most popular market anomalies include the day–of–the–week effect, the holiday effect, the turn–of–the–month effect, the time–of–the–year effect, the January effect, the maturity effect, and the size effect. All the above-mentioned market anomalies, except the size effect market anomaly, are frequently observed in the maize futures market (Viljoen, 2003:202). This leads to the following sub–sections in which the presence of these selected anomalies in the white maize market are further elaborated upon.

2.4.4.1 Day–of–the–week effect

This anomaly entails that returns observed on Mondays are lower than returns observed during the rest of the week (Latif *et al.,* 2003:5; Viljoen, 2003:118). The existence of this anomaly is noticeable in the white maize market, with returns being significantly lower on a Monday compared to any other day of the week (Viljoen, 2003:202). The weekend effect was also detected in the white maize market, where returns seemed to increase on a daily basis with the highest returns observed on a Friday (Viljoen, 2003:202). This anomaly may be ascribed to the fears related to new information released during the non–trading period over the weekend. This non–trading period may negatively affect hedgers' holding prices and thus encourage these market participants to clear these holdings out (Rogalski, 1984:1604–1606; Thaler, 1987:175). This also led to the finding of Monday returns in reality being positive.

[23] See Appendix B for a detailed list of market anomalies.

2.4.4.2 Holiday effect

The holiday effect can be described as returns that are affected by public holidays, such as Worker's Day on 1 May (South Africa, 2013:1; Viljoen, 2003:132). More specifically, the holiday effect stipulates that returns are higher on the day prior to a public holiday than the returns on the day following the public holiday (Viljoen, 2003:119). This anomaly was, however, not observed in the South African white maize market, where lower returns on the day preceding a public holiday were realised than on the day following a public holiday (Viljoen, 2003:203). However, since these public holidays were only taken into account when it occurred in the week, the results should be interpreted cautiously, as the discrepancies in the returns may also be due to the day–of–the–week effect (Viljoen, 2003:203).

2.4.4.3 Turn–of–the–month effect

The irregularity where returns tend to be higher at the beginning of the month than at the end of the previous month is labelled the turn–of–the–month effect (Thaler, 1987:173; Viljoen, 2003:203). The white maize market showed a significant turn–of–the–month pattern, with returns being negative at month–end and mainly positive at the beginning of the subsequent month (Viljoen, 2003:203–204). This effect may be due to human psychology, where investors close out their positions at the end of a month, expecting advantageous price movements at the beginning of the next month due to new information entering the market (Latif *et al.*, 2011:7). The logical explanation may be that since market participants need to close out their positions before month end to avoid compulsory delivery. For example, in the instance where a net–long position is closed out before a delivery month is entered to avoid receiving random delivery, the positions are rolled over to another futures month. In order to achieve this the near month long positions are sold to close them out, but to ensure that the long positions remain in the market they are bought again in the following futures month which may support prices in that month.

2.4.4.4 Time–of–the–year effect

This anomaly is defined as an increase in returns during certain months in a year compared to other months (Gultekin & Gultekin, 1983:4–5; Viljoen, 2003:204). Time–of–the–year effect is significantly evident in the white maize market, since white maize is subject to seasonal price changes in line with its production cycle. This phenomenon was validated by Viljoen (2003:204), in his findings that monthly returns tend to be high at the end of the year when there is a shortage in supply, but significantly lower in the middle of the year when supply is in excess.

2.4.4.5 Maturity effect

The phenomenon where a futures contract's volatility increases as the contract reaches maturity is better known as the maturity effect (Milonas, 1986:443). This is due to the high uncertainty surrounding futures contracts when a contract is far from maturity, which in turn leads to the contracts reacting slowly to new information. Conversely, a contract near to maturity entails more certainty, which in turn leads to the price discovery functioning more optimally (Sameulson, 1965:44–45). However, there is no significant evidence which suggested that the white maize market is affected by this anomaly (Viljoen, 2003:204).

2.5 Conclusion

The history of the South African agricultural market includes decades of government regulation in an attempt to minimise the negative effects of price volatility associated with the agricultural market. Being a risk inherent market, the South African white maize market necessitates risk management to ensure sustainable and profitable maize production. Since the abolition of the Maize Board in 1996, marketing and risk management responsibilities were placed in the hands of the individual producer. Producers, however, lacked the knowledge and understanding of the derivatives market and are therefore hesitant or reluctant to make use of these specific risk management tools, despite SAFEX's efforts to facilitate these responsibilities by providing an exchange traded platform for market participants to come together.

Since SAFEX's inception on the agricultural market in 1995, risk management responsibilities were simplified by means of the derivatives market, more specifically the futures market. These exchange traded futures contracts hold a number of disadvantages, including legal problems, standardised nature of contracts, mark–to–market, and residual default risk. These disadvantages, together with a "lack of capacity", "distrust of the market", and "bad experiences" discourage white maize producers to make use of derivative instruments. Despite this, futures contracts serve several significant functions and advantages, including price discovery, risk transfer, liquidity and standardisation. However, for most of these functions to be optimally employed an efficient derivatives market is necessary.

Within the agricultural market in South Africa, the efficiency of the white maize market has not yet been extensively investigated, however, evidence has been found with the majority of the South African studies confirming a weak form efficient market. Reasons for the market's relative inefficiency can be due to the relatively new South African futures market, the non–existent spot price reporting system and market anomalies. Market anomalies commonly observed in the white maize market include day–of–the–week effect, holiday effect, turn–of–the–month effect, time–of–the–year effect, and maturity effect.

These anomalies can decrease a market's efficiency in the short– to medium–run, and given that the market is considered to be weak form efficient, implying that prices are slow to adjust to new fundamental information entering the market, market participants may be presented with the opportunity to achieve above normal profits by means of superior analytic methods. Bearing in mind hedgers' apprehension to apply derivative instruments as a risk management tool, the possibility was considered of applying an analysis technique in the white maize market that would allow these market participants to hedge their produce accurately, effectively and without hesitation. The following chapter (Chapter 3) focuses specifically on the use of technical analysis as a method, which may enable producers to improve their hedging decision–making process.

Chapter 3

Technical Analysis

"… I've found that the most important thing in trading is always doing the right thing, whether or not you win or lose… this is market savvy… money management… I would go so far as to say that whether one makes money in the markets depends on whether or not one uses the proper money management – how much you make depends on where you enter and exit the markets."

~J. Welles Wilder (1986)

3.1 Introduction

The main aim of any investor or market participant is to achieve a required rate of return which at least accounts for inflation, as well as the risk associated with different assets (Marx *et al.*, 2010:4). The South African white maize market is no exception and investors attempt to achieve this required return by evaluating fundamental factors[24], which influence the South African white maize price, by means of various analytical methods, including fundamental and technical analysis (Reuters, 1999:8). Fundamental analysis is an analytical method of evaluating and forecasting price movements by means of a detailed macroeconomic, industry and company analysis (Marx *et al.*, 2010:75; Murphy, 1986:5; Reuters, 1999:8). However, this method has its challenges, which includes obtaining timely, reliable information and measuring the impact of these various examined variables on the market (Murphy, 1986:5–6; Reuters, 1999:8). Technical analysts, on the other hand, utilise the ability to capture market behaviour, which includes the psychological factors that influence market behaviour. All the underlying fundamental and psychological factors affecting the price are already incorporated into the price and reflected in daily price changes, making it profitable to only analyse data obtained

[24] Prices are affected by various factors, for example domestic supply; demand and stock levels; the Rand-Dollar exchange rate; the Chicago Board of Trade (CBOT) corn price that reflects international supply and demand; and weather (JSE, 2013a:2; Geyser & Cutts, 2007:296; Krugel, 2003:66; Cass, 2009:2).

from the market (Brown & Reilly, 2009:519–520). Since only the movements of the market are considered necessary and not the reasons behind the movements, trading opportunities can easily and rapidly be recognised and realised (Brown & Reilly, 2009:520; Roffey, 2008:1). This allows technicians the proficiency to ideally time investment decisions, which is considered another important advantage of technical analysis (Brown & Reilly, 2009:520).

Conversely, technical analysis still faces an important challenge, more specifically the human psychology entailed in the decision-making process. Firstly, technical analysis is extremely dependent on technicians' subjective judgement of trading rules (Brown & Reilly, 2009:521). Technical analysts may view the same graphs, and apply the same technical tools with similar results, but react differently according to their individual interpretations of the results. Technical analysts' subjectivity also affects their preference of technical rules despite a potentially high success rate of these rules in the past. This may also be the reason for technicians applying and interpreting several technical rules in order to reach a consensus about investment decisions (Brown & Reilly, 2009:520–521).

Secondly, herd behaviour is considered one of the main explanations for the most profitable opportunities to be missed or ignored, since emotional reactions tend to overpower logical reactions. The most recognised emotions of market participants are fear and greed, which leads to investors discarding the basic rule of "buy low, sell high" and conforming to the general market view (Geyser, 2013:20). It is, however, important to note that most market participants use technical analysis together with fundamental analysis to make more informed investment decisions, whereas the scope is to focus only on the implementation of technical indicators. The goal of this study is to improve the timing of a hedge decision for white maize, in order to realise a more effective hedge against adverse price movements (Reuters, 1999:9).

To elaborate on the use of technical analysis as an analytical method in this study, the background on the origin of technical analysis, more specifically the Dow Theory, is provided in Section 3.2, whereafter the assumptions regarding technical analysis are described in Section 3.3. The details regarding the direction of price movements, more precisely trending and trading price movements, are then provided in

Section 3.4, and the specific indicators aimed at verifying market trends are identified and described, in an attempt to determine the best possible indicators to apply. Following the trend determining indicators, traditionally applied technical indicators are covered in Section 3.5 in order to determine the best indicators to include in the construction of the composite technical indicator. Furthermore, to elaborate on the use of an indicator in a specific type of market, examples are demonstrated in the conclusion of Section 3.5 of false signals generated when implementing an indicator in the wrong type of market. Thereafter Section 3.6 concludes this chapter.

3.2 The Dow Theory

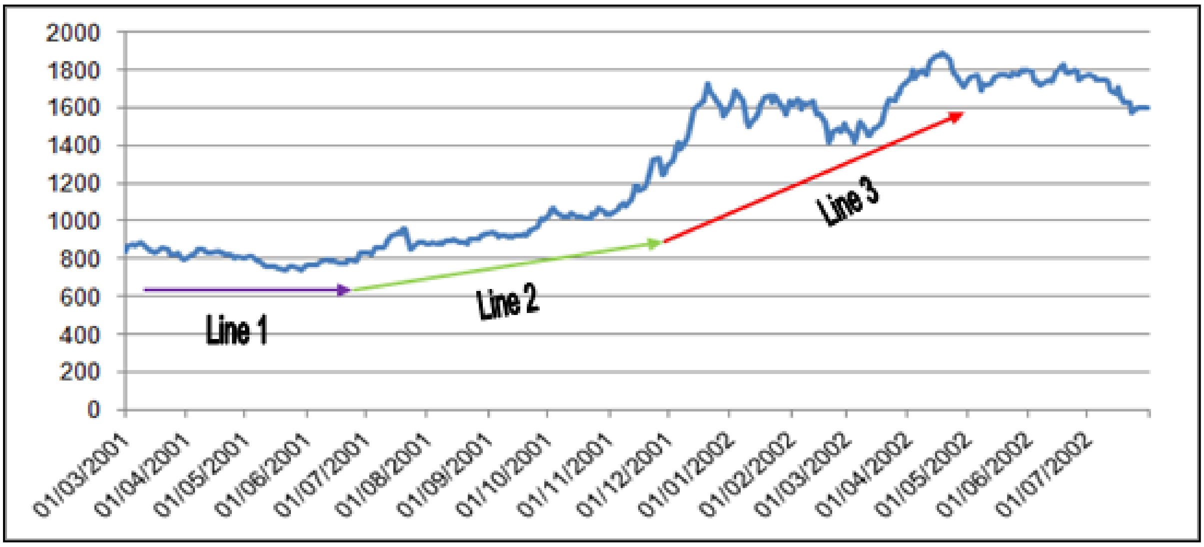
The Dow Theory, developed by Charles Henry Dow in the early 1900s, is considered to be the foundation of modern technical analysis (Achelis, 2001:122; Colby, 2003:224; Reuters, 1999:18). The theory relies on six fundamental assumptions, which include the following (Achelis, 2001:123–128; Murphy, 1986:26–32):

i. **The averages discount everything**. All new information regarding the market is rapidly and efficiently discounted in the price and accordingly reflected in the market averages;
ii. **The market consists out of three trends**, namely primary trends, secondary trends and minor trends. A primary trend can either be bullish (upward) or bearish (downward) long–term[25] price movements, which is interrupted by secondary changes. These secondary trends are intermediate changes or corrections in the primary trend and tend not to last more than three months. Lastly, secondary trends consist of several minor trends, which are short–term, usually daily, price movements. However, the Dow Theory considers minor trends as insignificant, since these trends are easily manipulated by market participants to a certain extent.
iii. **Primary trends have three phases**, as graphically illustrated by Figure 3.1 below. The first phase (purple Line 1), which is better known as the accumulation phase, is characterised by experienced and informed investors who are excessively buying with the expectation of an economic turnaround.

[25] A trend is considered long-run once the price movements continue for more than a year (Murphy, 1986:26-32).

When economic conditions then indeed make a turnaround and prices improve quickly other market participants will start to accumulate shares, which in turn make up the second phase (green Line 2). The third phase (red Line 3) is in progress when economic conditions further improve and the general public gain confidence in the trend, which cause trading volumes to increase. The selective few experienced investors, who invested during the first phase, will liquidate their holdings during the third phase, because they anticipate a turnaround in economic conditions.

Figure 3.1: Primary trend's three phases



Source: Compiled by the author.

iv. **The Dow Jones Industrial Average (DJIA) and the Dow Jones Transportation Average (DJTA) must confirm each other**. That is, for a justifiable change in the primary trend, both the DJIA and DJTA must show an indication of the reversal. For example, in the case of an upwards trend reversal, the DJIA and the DJTA must both show at least one lower high and one lower low as confirmation that the trend is changing to a downwards trend.

v. **Volume must confirm the trend**, however, volume is only considered as a secondary indicator of the trend. For instance, if the primary trend is downwards, higher volumes should be observed when the price decreases and lower volume when the price increases.

vi. **A trend holds until it reveals definite reversal signals**.

In an attempt to further develop the basic ideas put forward by the Dow Theory, extensive research[26] followed the work done by Dow. Some of the ideas are only partially applicable in several markets, which necessitated the need for more general ideas that would be applicable in any type of market (Murphy, 1986:33; Reuters, 1999:10). These general ideas, better known as the assumptions of technical analysis, are described in the following section.

3.3 Assumptions of technical analysis

In accordance with the basic ideas of the Dow Theory, technical analysis relies on three fundamental assumptions, as graphically illustrated in Figure 1.1 (Reuters, 1999:9). These assumptions, however controversial it may seem, form the foundation of technical analysis' functioning and success (Brown & Reilly, 2009:518). The assumptions include that the market discounts everything, history repeats itself, and trends exist (Brown & Reilly, 2009:518; Geyser, 2013:20; Murphy, 1986:2–4; Reuters, 1999:9).

The first assumption implies that all underlying fundamental factors that affect the price are already reflected in the price, which makes an additional study on the underlying factors unnecessary (Brown & Reilly, 2009:518; Murphy, 1986:2–3). Price movements regularly occur without market participants knowing the underlying reasons behind the adjustment, mainly due to market prices rapidly adjusting to new information entering the market (Murphy, 1986:3). The second assumption is concerned with trends that realise as a result of human behaviour that change little over time (Brown & Reilly, 2009:518; Geyser, 2013:20). Market participants tend to react similarly in certain circumstances, consequently influencing price movements to establish price trends (Geyser, 2013:20; Reuters, 1999:9). The last assumption complements the previous and entails that these price trends may have a tendency to recur or persist in the future, implying that history tends to repeat itself (Colby, 2003:6; Reuters, 1999:9).

Determining the effects of new information entering the market and the consequences of the reactions of market participants, which in turn form price

[26] Please see, for example, the study of Bollinger (1983), Chande (1994), Lambert (1982), and Wilder (1978).

trends, are relatively difficult. However, since the development of mathematical and statistical measures[27] in technical analysis, determining whether the market is exhibiting a price trend or not have become less complicated making it possible to more accurately determine subsequent trend changes. More detail with regard to determining price trends is provided in the section that follows.

3.4 Trending and trading markets

Taking into account the assumptions of technical analysis, accurate technical analysis is dependent on whether the market is in a trending or trading phase, since different technical indicators[28] were designed to function better in different market conditions (Achelis, 2001:35–36). Market prices can move in either an upwards or downwards direction or prices can move sideways, which is better known as a trending market or trading market, respectively (Achelis, 2001:35–36). Identifying the current type of primary market is simplified by means of technical indicators[29] specifically developed for this purpose. The following sub–sections elaborate on the most popular of these indicators, where the Aroon (Section 3.4.1), the Directional Movement Index (DMI) (Section 3.4.2), and the Chande Momentum Oscillator (CMO) (Section 3.4.3) are discussed (Achelis, 2001:36).

3.4.1 Aroon

Developed by Chande (1995), the Aroon indicates a change in the current trend or a change from a trending market to a trading market and vice versa. This indicator determines the type of market by evaluating the number of periods that have passed since prices achieved the most recent high value or recent low value. The Aroon can be divided into two different plotted lines, namely the Aroon Up, which measures the number of periods since the most recent high value and the Aroon Down, which measures the number of periods since the most recent low value (Achelis, 2001:64–65; Colby, 2003:102). This can be mathematically expressed as (Colby, 2003:102):

[27] Please refer to Section 3.5.

[28] Please refer to Footnote 27.

[29] The most popular indicators include Aroon, Chande Momentum Oscillator (CMO), Commodity Selection Index (CSI), Random Walk Index (RWI), and the Directional Movement Index (DMI) (Achelis, 2001:36).

$$Aroon\ Up = 100 \times \left[{(n-H)}/{n}\right], \tag{3.1}$$

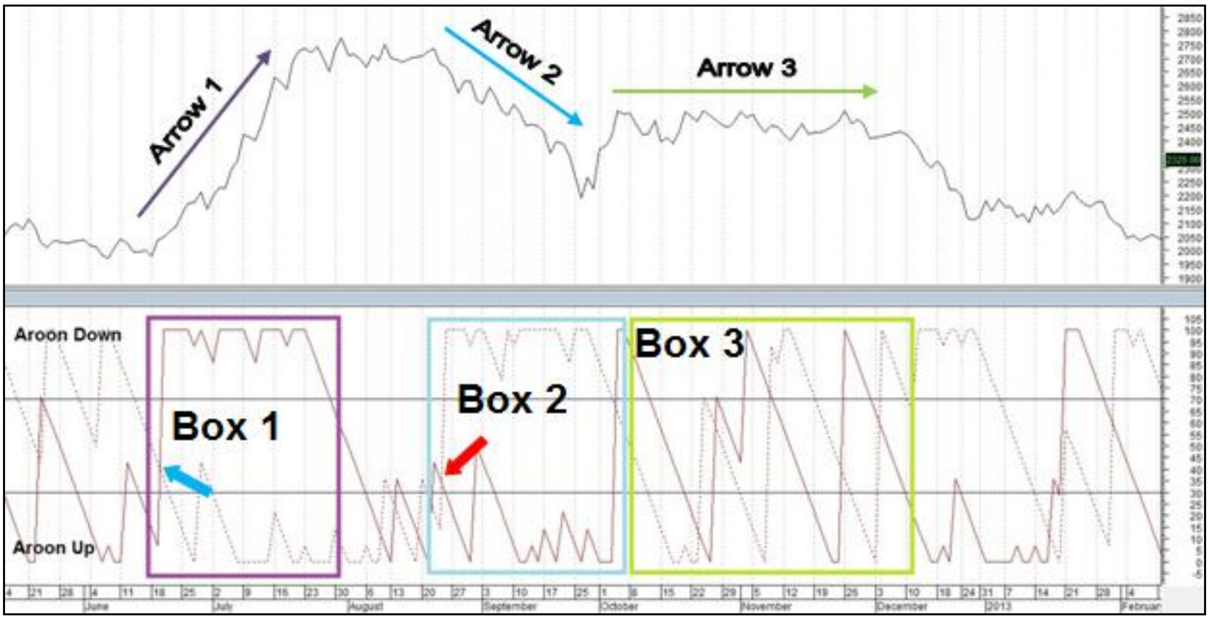
$$Aroon\ Down = 100 \times \left[{(n-L)}/{n}\right], \tag{3.2}$$

where:

- n represents the total number of periods in the time range under consideration;
- H represents the number of periods since the most recent high; and
- L represents the number of periods since the most recent low.

These equations can be interpreted by evaluating the extremes, the parallel movements or the crossovers (Achelis, 2001:65). The approaches are elaborated on in Figure 3.2 below, and is then followed by a detailed explanation.

Figure 3.2: Aroon indicator extremes interpretation



Source: Constructed in the Metastock (2011) database.

The potential strength[30] of an upwards trend is identified by the Aroon Up line reaching 100, whereas a potential weakness[31] of an upwards trend is indicated by the Aroon Up line reaching 0 (Achelis, 2001:65). The opposite is true for a downwards trend, indicating a potential strength[32] of the trend when the Aroon Down reaches 100, whereas a potential weakness[33] of the trend is indicated when the Aroon Down reaches 0. These are the most extreme scenarios for a trend, since the Aroon indicator oscillates between 0 and 100. Another interpretation of **extremes** is if the Aroon Up continuously moves between 70 and 100 or between 0 and 30, respectively, implying a strong upwards trend and a weak upwards trend (Achelis, 2001:65). The same concept applies to a downward trend.

A more significant interpretation of the Aroon entails that both Aroon Up and Aroon Down oscillate at **extremes**, suggesting a stronger trend (Achelis, 2001:65). Graphically this is illustrated clearly by Box 1 and Arrow 1 in Figure 3.2, where the Aroon Up moves between 70 and 100 and the Aroon Down moves between 0 and 30 indicating a stronger upwards trend (Achelis, 2001:65). The opposite is true for a downwards trend, as illustrated by Box 2 and Arrow 2, where a stronger downwards trend is indicated if the Aroon Down moves between 70 and 100 and the Aroon Up moves between 0 and 30.

In the event of the Aroon Up and Aroon Down **moving parallel** to one another, approximately at the same level, consolidation[34] is experienced (Achelis, 2001:65). Consolidation will stay intact until a trend change is indicated by an extreme level or crossover (Achelis, 2001:65). This can be graphically illustrated by Box 3 and Arrow 3 in Figure 3.2.

Prices are expected to trend downward when the Aroon Down line **crosses** the Aroon Up line from beneath, as illustrated by the red arrow in Figure 3.2 (Achelis, 2001:65). This signifies a potential weakness[35] in the upwards trend,

[30] Can be defined as an increase in the momentum of a trend.

[31] Can be defined as a decrease in the momentum of a trend.

[32] Please refer to Footnote 30.

[33] Please refer to Footnote 31.

[34] Price that is currently moving in a trading market.

[35] Please refer to Footnote 31.

indicating a possible sell signal as well (Colby, 2003:103). The opposite is also true for an expected upwards trend, when the Aroon Up line crosses the Aroon Down line from beneath, as illustrated by the blue arrow in Figure 3.2 (Achelis, 2001:65). This signifies a potential weakness[36] in the downtrend, indicating a possible buy signal as well (Colby, 2003:103).

3.4.2 Directional Movement Index (DMI)

The DMI, developed by Wilder (1978), is an extremely unique indicator in the sense that it diminishes the possibility of attempting to use an indicator in the wrong type of market. The DMI accomplishes this by determining the strength of the trend by more specifically analysing the Average Directional Movement Index[37] (ADX) line (Alexander, 1997:86; Colby, 2003:212). To enhance the understanding of the functioning of the DMI, the mathematical process is discussed in the following nine steps (Wilder, 1978:35–47):

Step 1:

Calculate the Directional Movement (DM) for each day. Only the largest absolute DM value of a specific day is considered, whereas the other Directional Movement value is set to zero for the respective day. The Directional Movement is calculated as the DM Plus (Equation 3.3) or the DM Minus (Equation 3.4):

$$+DM_t = High_t - High_{t-1} \tag{3.3}$$

$$-DM_t = Low_t - Low_{t-1} \tag{3.4}$$

Step 2:

Calculate a 14–day sum DM Plus (Equation 3.5) and DM Minus (Equation 3.6). Note that this step is only for calculating the first 14–day DM Plus and DM Minus (see step 3 for further calculations).

$$+DM_{14} = \sum_{i=1}^{14}(+DM_i) \tag{3.5}$$

[36] Please refer to Footnote 31.

[37] The ADX line is defined as a Moving Average (MA) of the Directional Movement (DM) (Colby, 2003:213). Also, please refer to Section 3.5.2.1.

$$-DM_{14} = \sum_{i=1}^{14}(-DM_i) \tag{3.6}$$

Step 3:

Calculate the subsequent 14–day DM Plus and DM Minus by making use of the following accumulation equations:

$$+DM_{14_t} = \left(+DM_{14_{t-1}}\right) - \left(\frac{+DM_{14_{t-1}}}{14}\right) + \left(+DM_{1_t}\right) \tag{3.7}$$

$$-DM_{14_t} = \left(-DM_{14_{t-1}}\right) - \left(\frac{-DM_{14_{t-1}}}{14}\right) + \left(-DM_{1_t}\right) \tag{3.8}$$

Step 4:

Calculate the True Range (TR) for the current day, which is the largest of the absolute value of Equation 3.9, Equation 3.10, or Equation 3.11.

$$TR_t = High_t - Low_t \tag{3.9}$$

$$TR_t = High_t - Close_{t-1} \tag{3.10}$$

$$TR_t = Low_t - Close_{t-1} \tag{3.11}$$

Step 5:

Calculate a 14–day sum TR (Equation 3.12). Note that this step is only for calculating the first 14–day TR (see step 6 for further calculations)

$$+TR_{14} = \sum_{i=1}^{14} TR_i \tag{3.12}$$

Step 6:

Calculate the subsequent 14–day TR by making use of the following accumulation equation:

$$TR_{14_t} = \left(TR_{14_{t-1}}\right) - \left(\frac{TR_{14_{t-1}}}{14}\right) + \left(TR_{1_t}\right) \tag{3.13}$$

Step 7:

Calculate the Directional Indicator (DI), by expressing DM as a function of TR:

$$+DI_{14} = \frac{+DM_{14}}{TR_{14}} \tag{3.14}$$

$$-DI_{14} = \frac{-DM_{14}}{TR_{14}} \tag{3.15}$$

Step 8:

Calculate the Directional Movement Index (DMI) as follow:

$$DX_t = \frac{(+DI_{14})-(-DI_{14})}{(+DI_{14})+(-DI_{14})} \times 100 \tag{3.16}$$

Step 9:

Calculate the ADX by first making use of Equation 3.17, and calculating all subsequent ADX values by making use of Equation 3.18:

$$ADX_t = \sum_{i=t}^{t-13} DX_i \tag{3.17}$$

$$ADX_t = \frac{(ADX_{t-1} \times 13) + DX_t}{14} \tag{3.18}$$

In addition, the ADX line can be interpreted as follows (Colby, 2003:213; Murphy, 1986:468; Wilder, 1978:47):

i. An ADX value above 25 indicates a possible trending market (graphically illustrated by the Arrow 1 in Figure 3.3).
ii. An ADX value below 25 indicates a possible trendless or trading market (graphically illustrated by Arrow 2 in Figure 3.3).

Figure 3.3: ADX interpretation

Source: Constructed in the Metastock (2011) database.

3.4.3 Chande Momentum Oscillator (CMO)

Developed by Chande (1994), the CMO can defined as a price momentum oscillator, ranging between –100 and +100, using both up[38] and down[39] days in the numerator, which can be expressed as follows (Achelis, 2001:100–101; Chande & Kroll, 1994:95,101; Colby, 2003:146):

$$CMO = \left[{(S_U - S_D)}\Big/{(S_U + S_D)} \right] \times 100, \tag{3.19}$$

where:

- S_U represents the summation of the difference between two consecutive days' closing prices for the up days; and

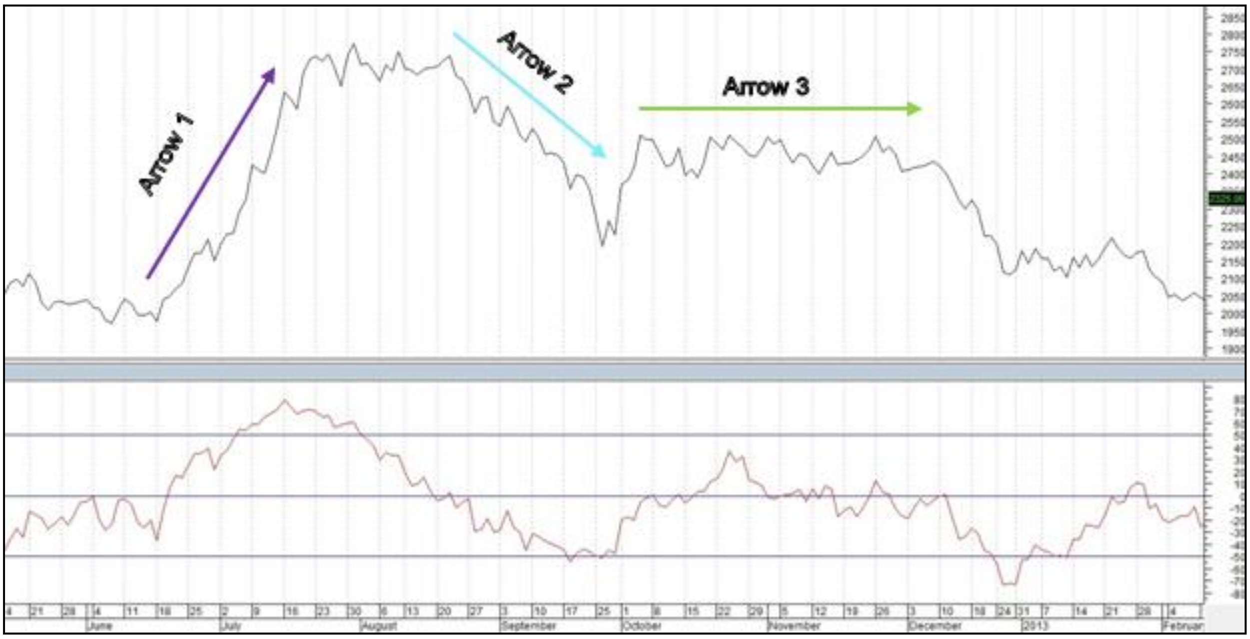
[38] The current day's closing price is lower than the consecutive day's closing price (Achelis, 2001:101).

[39] The current day's closing price is higher than the consecutive day's closing price (Achelis, 2001:101).

- S_D represents the summation of the absolute value of the difference between two consecutive days' closing prices for the down days.

The CMO is interpreted as the degree of a security's trend, with a higher CMO value above zero indicating a stronger trending market, as graphically illustrated by Arrow 1 and Arrow 2 in Figure 3.4 (Achelis, 2001:101; Chande & Kroll, 1994:108). Conversely, a lower CMO value below zero indicates a stronger trading market, as graphically illustrated by Arrow 3 in Figure 3.4 (Achelis, 2001:101; Chande & Kroll, 1994:108).

Figure 3.4: CMO interpretation



Source: Constructed in the Metastock (2011) database.

3.4.4 Summary

Up to this point the market indicators that are used to establish the primary tendency in a market, the Aroon, DMI and the CMO, have been discussed. Determining the primary tendency of prices is the first and foremost step for accurate technical analysis, as this ultimately assists in choosing the type of indicator that functions more optimally in the determined market. This leads to the following section where lagging indicators (Section 3.5.2) are discussed, which are primarily used in a trending market, as well as leading indicators (Section 3.5.1), which are primarily used in a trading market (Achelis, 2001:101).

3.5 Technical indicators

Prior to discussing the different technical indicators, it is important to first define and distinguish between an **overbought** and **oversold** market, since some indicators[40] indicate buy and sell signals based on these two concepts. An overbought market is associated with the number of sellers being significantly lower than the number of buyers, ultimately leading to a potential price peak as the sellers and buyers reach a new equilibrium. Contrary to an overbought market, an oversold market is recognised when the number of buyers is significantly lower than the number of sellers, consequently leading to a potential trough as the buyers and sellers reach a new equilibrium (Meyers, 1994:299).

3.5.1 Leading indicators

Leading indicators provide an investor with predictions of future price movements, mainly by determining how overbought or oversold the market is. These indicators have a higher probability of providing better returns, however, this type of indicators are associated with higher risk[41] (Murphy, 1986:35). The most common and popular leading indicators used by technicians include the Relative Strength Index (Section 3.5.1.1), the Stochastic oscillator (Section 3.5.1.2) and the Commodity Channel Index (Section 3.5.1.3) (Geyser, 2013:29).

3.5.1.1 Relative Strength Index (RSI)

Developed by Wilder (1978), the RSI is considered to be one of the most popular indicators used in modern technical analysis (Geyser, 2013:29; Murphy, 1986:296). The RSI is commonly a 5, 9 or 14–days price–following oscillator, fluctuating between 0 and 100, which allows for easily detecting buy and sell signals, as well as allowing the indicator to be easily compared to other indicators (Achelis, 2001:297; Murphy, 1986:296; Whistler, 2004:36–38). The name itself, however, can cause some level of confusion to inexperienced investors, since the indicator does not compare the "relative strength" of a security to a benchmark, but compares an

[40] See for example the Relative Strength Index (Section 3.5.1.1), Stochastic oscillator (Section 3.5.1.2), and Commodity Channel Index (Section 3.5.1.3).

[41] Leading indicators only suggest a future price change that may fail to realise in the future.

instrument to its own historical performance (Achelis, 2001:297). The RSI can be mathematically formulated as follows (Colby, 2003:610; Whistler, 2004:38):

$$\mathrm{RSI}=100-\left[{}^{100}/_{(1+RS)}\right], \tag{3.20}$$

where:

$$RS=\frac{Average\ of\ n\ days'\ higher\ closing\ prices}{Average\ of\ n\ days\ lower\ closing\ prices}, \tag{3.21}$$

with n indicating the number of days.

Wilder (1978:63) identified five uses for RSI analysis purposes, which include identifying failure swings[42], chart formations such as Head and Shoulders[43], support and resistance[44], divergences[45], and identifying tops and bottoms. The last mentioned use, the so–called **tops and bottoms**, is the most frequently applied use, where the RSI tops at 70 and bottoms at 30[46] (Achelis, 2001:297; Alexander, 1997:146; Wilder, 1978:68). When the RSI tops at 70, an overbought market is indicated, and this in turn generates a sell signal when the RSI crosses the 70 level from above. When the RSI bottoms at 30, an oversold market is indicated, and in turn generates a buy signal when the RSI crosses the 30 level from below. Both interpretations of tops and bottoms are graphically illustrated in Figure 3.5, where a buy signal is indicated by the blue arrow and a sell signal indicated by the red arrow.

[42] The RSI fails to surpass a previous high or previous low, with the previous high or low within the upper and lower boundaries (Achelis, 2001:298; Wilder, 1978:68).

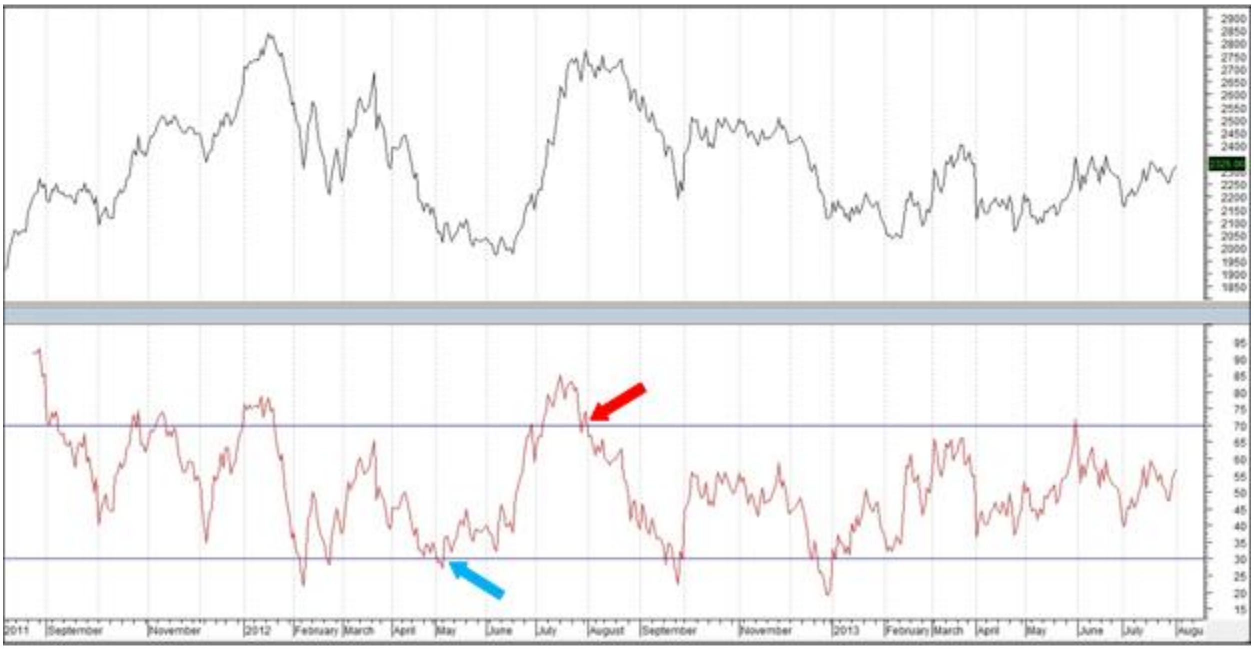
[43] A chart formation that occurs when the range between highs and lows recede (Achelis, 2001:248; Wilder, 1978:68-69).

[44] The theory that price movements will not break through a particular price level, but rather stop and move in the opposite direction (Achelis, 2001:14-16).

[45] The indicator fails to confirm the current price trend (Achelis, 2001:298; Wilder, 1978:68).

[46] These boundaries are only a guideline, and can be changed according to the volatility of the commodity or a trader's preference.

Figure 3.5: RSI interpretation



Source: Constructed in the Metastock (2011) database.

Another popular use of the RSI is to identify divergence, where the indicator fails to confirm the current price trend (Achelis, 2001:298; Wilder, 1978:68). This suggests a probable trend reversal, which can also indicate early buy or sell signals. A positive divergence is where the RSI is moving in an upwards direction and showing higher lows, while the price is moving in a downwards direction and showing lower lows (Meyers, 1994:150). Conversely, a negative divergence occurs when the RSI is declining and showing lower peaks, while the price is moving in an upwards direction and showing higher peaks (Meyers, 1994:150).

3.5.1.2 Stochastic oscillator

The Stochastic oscillator is a comparison between a security's most recent price relevant to its closing prices over a given time period (Achelis, 2001:321; Alexander, 1997:96; Murphy, 1986:304). This indicator is based on the theory that as prices increase the closing prices will be closer to the previous highs for the selected period (Meyers, 1994:165; Murphy, 1986:3–4). Conversely, as prices decrease, the closing prices will be closer to the previous lows for the selected period.

In addition, the Stochastic oscillator calculates two lines, namely the %K–line and the %D–line, of which %D is the more important line as it identifies the major signals

(Murphy, 1986:204; Meyers, 1994:165; Whistler, 2004:33). The %K–line can be mathematically expressed as follows (Achelis, 2001:324; Colby, 2003:664; Meyers, 1994:165; Whistler, 2004:34):

$$\%K = 100 \times \left[{(C-L)}\big/{(H-L)} \right], \tag{3.22}$$

where:

- C represents the most recent closing price;
- L represents the lowest low value for the selected time period; and
- H represents the highest high value for the selected time period.

The %K–line moves erratically, since the last observation is deleted each time a new observation is included (Colby, 2003:664). To solve this problem a smoothed version of the %K–line is calculated, also referred to as the %D–line. The %D–line is calculated by taking a 3–period MA[47] of the %K–line (Alexander, 1997:96; Colby, 2003:664; Murphy, 1986:304; Whistler, 2004:35).

[47] The MA can be calculated by applying any one of the several formulas. Please refer to Section 3.5.2.1.

Figure 3.6: Stochastic oscillator interpretation: Crossovers and Extremes

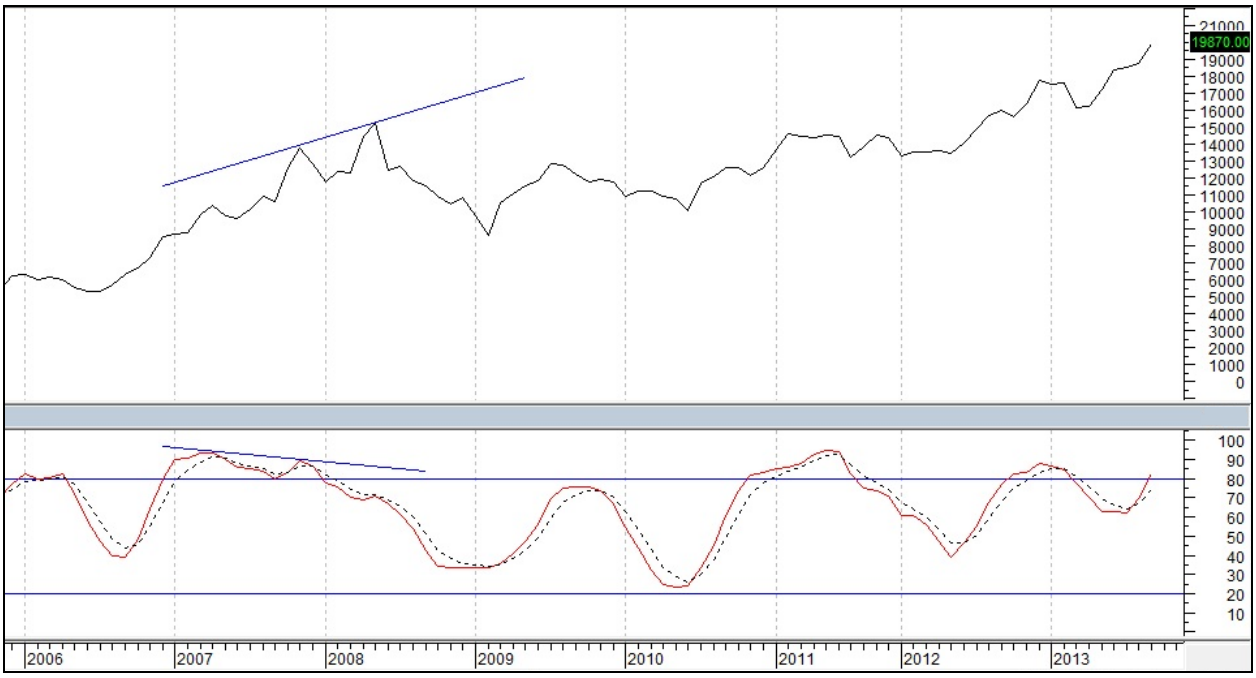
Source: Constructed in the Metastock (2011) database.

The %K and %D–lines are expressed as a value oscillating between 0 and 100 and can be interpreted as crossovers, extreme values or divergences (Achelis, 2001:321; Alexander, 1997:96). A crossover can be interpreted as a buy signal when the %K–line (the red solid line) crossed the %D–line (the black dotted line) from beneath, as indicated in Figure 3.6 by the blue arrow. Additionally, a sell signal is generated when the %K–line crossed the %D–line from above, as indicated in Figure 3.6 by the red arrow (Achelis, 2001:321; Meyers, 1994:186; Whistler, 2004:34). Another interpretation of the %K– and %D–lines are when either of the lines moves to extreme values (Achelis, 2001:321; Alexander, 1997:96; Colby, 2003:664; Murphy, 1986:304). An oversold market is indicated when either lines moves below a specified value48, whereafter a buy signal is generated when the lines cross the specified value from below, as graphically illustrated in Figure 3.6 by Arrow 1 and the green arrow. Conversely, an overbought market is indicated when either line moves above a specified value, whereafter a sell signal is generated when the lines cross

[48] The most popular values are 80 as the top value and 20 as the bottom value. However, these boundaries are only a guideline, and can be changed according to the volatility of the market (Murphy, 1986:304).

the specified value from above, as graphically illustrated in Figure 3.6 by Arrow 2 and the purple arrow.

Figure 3.7: Stochastic oscillator interpretation: Divergence



Source: Constructed in the Metastock (2011) database.

The last interpretation of the Stochastic oscillator is **divergences**, where the indicator fails to confirm the current price trend (Alexander, 1997:96; Meyers, 1994:186). This suggests a probable change in the current trend, indicating an early buy or sell signal (Achelis, 2001:321; Meyers, 1994:186; Murphy, 1986:304–305). A negative divergence is graphically illustrated in Figure 3.7, where the price is moving in an upwards direction and showing higher peaks, while the Stochastic oscillator is declining and showing lower peaks. The opposite is true for a positive divergence, where the price is moving in a downwards direction while the Stochastic oscillator is rising.

Despite its popularity, some technical analysts seem to prefer the slowed version of the Stochastic oscillator as a means to provide more accurate selling and buying signals (Murphy, 1994:309). The slowed Stochastic oscillator is constructed by replacing the original %K–line with the %D–line and replacing the %D–line with a 3–day MA of the original %D–line (Murphy, 1994:309). The interpretation of the newly constructed slowed Stochastic oscillator remains unchanged from the originally constructed Stochastic oscillator.

3.5.1.3 Commodity Channel Index (CCI)

The CCI is a price momentum indicator, developed by Lambert (1982), as a measurement of the deviation of a security's price from its statistical mean (Achelis, 2001:103). Despite its name, the CCI can be effectively applied to all types of securities, not only commodities (Achelis, 2001:103; Colby, 2003:155). Mathematically, the CCI can be expressed as follows (Colby, 2003:155):

$$CCI = {}^{(M-A)}\big/_{(0.015 \times D)}, \tag{3.23}$$

where:

- M represents the simple mean price for a selected period given by:

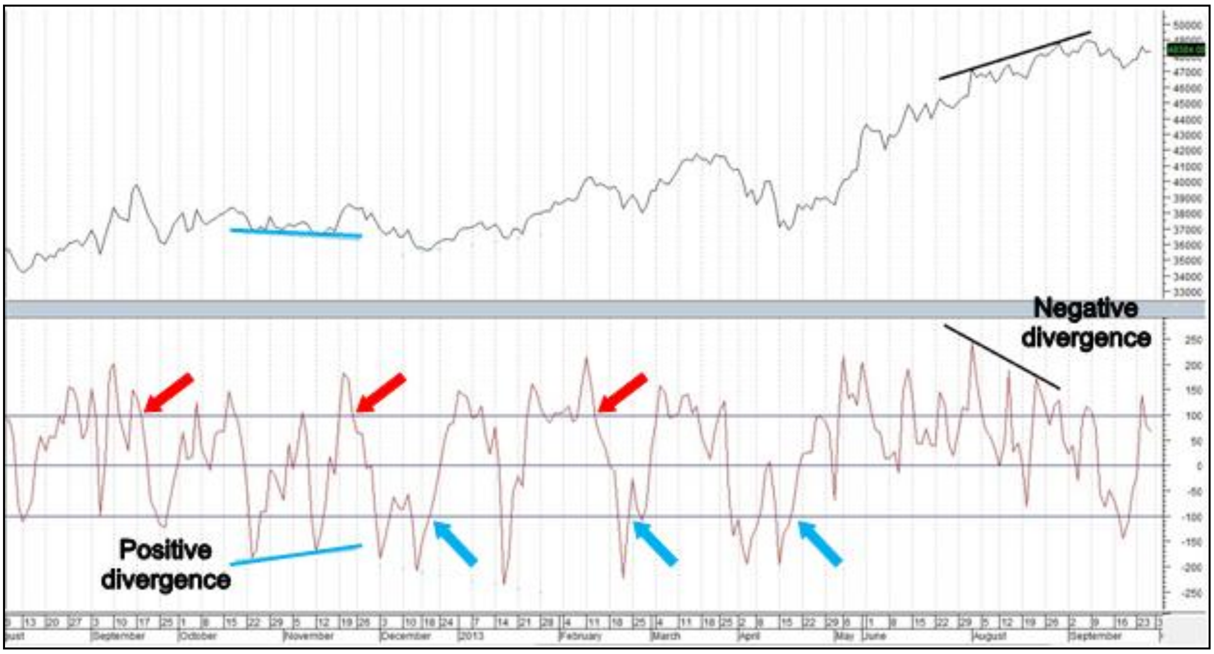
$$M = {}^{(H+L+C)}\big/_{3}, \tag{3.24}$$

- H represents the highest price for the selected period;
- L represents the lowest price for the selected period;
- C represents the closing price for a selected period;
- A represents an n–period SMA of M; and
- D represents the mean deviation of the absolute value of the difference between mean price and SMA of mean prices, mathematically represented by:

$$D = \frac{1}{n}\sum_{i=1}^{n}|M_i - A| \tag{3.25}$$

The CCI can generally be interpreted as divergences or overbought/oversold conditions (Achelis, 2001:104). A **divergence**, or trend reversal, is indicated by the CCI failing to confirm the current price trend, which implies a possible price correction in the near future (Achelis, 2001:104). This is graphically illustrated in Figure 3.8 by the blue and black lines. The blue lines indicate a positive divergence, where the CCI is reaching higher lows while the price is reaching lower lows. The opposite is true for a negative divergence, where the CCI reaches lower highs while the price reaches higher highs, as graphically illustrated by the black lines in Figure 3.8.

Figure 3.8: CCI interpretation



Source: Constructed in the Metastock (2011) database.

The CCI can also be used as an **overbought or oversold** indicator, where a value above +100 suggests an overbought market, which is an indication of a trend reversal in the near future. A sell signal generated when the CCI breaks through the upper band from above, as graphically illustrated in Figure 3.8 by the blue arrows. Conversely, a value below –100 suggests an oversold market, where a buy signal is generated when the CCI breaks through the lower band from below, as graphically illustrated in Figure 3.8 by the red arrows (Achelis, 2001:104; Colby, 2003:158).

3.5.1.4 Summary

Thus far, the technical indicators developed to function more optimally in a trading market have been discussed. These indicators include the RSI (Section 3.5.1.1), Stochastic oscillator (Section 3.5.1.2) and the CCI (Section 3.5.1.3). Other than leading indicators, lagging indicators exist which generate more accurate buy and sell signals when implemented in a trending market. A discussion on the different lagging indicators follows in Section 3.5.2.

3.5.2 Lagging indicators

Lagging indicators do not aim at indicating future price movements early as leading indicators do, but follow price trends instead (Murphy, 1986:33). These indicators generate buy and sell signals after an actual turn in the market price occurs, which in turn decreases returns. However, lagging indicators are significantly less risky[49] whilst still providing profitable opportunities (Murphy, 1986:33). The most commonly used lagging indicators include the Moving Average (Section 3.5.2.1), the Bollinger bands (Section **Error! Reference source not found.**) and the Moving Average Convergence/Divergence (Section 3.5.2.3), which is discussed in following sub–sections, respectively.

3.5.2.1 Moving Average (MA)

Considered one of the oldest, most flexible and commonly used technical indicators, the MA can be easily applied to any price data (Alexander, 1997:90; Colby, 2003:644; Murphy, 1986:234). A MA can be defined as a smoothed rendering of a commodity's price movements for a fixed time span, using only the most recent data available (Achelis, 2001:27; Murphy, 1986:234; Whistler, 2004:30). There are several different types of MAs[50], with the Simple Moving Average (SMA) as the most frequently used MA indicator (Murphy, 1986:237). The SMA can be mathematically expressed as follows (Achelis, 2001:207; Colby, 2003:644).

$$SMA = \frac{1}{n}\sum_{i=1}^{n} closing\ price_i, \tag{3.26}$$

where:

[49] Lagging indicators generate buy and sell signals only after a price movement occurred, which eliminates the risk of the price change not realising. Please refer to Footnote 41 for comparison purposes.

[50] These types include the Simple Moving Average (SMA), the Linearly Weighted Moving Average, Exponential Moving Average (EMA), Exponentially Smoothed Moving Average, Triangular Moving Average and Variable Moving Average to name but a few (Achelis, 2001:207-213; Murphy, 1986:237-239).

- n represents the number of time periods included in the SMA.

Despite its simplicity and popularity, the SMA's efficacy has been questioned by critics for several reasons. Firstly, the SMA does not assign more weight to the most recent data, but distributes the weight evenly over the selected time period (Murphy, 1986:238; Whistler, 2004:31). Also, the SMA considers only the selected time frame relevant for forecasting purposes and discards the data points outside the time frame (Murphy, 1986:237). It is, therefore, advantageous to use the SMA in conjunction with other technical indicators to enhance the ability of identifying accurate buy and sell signals (Murphy, 1986:265).

Another solution to the problems associated with the SMA, is to construct an EMA, which is increasingly preferred by many technical analysts to any other moving averages (Colby, 2003:261; Murphy, 1986:239). It is considered the best moving average technique, as well as being the most streamlined and least complicated in its calculations (Colby, 2003:261). The EMA assigns more weight to the most recent price data, while at the same time keeping the diminished, less important data in the calculation of the following EMA (Colby, 2003:261; Murphy, 1986:239; Whistler, 2004:31). Mathematically, the EMA can be defined as (Colby, 2003:262):

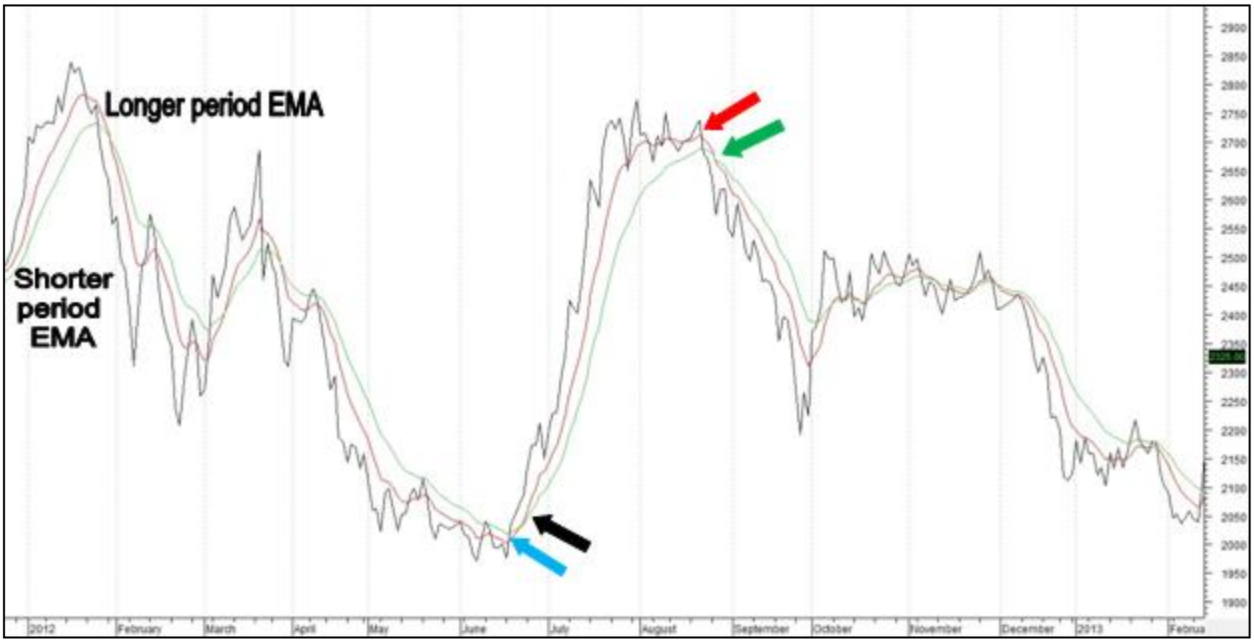
$$EMA = (C - E_p)K + E_p, \tag{3.27}$$

where:

- EMA represents the Exponential Moving Average for the current period;
- 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 in a SMA.

When comparing an EMA with a security's price movements, buy and sell signals are generated and interpreted accordingly with ease. A **buy signal** is generated when the security's price crosses the EMA from below and a **sell signal** is generated when the security's price crosses the EMA from above (Achelis, 2001:203). This is graphically illustrated in Figure 3.9 by the blue and red arrows, respectively. However, note that the EMA needs to be interpreted in conjunction with other indicators to ensure that accurate buy or sell signals are generated (Murphy, 1986:265).

Figure 3.9: EMA interpretation



Source: Constructed in the Metastock (2011) database.

Confirming an EMA's buy and sell signals can be done by not only applying an EMA in conjunction with other indicators, but applying a shorter period EMA with a longer period EMA (Alexander, 1997:92). When the red line (shorter EMA) crosses the green line (longer EMA) from beneath, a buy signal is generated, as graphically illustrated in Figure 3.9 by the green arrow. Conversely, when the red line crosses the green line from above, a sell signal is generated, as graphically illustrated in Figure 3.9 by the black arrow.

3.5.2.2 Bollinger bands

Developed by Bollinger (1983), the popular Bollinger bands are two moving averages that are plotted a calculated standard deviation[51] above and below a

[51] A statistical measure of the volatility of a security, given by Equation 3.28 (Achelis, 2001:308; Marx *et al.*, 2010:8)

SMA[52] (Achelis, 2001:71; Alexander, 1997:85; Colby, 2003:115). Given that standard deviation is a measure of volatility, Bollinger bands are self–adjusting, due to the current volatility in the market (Achelis, 2001:71; Alexander, 1997:85). Bollinger (1983) suggests using a 20–day SMA with a standard deviation of 2 as a guideline for analysing an intermediate–term trend (Achelis, 2001:72; Colby, 2003:114). For a longer trend Bollinger (1983) proposes a 50–day SMA, whereas for a shorter trend a 10–day SMA is recommended (Colby, 2003:114–115). The standard deviation and Bollinger bands are mathematically expressed as follows (Achelis, 2001:74,309; Bollinger, 2001:52):

$$\hat{\sigma} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Closing\ price_j - n\_period\ SMA\ of\ Closing\ prices\right)^2}, \tag{3.28}$$

$$Upper\ Band = SMA + \left[\hat{\sigma} \times \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Closing\ price_j - SMA\right)^2}\right], \tag{3.29}$$

$$Lower\ Band = SMA - \left[\hat{\sigma} \times \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(Closing\ price_j - SMA\right)^2}\right]. \tag{3.30}$$

where n represents the number of periods.

In addition, Bollinger bands can be used to determine **overbought or oversold** conditions by the price touching the bands, or by breaking through the upper band from above or the lower band from below (Alexander, 1997:85; Murphy, 1999:209; Colby, 2003:115). This is graphically illustrated in Figure 3.10, where an oversold market, as well as a buy signal, is indicated by the blue arrow and an overbought market, as well as a sell signal, is indicated by the red arrow. However, rather than solely interpreting the overbought and oversold conditions as buy and sell signals, it is suggested that these signals should also be verified by separate, autonomous[53] indicators to ensure accurate buy and sell signals (Colby, 2003:115).

[52] Please refer to Section 3.5.2.1.

[53] These indicators can include the RSI (Section 3.5.1.1), the Stochastic oscillator (Section 3.5.1.2), or the EMA (Section 3.5.2.1).

Figure 3.10: Bollinger bands interpretation

Source: Constructed in the Metastock (2011) database.

3.5.2.3 *Moving Average Convergence Divergence (MACD)*

The MACD is a momentum oscillator designed by Appel (2005), with the intention of determining the direction of a trend and signalling changes in a trend (Achelis, 2001:199; Reuters, 1999:104). The MACD is commonly calculated by subtracting a longer EMA, commonly the 26–day EMA, from a shorter EMA, commonly the 12–day EMA (Achelis, 2001:199; Alexander, 1997:88,143; Colby, 2003:412; Reuters, 1999:104). This calculated moving average is also better known as the fast MACD–line, graphically illustrated as a solid line in Figure 3.11 and measures price velocity (Reuters, 1999:104). A second line is constructed and plotted on top of the MACD–line in order to determine buy or sell signals (Achelis, 2001:199; Murphy, 1986:313). This line is better known as a signal or trigger line, which ultimately assists in identifying signals more accurately by reducing the lag effect of the MACD. The signal line is graphically illustrated as a dotted line in Figure 3.11 and is constructed by estimating a 9–day EMA of the MACD–line (Alexander, 1997:88,143; Colby, 2003:412; Murphy, 1986:313; Reuters, 1999:104).

Figure 3.11: MACD interpretation: Crossovers and overbought/oversold

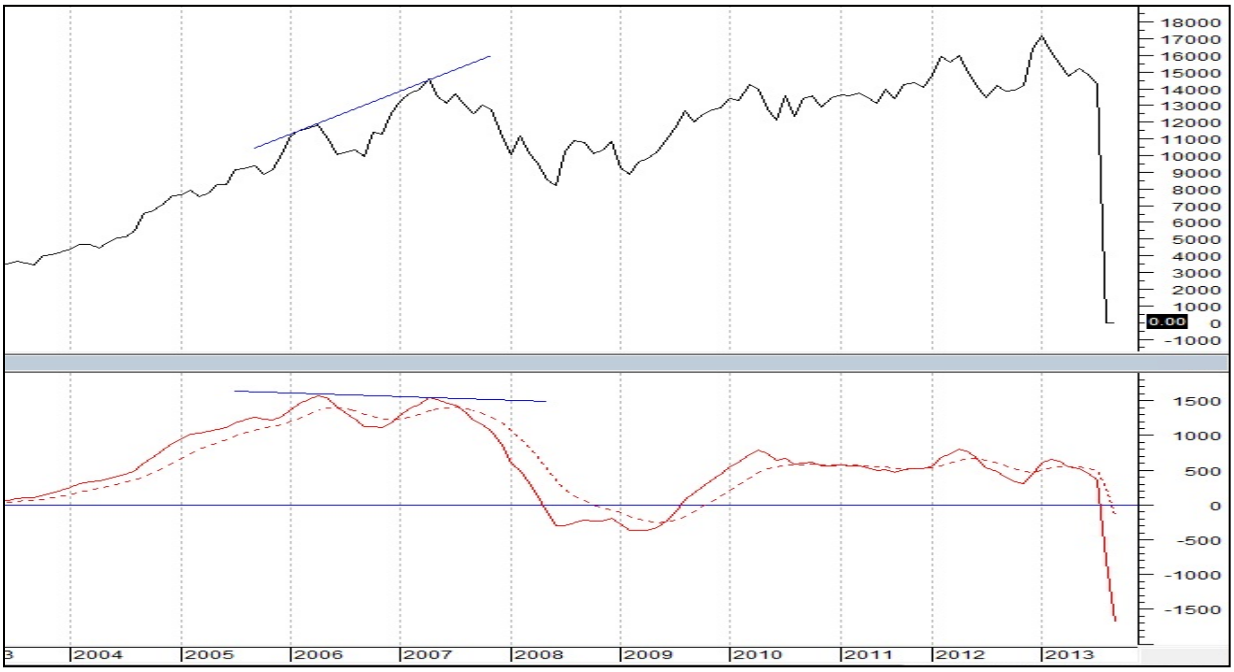
Source: Constructed in the Metastock (2011) database.

These two calculated averages can be interpreted as crossovers, overbought or oversold conditions, and divergences (Achelis, 2001:199). **Crossovers** are the most basic and probably the most useful trading rule of the MACD. When the MACD–line crosses the signal line from above, a sell signal is generated, as graphically illustrated in Figure 3.11 by the red arrow. Conversely, a buy signal is indicated when the MACD–line crosses the signal line from below, as graphically illustrated by Figure 3.11 by the blue arrow (Achelis, 2001:199; Alexander, 1997:88; Murphy, 1986:313).

Another useful purpose of the MACD is indicating **overbought and oversold** conditions, which is an early indication of a buy or sell signal (Achelis, 2001:200). This indication is given when the MACD significantly deviates from the signal line, as graphically illustrated by the Circle 1 and Circle 2 in Figure 3.11, which indicates that the price is overextended and will most probably shortly adjust to a new equilibrium (Achelis, 2001:200). When this does indeed occur, buy and sell signals are generated on the same principle as crossovers. However, a meaningful buy signal can only be generated when both lines are below the zero line, and a sell signal only when both lines are above the zero line (Achelis, 2001:200).

Recognising a trend reversal, or **divergence** from the current trend, is the third general use of the MACD. A trend reversal is indicated by a divergence of the MACD from the security price, which can either be bullish or bearish. A bearish divergence is exhibited when the MACD is declining (generating lower highs) while the price is rising (exhibiting higher highs), as graphically illustrated in Figure 3.12 (Achelis, 2001:200). The opposite is true for a bullish divergence, where the MACD is rising and the price is declining. These divergences are confirmed when both the MACD and signal line cross the zero line, which is also another indication of a buy[54] or sell[55] signal (Murphy, 1986:313).

Figure 3.12: MACD interpretation: Divergence



Source: Constructed in the Metastock (2011) database.

The best possible buy signal is indicated by a bullish divergence, followed by the MACD line crossing the signal line from above, whereafter both lines cross the zero line to confirm the buy signal (Murphy, 1986:313). The opposite is true for the best possible sell signal, indicated by a bearish divergence, followed by the MACD line

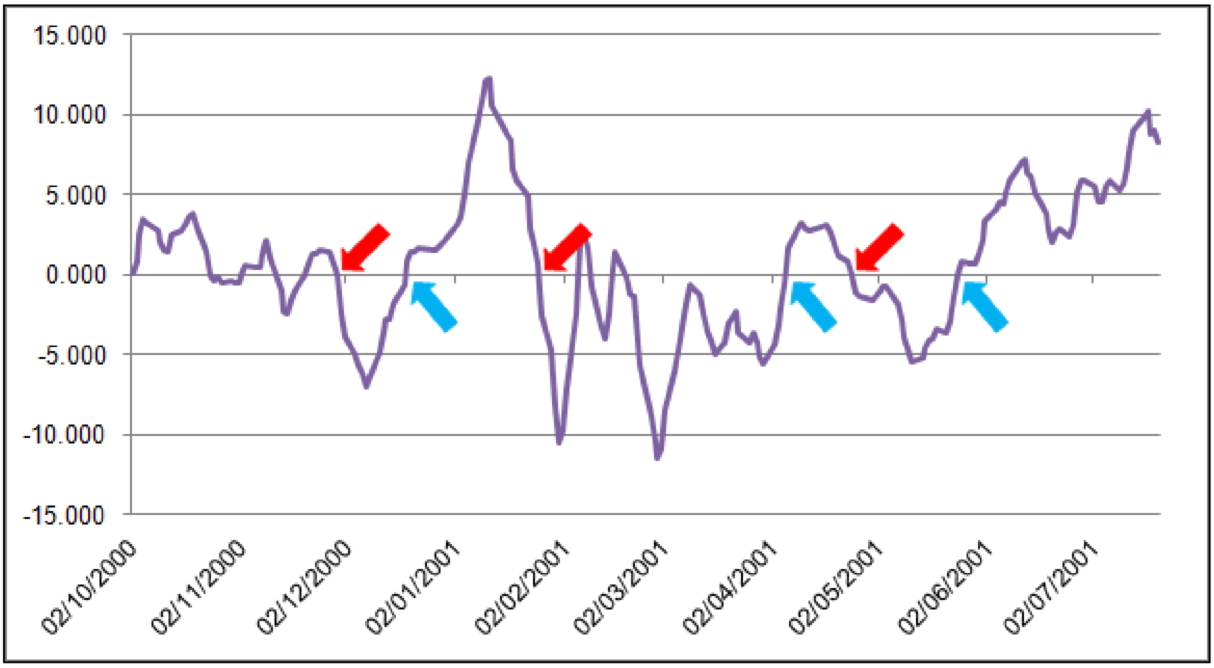
[54] A confirmation of a buy signal or that the trend will persist is indicated when the MACD line and the signal line cross the zero line from below with the MACD above the signal line.

[55] A confirmation of a sell signal or that the trend will persist is indicated when the MACD line and the signal line cross the zero line from above with the MACD line below the signal line.

crossing the signal line from below, whereafter both lines cross the zero line to confirm the sell signal (Murphy, 1986:313).

In addition, the interpretation of the MACD indicator can be improved by generating either a histogram or a single forest line, which is constructed by subtracting the signal line from the MACD–line (Murphy, 1996:126). The values generated will then fluctuate around zero, indicating a sell signal when the line moves from a positive value to a negative value and a buy signal when the line moves from a negative value to a positive value. This is graphically illustrated in Figure 3.13 by the red and blue arrows respectively.

Figure 3.13: MACD forest line



Source: Compiled by the author.

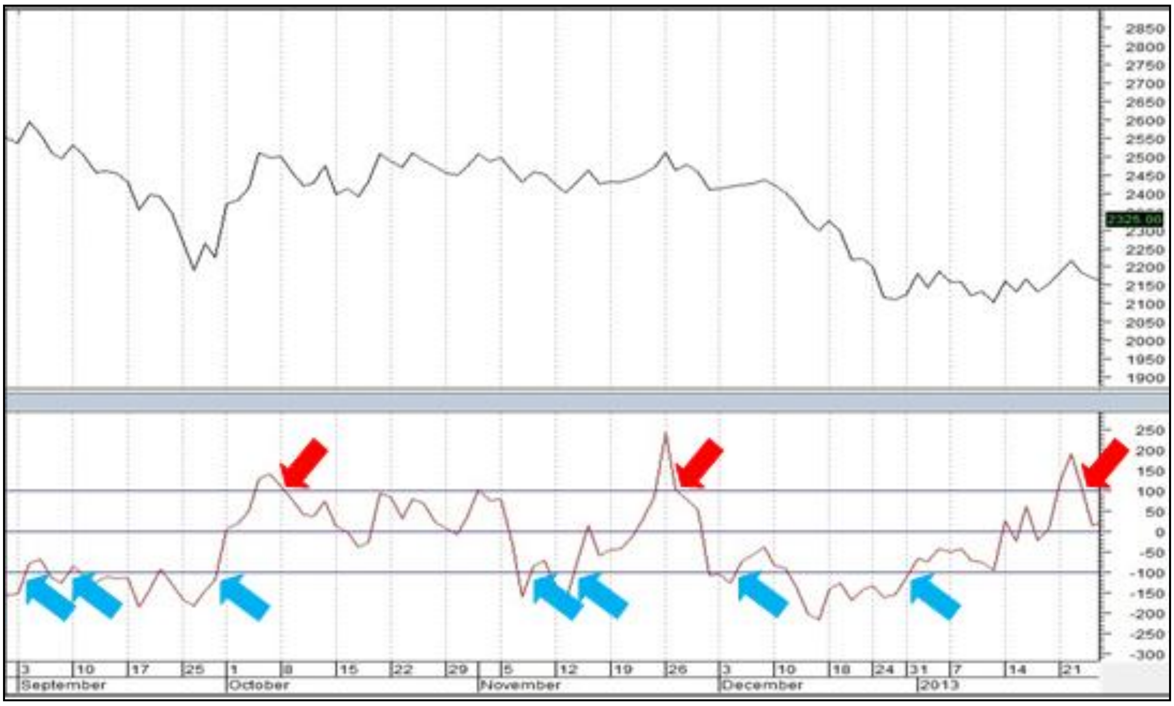
3.5.2.4 Summary

The technical indicators, which include the Moving Average (MA), Bollinger bands, and the Moving Average Convergence/Divergence (MACD), have thus far been discussed in detail. These indicators are aimed at generating more accurate signals when applied in a trending market. To accentuate the necessity of applying an indicator in the correct type of market, more specifically leading indicators in a trading market and lagging indicators in a trending market, the following section provides examples of indicators applied in the wrong type of market which can lead to false signals generated.

3.5.3 False signals

As a proxy, the CCI (Section 3.5.1.3) may generate false signals when applied in a trending market. This can be graphically illustrated by Figure 3.14, where several sell signals (illustrated by the red arrows in Figure 3.14) and buy signals (illustrated by the blue arrows in Figure 3.14) were generated within a trading market environment. Acting on these trading signals will most probably result in a loss as a market role–player will incur high trading costs[56] resulting in potential large cash flow requirements to sustain a futures position (see Section 2.3.1.2).

Figure 3.14: CCI false signals



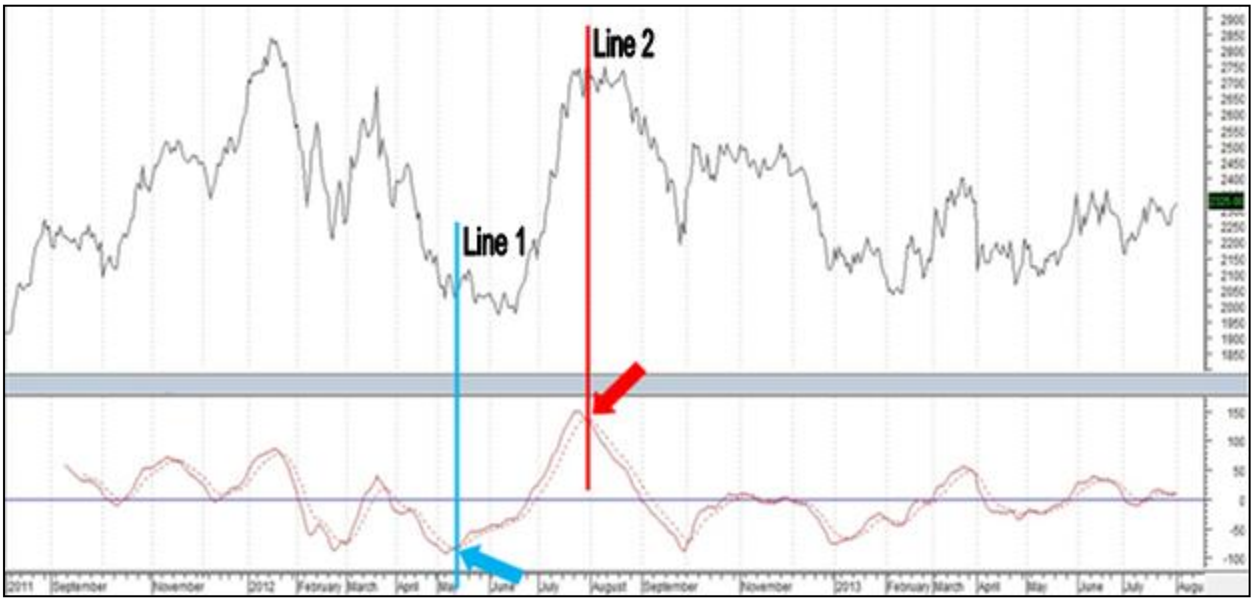
Source: Constructed in the Metastock (2011) database.

Similar to a leading indicator applied in a trending market, lagging indicators applied in a trading market may generate false signals as well, as confirmed by Figure 3.15. Using the MACD as a proxy, a buy signal was generated (illustrated by the blue

[56] Various costs can be incurred, for example brokerage costs, interest on initial margin, and variation margin.

arrow in Figure 3.15) some time before the upwards trend is underway. This may lead to significant losses resulting from unsustainably high variation margins forcing a position close out at a lower price than the entry point (illustrated by Line 1 in Figure 3.15). Conversely, a sell signal (illustrated by the red arrow in Figure 3.15) was generated before the trend reversal. As the price varied for some time after the selling level (illustrated by Line 2 in Figure 3.15), high variation margins (see Section 2.3.1.2) may have realised, resulting in a potential loss.

Figure 3.15: MACD false signals



Source: Constructed in the Metastock (2011) database.

3.6 Conclusion

In order to ensure meaningful and profitable transactions, various analytical methods are used by market participants in an attempt to benefit from price movements. A popular analytical method used in practice is technical analysis that aims to determine future price movements by means of examining market behaviour, which is quantified in graphs. This method holds several advantages, including the ability to capture and analyse market behaviour and experiencing ideal investment timing. However, the decision–making process associated with technical analysis holds a significant challenge, especially since human psychology plays an integral role in the implementation and interpretation of technical analysis. In addition to this challenge, are the assumptions of the Dow Theory, which forms the foundation of technical analysis and determines its creditability as a decision–making tool. These assumptions include the following:

i. The averages discounts everything.
ii. The market consists of three trends.
iii. Primary trends have three phases.
iv. The averages, the Dow Jones Industrial Average (DJIA) and the Dow Jones Transportation Average (DJTA), must confirm each other.
v. Volume must confirm the trend.
vi. A trend holds until it reveals definite reversal signals.

However, the Dow Theory is not applicable in all market types, which led to the development of additional assumptions regarding price movements (better known as the assumptions of technical analysis). These assumptions of technical analysis include that the market discounts everything, that history repeats itself and that trends exist (where the methods of evaluating trends forming the one of the focus points of this chapter). Determining the current direction of these trends, which are formed by market participants' persistent reactions to new information entering the market, are complicated by market prices moving either sideways (trading market) or upwards or downwards (trending market). It is, therefore, important to determine the primary tendency of prices as it aids in generating more accurate buy and sell signals. This can be accomplished with the use of certain indicators, which include the Aroon (Section 3.4.1), DMI (Section 3.4.2) and the CMO (Section 3.4.3).

After establishing the primary tendency of the trend, technical indicators can be applied to generate buy and sell signals. These indicators can be classified into two broad categories, namely leading (Section 3.5.1) and lagging (Section 3.5.2) indicators. The proposed approach is to use leading indicators in a trading market and lagging indicators in a trending market. Leading indicators generally present an investor with early indications of the future movement of prices, mainly by determining how overbought or oversold the market is. Popular leading indicators include the Relative Strength Index (Section 3.5.1.1), Stochastic oscillator (Section 3.5.1.2), and the Commodity Channel Index (Section 3.5.1.3). In contrast to leading indicators, lagging indicators can also be applied. However, lagging indicators are not used to determine future price movements, but are rather used to follow price movements. Popular lagging indicators include Moving Averages (Section 3.5.2.1), Bollinger bands (Section 3.5.2.2), and the Moving Average Convergence/Divergence (Section 3.5.2.3).

With all of these technical indicators available to assist the decision–making process in establishing the correct hedging level, it is crucial to ensure that the correct combination of technical indicator is continuously applied in conjunction with the pre–determined market type, where incorrect technical indicators can generate false buy/sell signals. These false signals may result in significant losses due to either variation margins or due to trading at unfavourable price levels. In order to prevent the possibility of these negative events, the next chapter will commence with determining the market type of the South African white maize market over several years. This will allow the establishment of the most applicable technical indicators in each market type. However, the goal of this study is to enhance the optimal hedging level in the white maize market. In order to accomplish this goal, the next chapter will also construct a composite indicator to determine if better hedging levels can be obtained in comparison of using only individual technical indicators.

Chapter 4

Methodology and Results

"To achieve the impossible, we must attempt the impossible again and again"

~ Hermann Hesse (1877–1962)

4.1 Introduction

In Chapter 2 a historical background of the derivatives market and more specifically of the South African white maize market was provided. The volatility of the white maize market and the necessity to hedge the price risk, which is associated with more volatile markets, was specifically emphasised. However, it was found that market participants are hesitant to use derivatives to hedge themselves, mainly as a result of their distrust of the market. Nonetheless, past evidence suggested that the market can be considered as weak form efficient, which implies that the white maize market provides some form of an efficient price discovery function. This may enable market participants to hedge effectively on the derivatives market by using technical analysis to facilitate their decision–making process. This discussion then continued in Chapter 3, where the different indicators that can be consulted to determine a more effective hedging level was elaborated on. However, determining the type of market (trending or trading) is crucial to ensure that the correct technical indicators is consulted during a hedging decision, whereas the wrong indicators can lead to false signals and ultimately to defective hedging decisions.

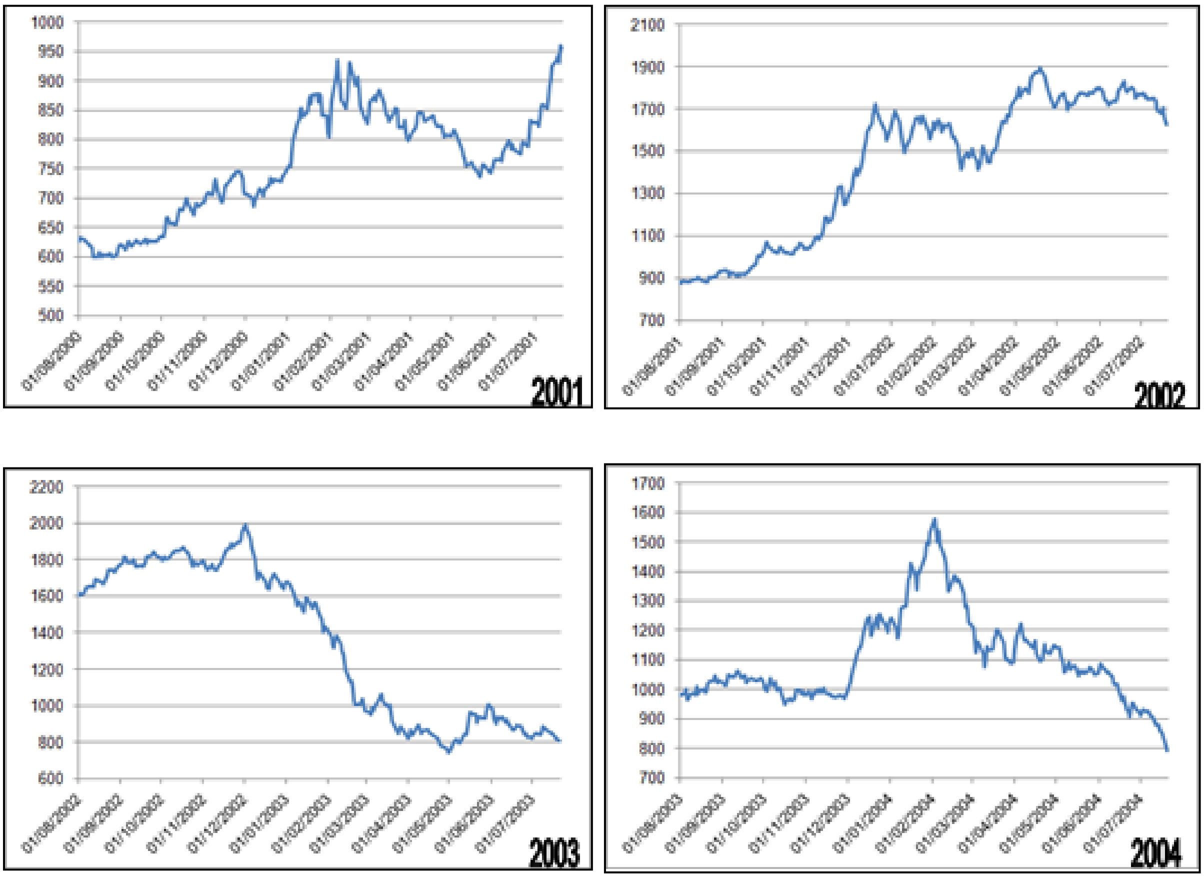
This chapter will, therefore, commence by applying technical indicators to determine if a more efficient hedging level can be established. The descriptive statistics of the data under evaluation (Section 4.2) will firstly be evaluated. This will be followed by the first step of technical analysis, which will constitute the determination of the current primary or secondary trend of the data (Section 4.3.1). Once the specific market type is determined it will be easier to establish more applicable technical indicators over the time period under investigation. In Section 4.3.2 the technical indicators that are chosen to evaluate the white maize market will be elaborated upon, after which the results of each indicator will be reported. However, the goal of this study was to determine if a more effective hedging level could be established through the appropriate use of technical indicators. In order to accomplish this goal, a composite indicator was constructed. The method of constructing such a composite indicator is described in Section 4.3.3, whereafter the results are reported. This empirical study then concludes by providing a comparison between the performance of both individual and composite indicators, which will determine the best technical indicator to apply in the South African white maize market. In Section 4.3.3.7 rankings are assigned to each indicator, which will be based on several criteria, for an accurate comparison.

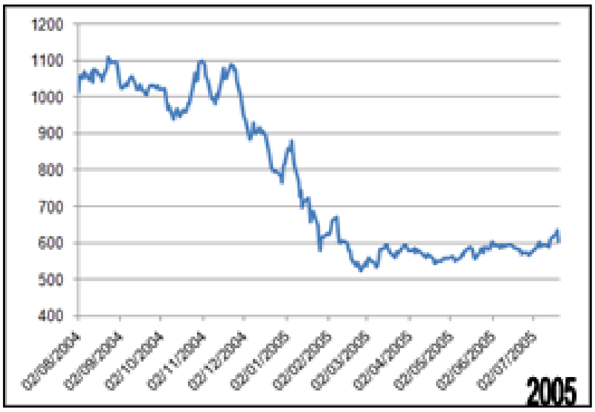
4.2 Data

The data that were used in this study were extracted from the Thomson Reuters database via the Metastock 11 software, which is created by Equis International and is a product of Thomson Reuters. The Metastock 11 software was also used to derive the required graphs of the technical analysis. The July white maize futures contract is utilised in this study, since it is currently the most liquid futures contract traded on SAFEX as well as the main delivery and consequent hedging month for white maize (JSE, 2013a:1). The time period that was evaluated spans from 1 August 2000 to 20 July 2013 (see Figure 4.1). The reason for choosing this time span is that prior to July 2000 market participation, and consequently liquidity, was low as a result of market participants' lack of knowledge and understanding of the derivatives market (Bown *et al.*, 1999:285–286).

In addition, the contract data consists out of the daily closing prices, high prices and low prices for every season, since the technical indicators that were applied in this study made use of at least one of these aforementioned prices in their respective calculations. Also, given that the exact beginning and expiry dates of each season's contract are inconsistent, fixed dates were chosen in order to ensure comparability between seasons. Consequently, each contract period starts on 1 August of a specific planting season and expires on 20 July of the next year, which will be during the harvesting season. For example, the 2013 July white maize futures contract was constructed to start on 1 August 2012 and end on 20 July 2013. Hedging opportunities were only considered from 1 October each season, since the effective planting season in South Africa traditionally starts from the beginning of October and consequently the liquidity of the futures contract would start to improve (JSE, 2010:10). However, to ensure that accurate opportunities could be recognised from 1 October each season, the indicators were applied to the data from 1 August every season, in order to diminish the lag effect of the respective calculations of the technical indicators.

Figure 4.1: White maize closing prices per season: August 2000 to 20 July 2013

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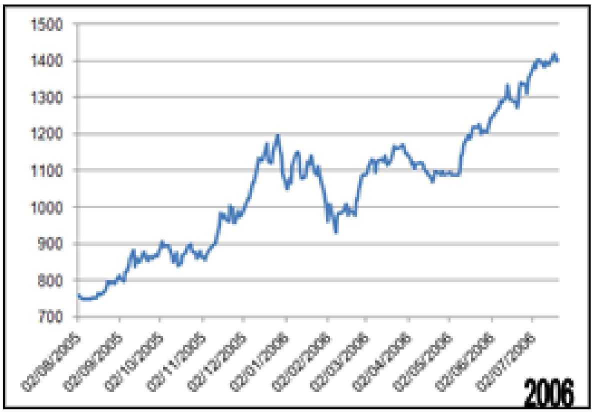
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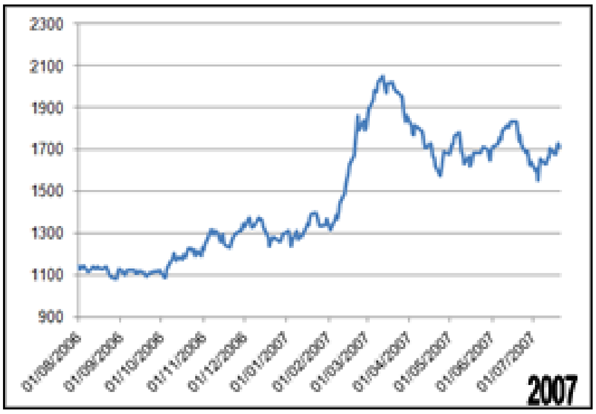
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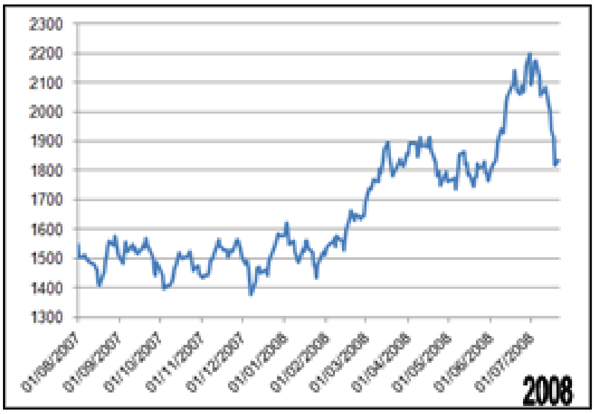
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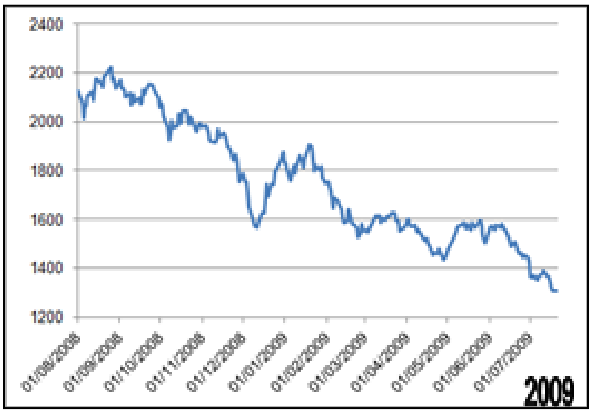
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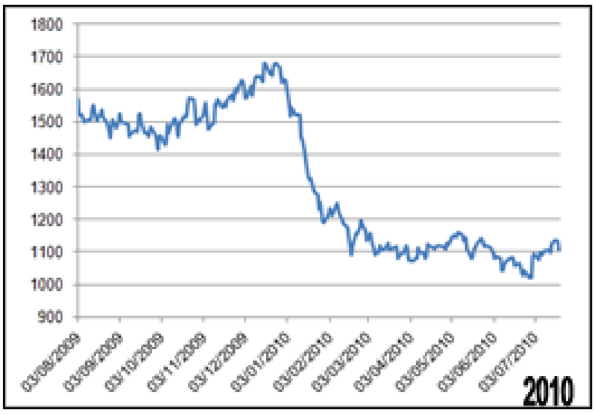
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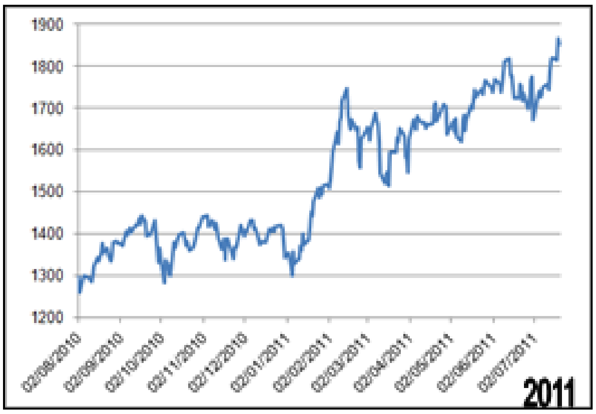
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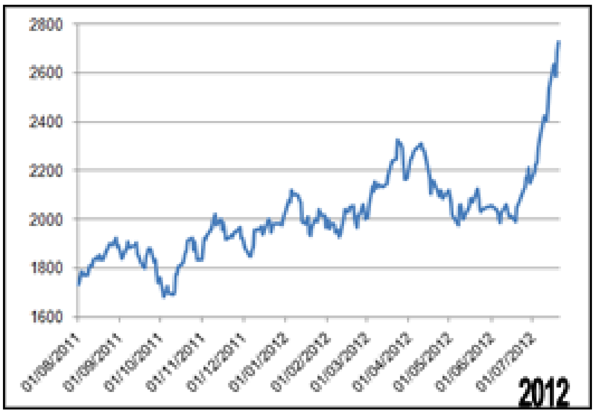
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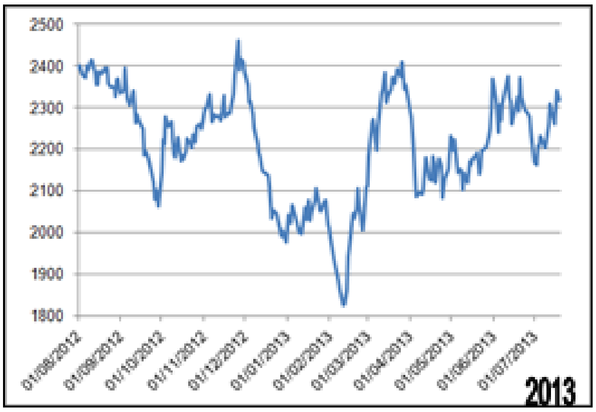


Source: Compiled by the author.

Figure 4.1 illustrates the price data of the different periods that will be evaluated, respectively. It is clear that significant volatility was present during the period under investigation, which supports market participants' increasing need to manage their price risk due to greater uncertainty. For example, 2005 and 2010 exhibited a significant declining trend in prices, which can be justified by the oversupply of white maize during 2005 and due to the international economic slowdown in 2010 (BFAP, 2012:23; JSE, 2005:4).

In order to elaborate on the findings derived from Figure 4.1, Table 4.1 below provides a summary of the descriptive statistics of the data, which were estimated with the Eviews 7 program (QMS, 2007). These descriptive statistics include the mean, maximum, minimum, standard deviation, skewness, kurtosis, and the Jacque–Bera normality test results, along with an average of each descriptive statistic over the entire time period. The differences between the minimum and maximum values for each season, as reported in Table 4.1, signify significant volatility (risk) present in the white maize prices. The highest difference of R1 246 is present in the 2003 contract, whereas the lowest difference of R324 is present in the 2001 contract. Also, the average difference between the maximum and minimum values for the whole period was R759.69, which further emphasise the presence of great volatility and thus great uncertainty in determining an appropriate hedging level. This argument is substantiated by the standard deviation, which indicates that the 2003 contract exhibited the highest risk with a standard deviation of R418.59, whereas the 2001 contract exhibited the lowest risk with a standard deviation of R74.24. Furthermore, the average standard deviation of R199.31 illustrates that the white maize market can easily move R400/ton in a season. Thus, the white maize market has been volatile during the entire period, which further supports the findings of Geyser and Cutts (2007:303) and Jordaan *et al*. (2007:320–321).

In addition, the findings reporting on the skewness and kurtosis of each contract are considered as a preliminary indication of the return distribution properties present in the data. The results suggest that a positive skewness were present in the 2001, 2003 to 2010 and 2012 contracts, whereas a negative skewness was only present in the 2002, 2011 and 2013 contracts. These results imply that producers generally experienced a positive return during the time periods under investigation, but losses were experienced during 2002, 2011 and 2013. These losses may be due to several adverse shocks, which can include (BFAP, 2012:23; Department of Agriculture, 2011:2):

i. the regional food crisis in 2002;
ii. the oversupply of white maize in 2011 and 2013; and
iii. the slow national economic growth during 2011 and 2013, due to the after effects of the 2009 financial crisis.

What should be noted is the inconsistency present in the skewness, which further emphasises the uncertainty that producers face in being able to produce a profitable crop. This provides an additional motivation for producers to minimise their uncertainty through hedging, as the possibility of surprise losses (downside surprise) can occur (see for example McFall Lamm, 2003). This argument is emphasised by the results reported on the kurtosis present, where the 2004 and the 2012 seasons are characterised as being leptokurtic (fat tailed), which imply that the distribution of the data peaks around the mean with a higher probability of outliers in the data (QMS, 2007:318). Conversely, the 2001 to 2003, 2005 to 2011 and the 2013 seasons are found to be platykurtic, implying that the distribution of the data is spread wider around the mean with a lower probability of extreme values (QMS, 2007:318). Again, since these results are not consistent throughout the whole period, producers are faced with high risk associated with the volatility of prices.

These results obtained from the skewness and kurtosis is an initial indication of the symmetry of the data's distribution compared to a normal distribution[57]. The results from the Jacque–Bera normality test confirm that the data is not normally distributed, with the exception of the 2006 contract. Given that the data is not normally distributed implies that the variance and the standard deviation will be unable to provide an accurate reflection of the true risk that producers face. This provides further uncertainty surrounding the erratic price movements, which emphasises the need to construct an indicator that will enable market participants to be able to manage price risk more effectively. This leads to the next section, which describes the application and construction of several technical indicators, with the main aim of constructing an appropriate composite indicator that producers can apply as an effective hedging decision tool with ease and confidence.

[57] A normal distribution has a skewness of 0 and a kurtosis of 3 (QMS, 2007:317–318).

Table 4.1 Data: Descriptive statistics

Contract Year	No of observations	Descriptive Statistics							
		Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jacque–Bera	
								Statistic	Probability
2001	202	790.281	959	635	74.239	0.018	2.143	6.188	0.045
2002	201	1536.275	1893	1012	262.621	–0.841	2.395	26.762	0.000
2003	200	1275.959	1989	743	418.593	0.275	1.352	25.148	0.000
2004	200	1117.285	1578	795	163.684	0.779	3.068	20.279	0.000
2005	201	717.202	1100	522	186.974	0.791	1.972	29.797	0.000
2006	199	1101.557	1419	839	148.126	0.251	2.483	4.304	0.116
2007	202	1536.658	2049	1087	256.006	0.102	1.727	13.987	0.001
2008	201	1695.135	2200	1377	212.702	0.507	2.160	14.527	0.001
2009	201	1674.706	2078	1305	192.774	0.341	2.106	10.588	0.005
2010	208	1285.488	1680	1019	216.467	0.507	1.551	27.114	0.000
2011	200	1560.875	1866	1282	157.466	–0.046	1.547	17.667	0.000
2012	201	2052.318	2728	1682	172.996	1.082	5.645	97.859	0.000
2013	201	2189.876	2459	1824	128.331	–0.502	2.830	8.700	0.013
Average	201.308	1425.663	1846.000	1086.308	199.306	0.251	2.383	23.302	0.014

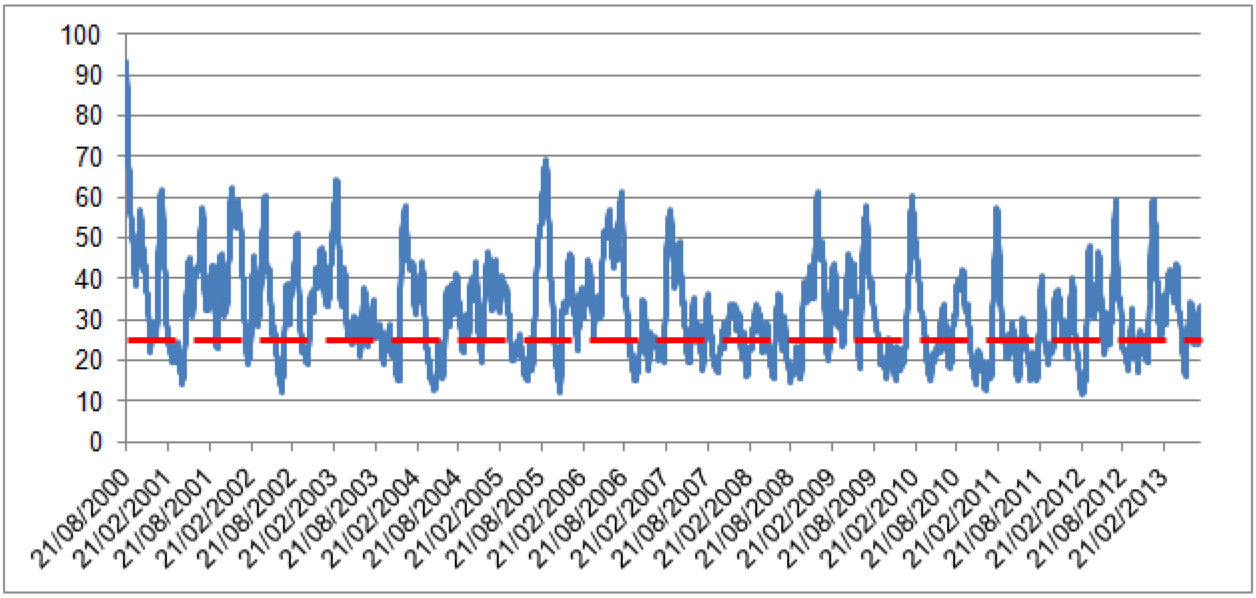
Source: Compiled by the author.

4.3 Method and results

The first step of technical analysis was to determine the current market trend (Section 4.3.1), as this would enable a more effective choice of applying individual technical indicators that are more applicable to the specified market trend (Section 4.3.2). To ensure the simplicity of the indicators, the assumption was made that each selling signal illustrated a suitable hedging possibility. For example, if an indicator generated 3 sell signals in a season a producer would have hedged at the respective price levels 3 times. The results of each individual technical indicator are reported in Section 4.3.2.5, where the best indicator was also determined. However, in order to enhance the hedging level a composite indicator was constructed (Section 4.3.3), and the results were also reported. This is followed by a comparison between the individual technical indicators and the composite indicator to establish dominance and validity of the composite indicator.

4.3.1 Determining the trend: Directional Movement Index (DMI)

Figure 4.2: DMI results



Source: Compiled by the author.

Prior to applying technical indicators in the white maize market, it was necessary to firstly determine the current trend of market prices. This was accomplished by applying the DMI (Section 3.4.2) and by more specifically examining the Average Directional Movement Index (ADX). As mentioned in Section 3.4.2, an ADX value above 25 indicates a current trending market, whereas an ADX value below 25 indicates a current trading market. The results of the DMI are graphically illustrated by Figure 4.2.

The results obtained from the DMI vary significantly between a trending and trading market. These results further confirm the previous indications of a relatively volatile market, highlighting the need to manage price risk more effectively. The next step of this study was to apply the most applicable individual technical indicators. Due to the market being extremely volatile (varying significantly between a trending and trading market), both leading and lagging indicators were applied. This leads to the following section, which elaborates on the success of applying these indicators.

4.3.2 Technical indicators

Once the trend of the market had been determined, individual technical indicators could be applied to the data from which meaningful interpretations could be drawn. The indicators that were chosen to apply, based on their simplicity and application frequency according to the literature study, included the Relative Strength Index (Section 4.3.2.1), Stochastic oscillator (Section 4.3.2.2), Exponential Moving Average (Section 4.3.2.3), and Moving Average Convergence/Divergence (Section 4.3.2.4). The applied methods of these indicators and the results obtained are examined in the following subsections.

4.3.2.1 Relative Strength Index (RSI)

The RSI is calculated by employing Equation 3.20 (Section 3.5.1.1) and interpreted by making use of tops and bottoms (Section 3.5.1.1). The default period, more specifically 14 days, were chosen to use in the calculation of the RSI, as proposed by Wilder (1978:65). Following the calculations of the RSI, sell signals were generated once the RSI crossed the upper limit[58] from above. Figure A.1 and Figure

[58] Given that the RSI functions more optimally in a trading market, the upper limit varies according to the type of market. Several upper limits were tested, whereafter the optimal limits were chosen

A.2 in the Appendix elaborate on the different upper limits that are implemented in different types of markets. As indicated in Figure A.1, sell signals (red arrows) were generated in a trending market once the RSI crossed an upper limit of 70%[59] from above. Conversely, Figure A.2 illustrates sell signals (red arrows) that were generated in a trading market once the RSI crossed an upper limit of 55%[60] from above.

Table 4.2: RSI results[61]

Contract Year	Max Price	Average hedge level	Sell signals	Hedge level : Max Price[62]
2001	959	751.233	6	78.335
2002	1893	1580.000	13	83.465
2003	1989	1573.000	3	79.085
2004	1578	1242.086	7	78.713
2005	1100	633.840	10	57.622
2006	1419	1193.455	11	84.105
2007	2049	1526.600	10	74.505
2008	2200	1716.889	9	78.040
2009	2078	1561.000	1	75.120
2010	1680	1391.769	13	82.843
2011	1866	1564.000	13	83.816
2012	2728	2048.833	12	75.104
2013	2459	2290.000	7	93.127
Average over entire period			**8.846**	**78.760**
Standard Deviation over entire period			**3.870**	**8.123**

Source: Compiled by the author.

base on the assumption that each season should generate at least one sell signal as well as the highest average hedge level.

[59] Please refer to Footnote 58.

[60] Please refer to Footnote 58.

[61] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[62] The average hedge level as a percentage of the maximum price during the specific season.

The results of the RSI are reported in Table 4.2, where the average hedge level, sell signals and hedge level as a percentage of the maximum price obtained from the calculations are presented. As indicated in Table 4.2, the 2005 season achieved the lowest average hedge level, where the lowest hedge level relative to the maximum price reached 57.622% during 2005. Also, the highest average hedge level was realised during 2013, where the highest hedge level relative to the maximum price reached 93.127% during 2013. On average the RSI achieved a relatively high hedging level of 78.760%. However, a significantly high standard deviation of 8.123 is observed over the entire period, which might be an indication of high risk involved in determining a possible hedge level.

With regards to the sell signals generated, the lowest number of signals was generated during 2009, where only 1 sell signal was realised, which poses the risk of not obtaining a desirable hedging level. However, a more desirable number of signals were generated during 2003. Conversely, the highest number of sell signals were generated in 2002, 2010 and 2011, with 13 sell signals generated each year. Overall, most seasons generated a relatively high number of sell signals, resulting in a significantly high average number of sell signals generated, which may have led to producers incurring considerably high hedging costs or potentially over–hedging their produce. The risk of applying only the RSI is also further highlighted by the high standard deviation of the number of sell signals generated (3.870), which further emphasise the importance of consulting additional technical indicators to ensure more reliable hedging levels.

4.3.2.2 Stochastic oscillator

The Stochastic oscillator is calculated by applying Equation 3.22 (Section 3.5.1.2) and Equation 3.25 (Section 3.5.2.1), as well as interpreting the equations as crossovers (Section 3.5.2.1). As proposed in the literature, the default periods were chosen to use in the calculation of the %K– and %D–lines (14 days and 3 days, respectively). Subsequently, sell signals are generated once the %K–line crosses the %D–line from above within the upper limit[63]. Figure A.3 and Figure A.4 elaborate

[63] Given that the Stochastic oscillator functions more optimally in a trading market, the upper limit varies according to the type of market. Several upper limits were tested, whereafter the optimal

on the different upper limits that are implemented in different types of market. As indicated in Figure A.3, sell signals (red arrows) are generated in a trending market once the Stochastic oscillator crosses an upper limit of 80%[64] from above. Conversely, Figure A.4 illustrates sell signals (red arrows) that are generated in a trading market once the Stochastic oscillator crosses an upper limit of 75%[65] from above.

Table 4.3: Stochastic oscillator results[66]

Contract Year	Max Price	Average hedge level	Sell signals	Hedge level : Max Price[67]
2001	959	801.091	11	83.534
2002	1893	1490.909	11	78.759
2003	1989	1570.833	6	78.976
2004	1578	1347.200	5	85.374
2005	1100	796.000	7	72.364
2006	1419	1162.333	18	81.912
2007	2049	1594.200	15	77.804
2008	2200	1776.188	16	80.736
2009	2078	1646.000	4	79.211
2010	1680	1423.083	12	84.707
2011	1866	1591.167	12	85.272
2012	2728	2166.538	13	79.419
2013	2459	2248.700	10	91.448
Average over entire period			**10.769**	**81.501**
Standard Deviation over entire period			**4.304**	**4.690**

Source: Compiled by the author.

limits were chosen based on the assumption that each season should generate at least one sell signal as well as the highest average hedge level.

[64] Please refer to Footnote 63.

[65] Please refer to Footnote 63.

[66] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results

[67] Please refer to Footnote 62.

The results of the Stochastic oscillator are reported in Table 4.3, where the average hedge level, sell signals and hedge level relative to the maximum price are presented. The data in Table 4.3 indicates that the 2005 season achieved the lowest average hedge level, where the lowest hedge level relative to the maximum price reached 72.364% during 2005. The highest average hedge level was realised during 2013, where the highest hedge level relative to the maximum price reached 91.448% during 2013. On average, the Stochastic oscillator achieved a significantly high hedging level of 81.501%. Furthermore, a standard deviation of 4.690 was observed during the period, still indicating risk regarding the volatility of the Stochastic oscillator’s success.

In addition, an evident drawback of the Stochastic oscillator is the significantly high number of sell signals produced during 2006. An average of 10.769 sell signals per season was generated, with the most number of sell signals (18) being produced during 2006 and the least number of signals (4) being generated during 2009. The difference between the most and least sell signals generated is 14, which validates the standard deviation of 4.304. This supports producers’ hesitancy to hedge by applying the Stochastic oscillator, since high hedging costs and potential over–hedging is a probable outcome. These results also emphasise the unreliability of applying this technical indicator individually and the necessity to consult other indicators additionally to ensure more precise hedging levels.

4.3.2.3 Exponential Moving Average (EMA)

The EMA is calculated by using Equation 3.27 (Section 3.5.2.1). A longer period of 20 days was used in the calculation of the EMA. A shorter period generated several false sell signals, whereas a longer period generated significantly less, delayed sell signals. Subsequently, sell signals (red arrow) are generated once the price series crosses the EMA from above, as graphically illustrated in Figure A.5 in the Appendix.

The results of the EMA are reported in Table 4.4, presenting the average hedge level, sell signals and hedge level relative to the maximum price. As indicated in

Table 4.4, the 2005 season achieved the lowest average hedge level, where the lowest hedge level relative to the maximum price reached 58.694% during 2003. On the other hand, the highest average hedge level was realised during 2013, where the highest hedge level relative to the maximum price reached 88.498% during 2013. Together with the other seasons, an average hedging level of 75.952% was realised by the EMA, which is lower compared to the previous two indicators. In accordance with the spread between the highest and lowest achieved hedge level, a standard deviation of 8.990 also confirms the high volatility and risk associated with applying only the EMA in the hedging decision–making process.

Another weakness that was highlighted by the results of the EMA includes the significantly high number of sell signals produced on average. An average of 11.538 sell signals per season was generated, with the most number of sell signals (18) being produced during 2006 and the least number of signals (4) being generated during 2009. The difference between the most and least sell signals generated is 14, which validates the standard deviation of 2.727. This supports producers' hesitancy to hedge, since this high number of sell signals provides an opportunity to over–hedge and generates uncertainty to which is the most efficient hedging level.

Table 4.4: EMA results[68]

Contract Year	Max Price	Average hedge level	Sell signals	Hedge level : Max Price[69]
2001	959	789.800	11	82.357
2002	1893	1653.100	10	87.327
2003	1989	1167.429	7	58.694
2004	1578	1085.176	17	68.769
2005	1100	713.055	11	64.823
2006	1419	989.222	9	69.713
2007	2049	1476.182	11	72.044
2008	2200	1684.636	11	76.574
2009	2078	1681.909	11	80.939
2010	1680	1351.100	10	80.423
2011	1866	1564.875	16	83.863
2012	2728	2001.143	14	73.356
2013	2459	2176.167	12	88.498
Average over entire period			**11.538**	**75.952**
Standard Deviation over entire period			**2.727**	**8.990**

Source: Compiled by the author.

4.3.2.4 Moving Average Convergence/Divergence (MACD)

The MACD is calculated by applying Equation 3.27 (Section 3.5.2.3) and interpreted as crossovers (Section 3.5.2.3). The default periods (26 days, 12 days and 9 days) were chosen to use in the calculation of the MACD line and signal line, respectively. Subsequently, sell signals are generated once the MACD line crosses the signal line from above, as graphically illustrated in Figure A.6 in the Appendix.

[68] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[69] Please refer to Footnote 62.

Table 4.5: MACD results[70]

Contract Year	Max Price	Average hedge level	Sell signals	Hedge level : Max Price[71]
2001	959	785.250	8	81.882
2002	1893	1555.500	4	82.171
2003	1989	1250.857	7	62.889
2004	1578	1089.000	7	69.011
2005	1100	731.750	8	66.523
2006	1419	1120.000	6	78.929
2007	2049	1496.714	7	73.046
2008	2200	1639.143	7	74.506
2009	2078	1657.375	8	79.758
2010	1680	1339.625	8	79.740
2011	1866	1578.000	9	84.566
2012	2728	2040.429	7	74.796
2013	2459	2198.625	8	89.411
Average over entire period			**7.231**	**76.710**
Standard Deviation over entire period			**1.235**	**7.522**

Source: Compiled by the author.

The results of the MACD are reported in Table 4.5, presenting the average hedge level, sell signals and hedge level relative to the maximum price. The results illustrate that the 2005 season achieved the lowest average hedge level, whereas the highest average hedge level was realised during 2013. The highest hedge level relative to the maximum price was also achieved during 2013 reaching 89.411%. Conversely, the lowest hedge level as a percentage of the maximum price was achieved during 2003, reaching a hedging level of only 62.889%. Together with the other seasons, an average hedging level of 76.710% was realised by the MACD. In accordance with the spread between the highest, lowest and average achieved hedge level, a standard deviation of 7.522 also validates the high volatility and risk

[70] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results

[71] Please refer to Footnote 62.

associated with applying only the MACD as an indicator to determine effective hedging levels.

The applicability of the MACD is further questioned when observing the relatively high number of sell signals generated on average. An average of 7.231 sell signals per season were generated, with the most number of sell signals (9) being produced during 2011 and the least number of signals (4) being generated during 2002. However, the drawback of the high number of sell signals is compensated for by the consistency in the number of signals generated, which is emphasised by the low standard deviation of 1.235. This provides producers with more certainty regarding the number of possible hedging opportunities, compared to the previous indicators.

4.3.2.5 Summary

Thus far the results obtained from applying the individual indicators, including the RSI (Section 4.3.2.1), the Stochastic oscillator (Section 4.3.2.2), the EMA (Section 4.3.2.3) and the MACD (Section 4.3.2.4), in the white maize market have been examined. To better determine the success of each indicator in the white maize market, the individual indicators are compared to one another in Table 4.6, Table 4.7 and Table 4.8, respectively. Note that the blue highlighted cells indicate the desired value for each season, whereas the red highlighted cell indicates the least desired value for each season.

Taking only Table 4.6 into consideration, it is evident that the Stochastic oscillator prevailed by achieving the highest average hedge level for a season the most times. Conversely, the RSI and EMA were only able to realise a few seasons with the highest average hedge level, whereas the MACD failed to produce any season with the highest average hedge level. Nonetheless, the MACD and RSI revealed more desirable results than the EMA. The results reported that the EMA produced the most number of seasons with the lowest average hedge level, whereas the MACD and RSI reported only a few seasons with the lowest average hedge level.

These results, however, do not correspond with the results in Table 4.7, indicating that the MACD succeeded in generating an average of 7.231 sell signals per season with a standard deviation of 1.235. Conversely, the EMA generated the highest level of sell signals, with an average of 11.538 sell signals per season along with a standard deviation of 2.727. Generating too many sell signals involves the risk of higher variation margin requirements. Additionally, too many sell signals may also add to hedgers' uncertainty, since the hedger may only need to hedge two contracts or 200 metric tonnes, but the indicator on average generates six signals. In this instance it becomes virtually impossible to identify two optimal signals from the six expected signals as a season progresses. On the other hand, generating too little sell signals pose the risk of remaining unhedged for an entire season.

Lastly, the data in Table 4.8 reports a summary of the results of the average hedge level per season as a percentage of the highest closing price for the season. The EMA generated inferior results when compared to the other indicators, with the lowest average hedge level to maximum price ratio and the highest standard deviation of this ratio between seasons. The Stochastic oscillator surpassed the other technical indicators, indicating an average of 81.501% average hedge level to maximum price ratio per season with a standard deviation of 4.690.

The results obtained by the individual indicators and the comparison between the indicator revealed several weaknesses. These weaknesses include significantly high number of sell signals generated, which also varied considerably, as well as a high inconsistency of achieved hedge levels. This may be due to the indicators being applied in the wrong type of market, which in turn may lead to false signals being generated. This challenge can be addressed by applying the indicators in conjunction with one another. However, this may discourage producers to apply this type of approach, given that market participants already lack the knowledge and understanding of derivatives instruments (see Section 2.3.1.3). To address the need of applying individual indicators in conjunction with one another, the following section aims at constructing a composite indicator, which will enable producers to determine more suitable and convincing hedging levels with greater efficiency.

Table 4.6: Comparison of average hedge level: Individual indicators[72]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD
2001	959	751.233	801.091	789.800	785.250
2002	1893	1580.000	1490.909	1653.100	1555.500
2003	1989	1573.000	1570.833	1167.429	1250.857
2004	1578	1242.086	1347.200	1085.176	1089.000
2005	1100	633.840	796.000	713.055	731.750
2006	1419	1193.455	1162.333	989.222	1120.000
2007	2049	1526.600	1594.200	1476.182	1496.714
2008	2200	1716.889	1776.188	1684.636	1639.143
2009	2078	1561.000	1646.000	1681.909	1657.375
2010	1680	1391.769	1423.083	1351.100	1339.625
2011	1866	1564.000	1591.167	1564.875	1578.000
2012	2728	2048.833	2166.538	2001.143	2040.429
2013	2459	2290.000	2248.700	2176.167	2198.625

Source: Compiled by the author.

[72] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.7: Comparison of sell signals: Individual indicators[73]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD
2001	959	6	11	11	8
2002	1893	13	11	10	4
2003	1989	3	6	7	7
2004	1578	7	5	17	7
2005	1100	10	7	11	8
2006	1419	11	18	9	6
2007	2049	10	15	11	7
2008	2200	9	16	11	7
2009	2078	1	4	11	8
2010	1680	13	12	10	8
2011	1866	13	12	16	9
2012	2728	12	13	14	7
2013	2459	7	10	12	8
Average over entire period		**8.846**	**10.769**	**11.538**	**7.231**
Standard Deviation over entire period		**3.870**	**4.304**	**2.727**	**1.235**

Source: Compiled by the author.

[73] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.8: Comparison of the average hedge level as percentage of maximum price: Individual indicators[74]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD
2001	959	78.335	83.534	82.357	81.882
2002	1893	83.465	78.759	87.327	82.171
2003	1989	79.085	78.976	58.694	62.889
2004	1578	78.713	85.374	68.769	69.011
2005	1100	57.622	72.364	64.823	66.523
2006	1419	84.105	81.912	69.713	78.929
2007	2049	74.505	77.804	72.044	73.046
2008	2200	78.040	80.736	76.574	74.506
2009	2078	75.120	79.211	80.939	79.758
2010	1680	82.843	84.707	80.423	79.740
2011	1866	83.816	85.272	83.863	84.566
2012	2728	75.104	79.419	73.356	74.796
2013	2459	93.127	91.448	88.498	89.411
Average over entire period		**78.760**	**81.501**	**75.952**	**76.710**
Standard Deviation over entire period		**8.123**	**4.690**	**8.990**	**7.522**

Source: Compiled by the author.

[74] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

4.3.3 Composite indicators

The findings from the previous section highlighted the challenge of determining the optimal hedging level with the use of only individual technical indicators. Subsequently, the researcher aimed to construct a composite indicator in this section, which will enhance the optimal hedging level. A composite indicator may also assist producers in terms of simplicity and greater accuracy to ensure more successful hedging decisions. The process of constructing the composite indicator (Section 4.3.3.1) is elaborated upon first. The results of the composite indicator are then reported, where the validity of the composite indicator is verified by comparing the performance of the individual technical indicators with that of the composite indicator.

4.3.3.1 The basic idea

The proposed composite indicator entails combining individual technical indicators, including leading indicators, namely the RSI (Section 4.3.2.1) and the Stochastic oscillator (Section 4.3.2.2), and lagging indicators, namely the EMA (Section 4.3.2.3) and the MACD (Section 4.3.2.4). Both leading and lagging indicators were chosen since the type of market varies significantly between a trending and trading market, which complicates the application of only leading or lagging indicators. The specific leading and lagging indicators were chosen due to their simplicity and frequent application in the literature (Chapter 3).

The first step of constructing the composite indicator was to calculate the value of each individual indicator, based on the following calculations:

i. The RSI is assigned a value that is calculated by means of Equation 3.20 (Section 3.5.1.1), with a default period of 14 days (Section 4.3.2.1).
ii. The Stochastic oscillator is assigned the %K value as calculated by means of Equation 3.22 (Section 3.5.1.2), with a default period of 14 days (Section 4.3.2.2).
iii. The EMA is assigned the values as calculated by Equation 3.27 (Section 3.5.2.1), with a period of 20 days (Section 4.3.2.3).

iv. The MACD is assigned the value as calculated by Equation 3.27 (Section 3.5.2.1), with a default period of 26 days and 12 days (Section 4.3.2.4).

The second step involved assigning a weight, according to the type of market, to each individual indicator[75] in an attempt to generate more accurate sell signals. More specifically, greater weights were assigned to leading indicators and smaller weights to lagging indicators in a trading market. Similarly, greater weights were assigned to lagging indicators and smaller weights to leading indicators in a trending market. To further ensure the accuracy of the composite indicator, a trending market was divided into three scenarios, based on the value of ADX. These scenarios included an ADX value between 25 and 50, 50 and 75, and 75 and 100. Several different weight combinations were tested by means of a trial and error method, however, it was found that these different weights did not significantly affect the results of the composite indicator. The weights were determined based on the optimal hedge level achieved from assigning different weights to the individual indicators in different market types in order to derive the composite indicator value.

The third step involved multiplying the calculated value of each indicator (first step) with the respective weights assigned to the indicator (second step). The individual indicators' weighted values were then added together to obtain the composite indicator's value, which was interpreted accordingly. Sell signals are generated once the composite value crosses an upper limit. Different upper limits were tested to ensure the highest possible hedge level in accordance with the requirements of at least two sell signals per contract and an average of four sell signals over the entire period. Three different composite indicators were constructed so as to ensure that the best results were achieved. Composite Indictor A1 (Section 4.3.3.2) and Composite Indicator A2 (Section 4.3.3.4) were based on the same principle calculations, except for the calculation of the RSI, where Composite Indicator B's calculations of the indicator values differed from the first two composite indicators. The specific details and relevant interpretation of the composite indicators follow below in the respective sections.

[75] Please refer to Section 3.4.

4.3.3.2 Composite Indicator A1

Composite Indicator A1 was constructed on the same basis as the basic idea described in Section 4.3.3.1, with the specific details and variations explained within the current section. Combining the individual indicators into one composite indicator was complicated by the fact that only the RSI and Stochastic oscillator are bound between 0 and 100, whereas the EMA and MACD lack such boundaries. To overcome this challenge the EMA and MACD were given boundaries by transforming both indicators into a stochastic version of the indicator (Roffey, 2008:157–158,162). Consequently, this allows for each individual indicator to fluctuate between 0 and 100. The Stochastic EMA and Stochastic MACD are calculated as follows, assuming a default period of 14 days (Roffey, 2008:157):

$$StochEMA = 100 \times \left[{(EMA_t - EMA_{low})}\big/{(EMA_{high} - EMA_{low})} \right], \tag{4.1.}$$

$$StochMACD = 100 \times \left[{(MACD_t - MACD_{low})}\big/{(MACD_{high} - MACD_{low})} \right], \tag{4.2.}$$

where:

- EMA_t and $MACD_t$ represents the most recent EMA value and MACD value respectively;
- EMA_{low} and $MACD_{low}$ represents the lowest low value for EMA and MACD respectively, for a 14-day time period; and
- EMA_{high} and $MACD_{high}$ represents the highest high value for EMA and MACD respectively, for a 14-day time period.

Once a value was calculated for each indicator, respective weights were allocated. The weights[76] assigned to each individual indicator varied as follows:

[76] Please refer to Section 4.3.3.1.

i. In a trading market, the RSI and Stochastic oscillator were assigned a weight of 0.3 each, whereas the EMA and MACD were assigned a weight of 0.2 each.
ii. In a trending market, the trend is broken up into three scenarios: an ADX value between 25 and 50, 50 and 75, and 75 and 100. According to these scenarios, the RSI and Stochastic oscillator were each assigned a weight of 0.25, 0.225 and 0.2 respectively. Conversely, the EMA and MACD were each assigned a weight of 0.25, 0.275 and 0.3 respectively.

The next step in constructing the composite indicator was to multiply each individual indicator's value with its assigned weight to obtain a weighted value. Thereafter, a composite indicator value was calculated by adding the individual indicators' weighted values together. The composite indicator value was interpreted accordingly, assuming an optimal upper limit of 87%[77]:

i. In a trending market, a sell signal is generated once the composite indicator crosses the upper limit from above; and
ii. In a trading market, a sell signal is generated once the composite indicator crosses the upper limit from below.

The results of the Composite Indicator A1 are reported in Table 4.9, presenting the average hedge level, sell signals and hedge level relative to the maximum price. It is evident from Table 4.9 that the 2005 season achieved the lowest average hedge level, whereas the highest average hedge level was realised in 2013. Furthermore, the highest hedge level relative to the maximum price was achieved during 2010, reaching 95.464%. Conversely, the lowest hedge level as a percentage of the maximum price was achieved during 2005, reaching a hedging level of 69.273%. Overall, an average hedging level of 80.997% was realised by Composite Indicator A1. Although a significantly high standard deviation of 7.821 was also realised, these results are much more promising compared to the performance reported by some individual indicators.

[77] Please refer to Section 4.3.3.1.

Furthermore, despite the inconsistency in the hedge levels realised, producers are presented with a rather steady number of sell signals generated when applying Composite Indicator A1. On average, 7 sell signals per season were generated, with the most number of sell signals (11) being produced in 2006 and the least number of signals (2) being generated in 2009. The number of sell signals generated remained relatively consistent during the entire period, which is validated by a standard deviation of only 2.769. This may provide producers with greater certainty regarding the number of possible hedging opportunities per season.

Table 4.9: Composite Indicator A1 results[78]

Contract Year	Max Price	Average Hedge level	Average Sell Signals	Hedge level : Max Price[79]
2001	959	782.171	7	81.561
2002	1893	1540.444	9	81.376
2003	1989	1415.500	4	71.166
2004	1578	1268.143	7	80.364
2005	1100	762.000	3	69.273
2006	1419	1147.364	11	80.857
2007	2049	1511.625	8	73.774
2008	2200	1789.300	10	81.332
2009	2078	1738.500	2	83.662
2010	1680	1603.800	5	95.464
2011	1866	1622.000	7	86.924
2012	2728	2020.667	9	74.071
2013	2459	2290.111	9	93.132
Average over entire period			**7.000**	**80.997**
Standard Deviation over entire period			**2.769**	**7.821**

Source: Compiled by the author.

[78] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[79] Please refer to Footnote 62.

4.3.3.3 Summary

To conclude the findings of the Composite Indicator A1, the performance of the composite indicator relative to the individual indicators (Section 4.3.2.5) are reported in Table 4.10, Table 4.11 and Table 4.12. Table 4.10 revealed that Composite Indicator A1 and the Stochastic oscillator prevailed by achieving the highest average hedge level per season the most times. Also noteworthy, is the fact that Composite Indicator A1 avoided the worst performance in any season, which may also provide producers with greater certainty. In line with the results contained in Table 4.10, the results in Table 4.11 indicate that Composite Indicator A1 again surpassed the other indicators by generating an average of 7 sell signals per season along with a standard deviation of 2.769. Similarly, the MACD also revealed favourable results, generating an average of 7.231 sell signals per season along with a standard deviation of 1.235. The results in Table 4.12 corroborates the results in Table 4.10 and Table 4.11, revealing that the Stochastic oscillator surpassed the other technical indicators, indicating an average of 81.501% hedge level to maximum price ratio per season with a standard deviation of 4.690. Similar to the Stochastic oscillator, Composite Indicator A1 also presented desirable results, with a hedge level to maximum price ratio of 80.997 along with a standard deviation of 7.821.

Despite the success of Composite Indicator A1 compared to the individual indicators, the results were not the most desirable. It may be argued that the inconsistencies in the results were as a result of the inconsistency in the calculation of the RSI. The EMA and MACD's calculations were based on the Stochastic oscillator's formula, whereas the RSI's formula was not adjusted to also be stochastic. Thus, the possibility of improving Composite Indicator A1's results by applying the Stochastic oscillator's formula existed.

Table 4.10: Comparison of average hedge level: Individual indicators vs. Composite Indicator A1[80]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1
2001	959	751.233	801.091	789.800	785.250	782.171
2002	1893	1580.000	1490.909	1653.100	1555.500	1540.444
2003	1989	1573.000	1570.833	1167.429	1250.857	1415.500
2004	1578	1242.086	1347.200	1085.176	1089.000	1268.143
2005	1100	633.840	796.000	713.055	731.750	762.000
2006	1419	1193.455	1162.333	989.222	1120.000	1147.364
2007	2049	1526.600	1594.200	1476.182	1496.714	1511.625
2008	2200	1716.889	1776.188	1684.636	1639.143	1789.300
2009	2078	1561.000	1646.000	1681.909	1657.375	1738.500
2010	1680	1391.769	1423.083	1351.100	1339.625	1603.800
2011	1866	1564.000	1591.167	1564.875	1578.000	1622.000
2012	2728	2048.833	2166.538	2001.143	2040.429	2020.667
2013	2459	2290.000	2248.700	2176.167	2198.625	2290.111

Source: Compiled by the author.

[80] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.11: Comparison of sell signals: Individual indicators vs. Composite Indicator A1[81]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1
2001	959	6	11	11	8	7
2002	1893	13	11	10	4	9
2003	1989	3	6	7	7	4
2004	1578	7	5	17	7	7
2005	1100	10	7	11	8	3
2006	1419	11	18	9	6	11
2007	2049	10	15	11	7	8
2008	2200	9	16	11	7	10
2009	2078	1	4	11	8	2
2010	1680	13	12	10	8	5
2011	1866	13	12	16	9	7
2012	2728	12	13	14	7	9
2013	2459	7	10	12	8	9
Average over period		**8.846**	**10.769**	**11.538**	**7.231**	**7.000**
Standard Deviation		**3.870**	**4.304**	**2.727**	**1.235**	**2.769**

Source: Compiled by the author.

[81] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.12: Comparison of the average hedge level as percentage of maximum price: Individual indicators vs. Composite Indicator A1[82]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1
2001	959	78.335	83.534	82.357	81.882	81.561
2002	1893	83.465	78.759	87.327	82.171	81.376
2003	1989	79.085	78.976	58.694	62.889	71.166
2004	1578	78.713	85.374	68.769	69.011	80.364
2005	1100	57.622	72.364	64.823	66.523	69.273
2006	1419	84.105	81.912	69.713	78.929	80.857
2007	2049	74.505	77.804	72.044	73.046	73.774
2008	2200	78.040	80.736	76.574	74.506	81.332
2009	2078	75.120	79.211	80.939	79.758	83.662
2010	1680	82.843	84.707	80.423	79.740	95.464
2011	1866	83.816	85.272	83.863	84.566	86.924
2012	2728	75.104	79.419	73.356	74.796	74.071
2013	2459	93.127	91.448	88.498	89.411	93.132
Average over period		**78.760**	**81.501**	**75.952**	**76.710**	**80.997**
Standard Deviation		**8.123**	**4.690**	**8.990**	**7.522**	**7.821**

Source: Compiled by the author.

[82] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

4.3.3.4 Composite Indicator A2

To address the shortcoming of Composite Indicator A1, Composite Indicator A2 was constructed. The second proposed composite indicator is similar to Composite Indictor A1 (Section 4.3.3.2), with the exception of the calculation of the RSI. To ensure that all the indicators' calculations were consistent, a Stochastic RSI value was calculated as follow, assuming a default period of 14 days (Roffey, 2008:157;161):

$$StochRSI = 100 \times \left[{(RSI_t - RSI_{low})}\big/{(RSI_{high} - RSI_{low})} \right], \quad (4.3.)$$

where:

- RSI_t represents the most recent RSI value;
- RSI_{low} represents the lowest low value for RSI for a 14-day time period; and
- RSI_{high} represents the highest high value for RSI for a 14-day time period.

In addition to modifying the value of the RSI, Composite Indicator A2 required a higher upper limit than Composite Indicator A1, more specifically 96%[83], in order to generate sell signals that would ultimately assist in an optimal average hedge level. The remainder of the calculations and interpretations of the composite indicator remain similar to Composite Indicator A1.

The results of Composite Indicator A2 are reported in Table 4.13, presenting the average hedge level, number of sell signals and the hedge level relative to the maximum price. It is clear from the data in Table 4.13 that the 2005 season achieved the lowest average hedge level (725.000) as well as the lowest hedge level as a percentage of the maximum price (65.909). Conversely, the highest average hedge level (2262.889) and hedge level relative to the maximum price (92.025) were realised in 2013. On average, a hedge level of 80.754% of the maximum price was achieved by Composite Indicator A2 with a standard deviation of 6.558. Despite a

[83] Please refer to Section 4.3.3.1.

relatively high standard deviation which may encourage producers' hesitancy towards Composite Indicator A2, these results are more desirable than the individual indicators. However, the results seem less desirable than Composite Indicator A1.

Table 4.13: Composite Indicator A2 results[84]

Contract Year	Max Price	Average Hedge level	Average Sell Signals	Hedge level : Max Price[85]
2001	959	793.250	8	82.716
2002	1893	1513.700	10	79.963
2003	1989	1438.500	4	72.323
2004	1578	1303.250	4	82.589
2005	1100	725.000	4	65.909
2006	1419	1163.250	12	81.977
2007	2049	1577.667	9	76.997
2008	2200	1773.564	11	80.617
2009	2078	1728.000	2	83.157
2010	1680	1396.917	12	83.150
2011	1866	1653.417	12	88.608
2012	2728	2176.200	10	79.773
2013	2459	2262.889	9	92.025
Average over entire period			**8.231**	**80.754**
Standard Deviation over entire period			**3.539**	**6.558**

Source: Compiled by the author.

The high number of sell signals generated may further discourage producers. An average of 8.231 sell signals per season were generated, with the most number of sell signals (12) produced in 2006, 2010 and 2011, whereas the least number of signals (2) were generated in 2009. The standard deviation of the number of sell signals generated was consistent with the number of sell signals, indicating that a producer may expect a deviation of 3.539 from the average. This may lead to high

[84] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[85] Please refer to Footnote 62.

producer uncertainty regarding the applicability of Composite Indicator A2 in the white maize market.

4.3.3.5 Summary

To conclude the findings of Composite Indicator A2, a comparison between Composite Indicator A2, Composite Indicator A1 and the individual indicators is reported in Table 4.14, Table 4.15, and Table 4.16. It is evident from Table 4.14 that Composite Indicator A2 could not surpass Composite Indicator A1 and Stochastic oscillator in realising the highest average hedge level for a season the most times. However, the results also revealed that both Composite Indicator A1 and Composite Indicator A2 failed to produce any season with the lowest average hedge level.

The results in Table 4.15 generally correspond with the results obtained in Table 4.14, reporting that Composite Indicator A2 did not surpass the other indicators, averaging 8.231 sell signals per season along with a standard deviation of 3.539. Finally, Table 4.16 presents the results of the average hedge level per season as a percentage of the highest closing price for the season. Composite Indicator A2 could not surpass Composite Indicator A1 and the Stochastic oscillator, but did however report desirable results. Composite Indicator A2 managed to achieve the third highest average hedge level to maximum price ratio (80.754%) and a significantly low standard deviation (6.558) of this ratio between seasons.

From the above discussed results, it is evident that Composite Indicator A2 failed to improve on Composite Indicator A1, which can be due to the change in the characteristics of the indicators when applying the Stochastic oscillator’s formula to the indicators’ values (Roffey, 2008:158). More specifically, the lag effect of the lagging indicators was eliminated, ultimately altering lagging indicators to act as leading indicators (Roffey, 2008:158). Consequently, the weights of the individual indicators in the composite indicator may have been assigned incorrectly in accordance to the trend of the market, resulting in the construction of a worse performing composite indicator. This lead to the construction of a third composite indicator aimed at assigning values to the indicators without altering the characteristics of the indicators, as described in the following subsection.

Table 4.14: Comparison of average hedge level: Individual indicators vs. Composite Indicator A1 and Composite Indicator A2[86]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2
2001	959	751.233	801.091	789.800	785.250	782.171	793.250
2002	1893	1580.000	1490.909	1653.100	1555.500	1540.444	1513.700
2003	1989	1573.000	1570.833	1167.429	1250.857	1415.500	1438.500
2004	1578	1242.086	1347.200	1085.176	1089.000	1268.143	1303.250
2005	1100	633.840	796.000	713.055	731.750	762.000	725.000
2006	1419	1193.455	1162.333	989.222	1120.000	1147.364	1163.250
2007	2049	1526.600	1594.200	1476.182	1496.714	1511.625	1577.667
2008	2200	1716.889	1776.188	1684.636	1639.143	1789.300	1773.564
2009	2078	1561.000	1646.000	1681.909	1657.375	1738.500	1728.000
2010	1680	1391.769	1423.083	1351.100	1339.625	1603.800	1396.917
2011	1866	1564.000	1591.167	1564.875	1578.000	1622.000	1653.417
2012	2728	2048.833	2166.538	2001.143	2040.429	2020.667	2176.200
2013	2459	2290.000	2248.700	2176.167	2198.625	2290.111	2262.889

Source: Compiled by the author.

[86] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.15: Comparison of sell signals: Individual indicators vs. Composite Indicator A1 and Composite Indicator A2[87]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2
2001	959	6	11	11	8	7	8
2002	1893	13	11	10	4	9	10
2003	1989	3	6	7	7	4	4
2004	1578	7	5	17	7	7	4
2005	1100	10	7	11	8	3	4
2006	1419	11	18	9	6	11	12
2007	2049	10	15	11	7	8	9
2008	2200	9	16	11	7	10	11
2009	2078	1	4	11	8	2	2
2010	1680	13	12	10	8	5	12
2011	1866	13	12	16	9	7	12
2012	2728	12	13	14	7	9	10
2013	2459	7	10	12	8	9	9
Average over period		**8.846**	**10.769**	**11.538**	**7.231**	**7.000**	**8.231**
Standard Deviation		**3.870**	**4.304**	**2.727**	**1.235**	**2.769**	**3.539**

Source: Compiled by the author.

[87] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.16: Comparison of the average hedge level as percentage of maximum price: Individual indicators vs. Composite Indicator A1 and Composite Indicator A2[88]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2
2001	959	78.335	83.534	82.357	81.882	81.561	82.716
2002	1893	83.465	78.759	87.327	82.171	81.376	79.963
2003	1989	79.085	78.976	58.694	62.889	71.166	72.323
2004	1578	78.713	85.374	68.769	69.011	80.364	82.589
2005	1100	57.622	72.364	64.823	66.523	69.273	65.909
2006	1419	84.105	81.912	69.713	78.929	80.857	81.977
2007	2049	74.505	77.804	72.044	73.046	73.774	76.997
2008	2200	78.040	80.736	76.574	74.506	81.332	80.617
2009	2078	75.120	79.211	80.939	79.758	83.662	83.157
2010	1680	82.843	84.707	80.423	79.740	95.464	83.150
2011	1866	83.816	85.272	83.863	84.566	86.924	88.608
2012	2728	75.104	79.419	73.356	74.796	74.071	79.773
2013	2459	93.127	91.448	88.498	89.411	93.132	92.025
Average over period		**78.760**	**81.501**	**75.952**	**76.710**	**80.997**	**80.754**
Standard Deviation		**8.123**	**4.690**	**8.990**	**7.522**	**7.821**	**6.558**

Source; Compiled by the author.

[88] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

4.3.3.6 Composite Indicator B

Composite Indicator B attempted to address the shortcomings of both Composite Indicator A1 and Composite Indicator A2. As mentioned in Section 4.3.3.2, constructing a composite indicator by means of merging leading and lagging indicators, was complicated by the fact that the EMA and MACD are not bounded, whereas the RSI and Stochastic oscillator are bounded between 0 and 100. Composite Indicator A1 and Composite Indicator A2 applied a stochastic formula to the EMA, MACD and RSI. Despite the success of the indicators, the statistical properties of lagging indicators may have been altered to reflect that of a leading indicator (Roffey, 2008:158). Composite Indicator B attempts to eliminate this complication and address the drawback regarding the lack of boundaries by assigning a value of 100 to a sell signal and a value of 0 otherwise. Also, the individual indicators applied in the construction of Composite Indicator B generated sell signals on the same basis as explained in Section 4.3.2, which will serve as a benchmark to determine if Composite Indicator B can improve the timing of implementing a hedge decision.

Consequently, Composite Indicator B still includes the individual indicators as discussed and explained in Section 4.3.2 and their original statistical methods of generating values are applied as intended. Composite Indicator B then, for example, generated a value as follows. If, for instance, the individual MACD indicator (Section 4.3.2.4) generates a sell signal, a value of 100 was assigned to the MACD. If the individual RSI indicator (4.3.2.1) also generated a sell signal on the same day, a value of 100 was also assigned to the RSI. In the same way the individual Stochastic oscillator indicator (Section 4.3.2.2) and the individual EMA indicator (Section 4.3.2.3) could also have generated a sell signal or not, where a value of 100 or 0 was assigned, respectively. In order to calculate Composite Indicator B's value, respective weights were allocated to each individual indicator. Each individual indicator's weights were assigned on the same basis as explained in Composite Indicator A1 (Section 4.3.3.2) and Composite Indicator A2 (Section 4.3.3.4). Following the allocation of the respective weights, each individual indicator's value was multiplied with its assigned weight to obtain a weighted value. Thereafter, a composite indicator value was computed by adding the individual indicators' weighted values together. Subsequently, this value was interpreted as a sell signal when the composite indicator reached or crossed the upper limit, assuming an upper limit of 40[89].

The results of Composite Indicator B are reported in Table 4.17, presenting the average hedge level, sell signals and hedge level relative to the maximum price. It is evident from Table 4.17 that the 2001 season realised the lowest average hedge level, whereas the highest average hedge level was achieved in 2013. Contrary to the highest average hedge level, the highest hedge level relative to the maximum price was achieved in 2003 reaching 94.444%. Alternatively, the lowest hedge level as a percentage of the maximum price was achieved in 2001, reaching a hedge level of only 71.470%. Composite Indicator B managed to average a hedging level of 81.722%. However, a significantly high standard deviation of 7.547 was realised. Such a significantly high standard deviation may encourage market participants' hesitancy to make use of Composite Indicator B as it is an indication of inconsistent hedging levels.

Despite the high spread in the hedging level, Composite Indicator B compensates by generating an average of only 3.769 sell signals per season. The applicability of Composite Indicator B is further justified by a standard deviation of only 1.739. As mentioned, a low standard deviation regarding the number of sell signals generated may provide producers with more confidence regarding the number of possible future sell signals.

[89] Please refer to Section 4.3.3.1.

Table 4.17: Composite Indicator B results[90]

Contract Year	Max Price	Average Hedge level	Average Sell Signals	Hedge level : Max Price[91]
2001	959	685.400	3	71.470
2002	1893	1554.000	5	82.092
2003	1989	1878.500	2	94.444
2004	1578	1281.500	2	81.210
2005	1100	824.300	2	74.936
2006	1419	1306.250	4	92.054
2007	2049	1491.500	2	72.792
2008	2200	1811.400	5	82.336
2009	2078	1578.500	2	75.962
2010	1680	1395.667	6	83.075
2011	1866	1639.000	5	87.835
2012	2728	2036.571	7	74.654
2013	2459	2201.500	4	89.528
Average over period			**3.769**	**81.722**
Standard Deviation			**1.739**	**7.547**

Source: Compiled by the author.

Following the construction of Composite Indicator B, comparisons between the indicators are reported in Table 4.18, Table 4.19 and Table 4.20. When considering only Table 4.18, it is evident that Composite Indicator B prevailed by achieving the highest average hedge level for a season the most times. Similarly, the results in Table 4.19 indicated that Composite Indicator B surpassed the other indicators by generating the lowest average sell signals (4) per season along with a low standard deviation of 1.739. This is significantly lower than the other indicators, validating the construction of Composite Indicator B. Lastly, the results of the average hedge level per season as a percentage of the highest closing price for the season are presented in Table 4.20. Again, Composite Indicator B surpassed the other technical indicators,

[90] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[91] Please refer to Footnote 62.

indicating an average of 81.04% average hedge level to maximum price ratio per season with a standard deviation of 7.81.

Table 4.18 Comparison: Average hedge level[92]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2	Composite Indicator B
2001	959	751.233	801.091	789.800	785.250	782.171	793.250	685.400
2002	1893	1580.000	1490.909	1653.100	1555.500	1540.444	1513.700	1554.000
2003	1989	1573.000	1570.833	1167.429	1250.857	1415.500	1438.500	1878.500
2004	1578	1242.086	1347.200	1085.176	1089.000	1268.143	1303.250	1281.500
2005	1100	633.840	796.000	713.055	731.750	762.000	725.000	824.300
2006	1419	1193.455	1162.333	989.222	1120.000	1147.364	1163.250	1306.250
2007	2049	1526.600	1594.200	1476.182	1496.714	1511.625	1577.667	1491.500
2008	2200	1716.889	1776.188	1684.636	1639.143	1789.300	1773.564	1811.400
2009	2078	1561.000	1646.000	1681.909	1657.375	1738.500	1728.000	1578.500
2010	1680	1391.769	1423.083	1351.100	1339.625	1603.800	1396.917	1395.667
2011	1866	1564.000	1591.167	1564.875	1578.000	1622.000	1653.417	1639.000
2012	2728	2048.833	2166.538	2001.143	2040.429	2020.667	2176.200	2036.571
2013	2459	2290.000	2248.700	2176.167	2198.625	2290.111	2262.889	2201.500

Source: Compiled by the author.

[92] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.19 Comparison: Sell signals[93]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2	Composite Indicator B
2001	959	6	11	11	8	7	8	3
2002	1893	13	11	10	4	9	10	5
2003	1989	3	6	7	7	4	4	2
2004	1578	7	5	17	7	7	4	2
2005	1100	10	7	11	8	3	4	2
2006	1419	11	18	9	6	11	12	4
2007	2049	10	15	11	7	8	9	2
2008	2200	9	16	11	7	10	11	5
2009	2078	1	4	11	8	2	2	2
2010	1680	13	12	10	8	5	12	6
2011	1866	13	12	16	9	7	12	5
2012	2728	12	13	14	7	9	10	7
2013	2459	7	10	12	8	9	9	4
Average over period		**8.846**	**10.769**	**11.538**	**7.231**	**7.000**	**8.231**	**3.769**
Standard Deviation		**3.870**	**4.304**	**2.727**	**1.235**	**2.769**	**3.539**	**1.739**

Source: Compiled by the author.

[93] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

Table 4.20 Comparison: Hedge level as a percentage of the maximum price[94]

Contract Year	Max Price	RSI	Stochastic oscillator	EMA	MACD	Composite Indicator A1	Composite Indicator A2	Composite Indicator B
2001	959	78.335	83.534	82.357	81.882	81.561	82.716	71.470
2002	1893	83.465	78.759	87.327	82.171	81.376	79.963	82.092
2003	1989	79.085	78.976	58.694	62.889	71.166	72.323	94.444
2004	1578	78.713	85.374	68.769	69.011	80.364	82.589	81.210
2005	1100	57.622	72.364	64.823	66.523	69.273	65.909	74.936
2006	1419	84.105	81.912	69.713	78.929	80.857	81.977	92.054
2007	2049	74.505	77.804	72.044	73.046	73.774	76.997	72.792
2008	2200	78.040	80.736	76.574	74.506	81.332	80.617	82.336
2009	2078	75.120	79.211	80.939	79.758	83.662	83.157	75.962
2010	1680	82.843	84.707	80.423	79.740	95.464	83.150	83.075
2011	1866	83.816	85.272	83.863	84.566	86.924	88.608	87.835
2012	2728	75.104	79.419	73.356	74.796	74.071	79.773	74.654
2013	2459	93.127	91.448	88.498	89.411	93.132	92.025	89.528
Average over period		**78.760**	**81.501**	**75.952**	**76.710**	**80.997**	**80.754**	**81.722**
Standard Deviation		**8.123**	**4.690**	**8.990**	**7.522**	**7.821**	**6.558**	**7.547**

Source: Compiled by the author.

94 The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

4.3.3.7 Summary

From all the above mentioned results it can be deduced that the EMA is the most inadequate indicator to implement in the South African white maize market, whereafter the MACD and RSI also demonstrated undesirable results. Despite the highly advantageous results demonstrated by the Stochastic oscillator, Composite Indicator A1 and/or Composite Indicator B seem to surpass the Stochastic oscillator, as well as the other individual technical indicators. Furthermore, significant to note is that the indicators (individual indicators and composite indictors) managed to achieve an average hedge level relative to the maximum price above the 75% hedge level. However, these results are indefinite and allow for subjective interpretation. Thus, a more exact comparison between the technical indicators are necessary, so as to more specifically determine the superior indicator to implement in the South African White maize market. This comparison follows in Section 4.3.4.

4.3.4 Comparison: Indicator rankings

In this section, the researcher aimed to objectively identify a technical indicator that could be implemented in the South African white maize market with ease and confidence. Ultimately the goal was to determine whether a composite indicator surpassed the individual indicators. Identifying this indicator was done by means of a ranking process. A ranked value was assigned to each indicator, where 1 represents the best and 7 represents the worst, in each respective category. The categories and the best scenario include the following:

- the average hedge level per season, where the highest value is the best;
- the sell signals per season, where the lowest value is deemed the best;
- the standard deviation of the sell signals over the entire period, where the lowest value is deemed the best;
- the average hedge level to maximum price ratio per season, where the highest value is the best; and
- the standard deviation of the average hedge level to maximum price ratio over the entire period, where the lowest value is deemed the best.

Subsequently, the rankings for each indicator was added together in order to obtain an overall index value. The indicator with the lowest index value (highest ranking) was identified as the best indicator to implement in the South African white maize market. From the results reported in Table 4.21 the conclusion can be made that Composite Indicator B is the best technical indicator to implement in the South African white maize market over the period under investigation. Composite Indicator B achieved the highest hedge level for the most number of seasons, the lowest average sell signals generated over the period, as well as the highest average hedge level as a percentage of the maximum price over the entire period. Furthermore, Composite Indicator B achieved the third lowest number of seasons with the lowest hedge level over the period, as well as the second lowest sell signal standard deviation.

The success of Composite Indicator B is further validated when referring to the application of the composite indicator. Given that Composite Indicator B's hedging levels are fairly consistent throughout different seasons, producers can make use of the indicator to effectively and confidently determine advantageous hedging levels. Furthermore, since there was little variation between the generated number of sell signals in seasons, producers' uncertainty regarding how much to hedge, more specifically over–hedging and under–hedging, was also diminished. This is a significant validation of the construction of a composite indicator.

The MACD followed Composite Indicator B, achieving the lowest standard deviation of sell signals over the entire period. Furthermore, the MACD achieved the third lowest standard deviation over the entire period of the average hedge level to the maximum price ratio. It is also significant to note that Composite Indicator A1 followed Composite Indicator B and the MACD in third place, achieving the lowest number of seasons with the lowest hedge level over the entire period. Also, Composite Indicator A1 managed to achieve the second most number of seasons with the lowest average hedge level over the period, the second lowest average sell signals generated over the period, and the third highest average hedge level as a percentage of the maximum price over the entire period.

Lastly, Composite Indicator A2 followed Composite Indicator A1 in the fourth place, also achieving the lowest number of seasons with the lowest average hedge level over the period. Additionally, Composite Indicator A2 realised the lowest standard deviation of the average hedge level as a percentage of the maximum price over the entire period.

Table 4.21 Comparison: Indicators according to rankings[95]

Year	Rankings					Total	Final Ranking
	Highest hedge level	Sell signals	Standard deviation of sell signals over the entire period	Average hedge level:Max price[96]	Standard deviation of hedge level:max price over the entire period		
Composite Indicator B							
2001	7	1		1			1
2002	4	2		4			
2003	1	1		7			
2004	3	1		5			
2005	1	1		7			
2006	1	1		7			
2007	6	1		2			
2008	1	1		7			
2009	6	2		2			
2010	4	2		4			
2011	2	1		6			
2012	5	1		3			
2013	5	1		3			
Total	**46**	**16**	**2**	**58**	**4**	**126**	

[95] The blue highlighted cells indicate the most desirable results, whereas the red highlighted cells indicates the least desirable results.

[96] Please refer to Footnote 62.

MACD							
2001	4	4		4			
2002	3	1		5			
2003	6	6		2			
2004	6	4		2			
2005	4	5		4			
2006	6	2		2			
2007	5	2		3			
2008	7	2		1			**2**
2009	4	6		4			
2010	7	3		1			
2011	5	3		3			
2012	4	1		4			
2013	6	3		2			
Total	**67**	**42**	**1**	**37**	**3**	**150**	
Composite Indicator A1							
2001	5	3		3			
2002	5	3		3			
2003	5	3		3			
2004	4	4		4			
2005	3	2		5			**3**
2006	5	4		3			
2007	4	3		4			
2008	2	4		6			

2009	1	2		7			
2010	1	1		7			
2011	3	2		5			
2012	6	3		2			
2013	1	4		7			
Total	**45**	**38**	**4**	**59**	**5**	**151**	
Composite Indicator A2							
2001	2	4		6			**4**
2002	6	4		2			
2003	4	3		4			
2004	2	2		6			
2005	5	3		3			
2006	3	6		5			
2007	2	4		6			
2008	4	5		4			
2009	2	2		6			
2010	3	5		5			
2011	1	4		7			
2012	1	4		7			
2013	3	4		5			
Total	**38**	**50**	**5**	**66**	**2**	**161**	
RSI							
2001	6	2		2			**5**
2002	2	7		6			

2003	2	2		6			
2004	5	4		3			
2005	7	6		1			
2006	2	4		6			
2007	3	5		5			
2008	5	3		3			
2009	7	1		1			
2010	5	7		3			
2011	7	6		1			
2012	3	5		5			
2013	2	2		6			
Total	**56**	**54**	**6**	**48**	**6**	**170**	
Stochastic oscillator							
2001	1	6		7			
2002	7	6		1			
2003	3	5		5			
2004	1	3		7			
2005	2	4		6			
2006	4	7		4			**6**
2007	1	7		7			
2008	3	7		5			
2009	5	5		3			
2010	2	5		6			
2011	4	4		4			

2012	2	6		6			
2013	4	6		4			
Total	**39**	**71**	**7**	**65**	**1**	**183**	
EMA							
2001	3	6		5			
2002	1	4		7			
2003	7	6		1			
2004	7	7		1			
2005	6	7		2			
2006	7	3		1			
2007	7	6		1			**7**
2008	6	5		2			
2009	3	7		5			
2010	6	4		2			
2011	6	7		2			
2012	7	7		1			
2013	7	7		1			
Total	**73**	**76**	**3**	**31**	**7**	**190**	

Source: Compiled by the author.

4.4 Conclusion

Given that risk management is essential in the white maize market, the researcher's primary aim was to construct a composite technical indicator with the ability to generate better timed sell signals that would ultimately assist in achieving higher hedging levels. The first step in achieving this goal was to determine the current tendency of the market by means of the DMI in order to implement the different technical indicators more effectively in the white maize market. The DMI indicated that the white maize market is significantly volatile, where the market moves erratically between a trending and trading market.

After the primary trend of the market was established, the individual indicators were applied to the data. Given that the market trend varies significantly, both leading and lagging indicators were chosen to analyse. The selected individual indicators include the RSI (Section 4.3.2.1) and Stochastic oscillator (Section 4.3.2.2) as leading indicators, and the EMA (Section 4.3.2.3) and MACD (Section 4.3.2.4) as lagging indicators. Comparing the results obtained from applying the individual indicators in the white maize market, it may have been subjectively evident that the Stochastic oscillator surpassed the other individual indicators. However, since the market was not primarily a trading market, the Stochastic oscillator may have provided false signals. Thus, the Stochastic oscillator needed to be applied in conjunction with other indicators to provide more effective and accurate sell signals.

This led to the construction of the composite indicator in an attempt to address the drawback of the individual indicators. Composite indicators were constructed by combining leading indicators, specifically the RSI (Section 4.3.2.1) and the Stochastic oscillator (Section 4.3.2.2), as well as lagging indicators, specifically the EMA (Section 4.3.2.3) and the MACD (Section 4.3.2.4). Three different composite indicators (Section 4.3.2.5) were constructed to address several drawbacks of the individual indicators and of the first composite indicators. Composite Indicator A1 was constructed to address the risk of applying an indicator in the wrong type of market. However, Composite Indicator A1's results were inconsistent over the period, as a probable result of not applying the same formula to all the indicators. Consequently, Composite Indicator A2 was constructed, applying a consistent formula, based on the Stochastic oscillator's calculations, to each indicator. However, this formula changed the statistical properties of specifically the RSI, EMA and MACD, which may have been the reason for the more undesirable results compared to Composite Indicator A1. This led to the construction of Composite Indicator B, which attempted to eliminate the drawbacks of the individual indicators as well as address the problems associated with Composite Indicator A1 and Composite Indicator A2.

In order to achieve the main objective of this chapter, the individual technical indicators and the constructed composite indicators were compared to one another according to the indicators' average achieved hedge level, sell signals, and average achieved hedge level as a percentage of the maximum price of the season. Significant results were obtained, which specifically validated the construction of a composite technical indicator. Not only did the composite indicators prove to be the most adequate indicators to apply in the white maize market, but it also indicated a significantly high hedge level compared to the maximum price for each season. This allows market participants the opportunity to hedge at a significantly advantageous level within a season, diminishing some of the disadvantages associated specifically with hedging with futures contracts. Firstly, a hedger faces less risk associated with over–hedging. Secondly, there exists a higher probability of lower initial and variation margins associated with hedging on a formal exchange.

The results specifically reported that Composite Indicator B is the best technical indicator to apply in the South African white maize market, followed by Composite Indicator A1. Conversely, the EMA proved to be the most inadequate indicator to use. However, these results were subject to a biased interpretation, which necessitated an objective method of comparison.

This comparison was done by means of assigning rankings to several criteria, including:

- the average hedge level per season, where the highest value would be the best;
- the sell signals per season, where the lowest value was deemed the best;

- the standard deviation of the sell signals over the entire period, where the lowest value was deemed the best;
- the average hedge level to maximum price ratio per season, where the highest value would be the best; and
- the standard deviation of the average hedge level to maximum price ratio over the entire period, where the lowest value was deemed the best.

According to these rankings, Composite Indicator B again prevailed superior to the other technical indicators, followed by the MACD as the second best indicator. Although the MACD at first glance in Table 4.18, Table 4.19, and Table 4.20 seems to achieve inferior results when compared to the individual and composite indicators, the fact that it objectively ranks second is not entirely unexpected. The reason is clear from Figure 4.2, where prices seem to be moving in a trending market environment more often than in a trading market environment. This is shown by the DMI value that moves above 25 for a greater part of the time frame in the analysis. Since the MACD is a lagging indicator, which is expected to be better suited to a trending market environment, it makes sense that it should in fact perform well.

Furthermore, Composite Indicator A1 and Composite Indicator A2 are deemed the third best and fourth best indicators, respectively. Composite Indicator B achieved the highest hedge level for the most number of seasons, the lowest average sell signals generated over the period, as well as the highest average hedge level as a percentage of the maximum price over the entire period. Conversely, in accordance with the initial comparison, the EMA proved to fall short of the other indicators, ranking last. These results are a significant validation of the use of the right type of indicator for the type of market, as well as for the development of a composite technical indicator in the South African white maize market in order to identify and realise higher hedging levels more accurately.

Chapter 5

Concluding Remarks and Recommendations

"If the facts don't fit the theory, change the facts."

~Albert Einstein (1879–1955)

5.1 Introduction

As one of the most volatile agricultural products traded on the South African Futures Exchange (SAFEX), the need to effectively and accurately manage price risk in the white maize market is highlighted. The researcher of this study attempted to address this challenge by making use of technical analysis as a determinant of accurate hedging opportunities. More specifically, this study's research primarily focused on the development of a practical and applicable composite technical indicator, compiled from several individual technical indicators, with the purpose of improving the timing aspect of price risk management decisions which may ultimately assist producers in realising more advantageous hedging levels. To ensure the accuracy and validity of the composite indicator, the following secondary objectives were also recognised. Firstly, in order to evaluate if the market is currently in a trending or trading phase, indicators which could distinguish between these two market types needed to be considered. Secondly, since individual technical indicators are used in the construction of the composite indicator, it is essential to determine and evaluate the most popular and basic technical indicators to use. Lastly, to determine the average hedge level of each individual indicator and to compare it to the composite indicators' achieved hedge level.

These objectives were address by means of a literature and empirical study. The following section (Section 5.2) provides a summary of the findings and empirical results of the study and how the abovementioned objectives were addressed throughout the study. Thereafter, Section 5.3 concludes this chapter with concluding remarks and recommendations of this study and further studies.

5.2 Findings

Chapter 2 commenced by providing a background of the South African agricultural market, with particular reference to the white maize market (Section 2.2). The white maize market necessitates price risk management to ensure a sustainable and profitable maize production, as the market is considered to be significantly volatile. The price volatility is mainly due to the inelasticity of the white maize price and market deregulation. Another drawback of market deregulation was producers' lack of knowledge and understanding of price risk management. These price risk management responsibilities are facilitated by SAFEX by means of providing producers with an exchange traded platform, namely the derivatives market.

The derivatives market is focused primarily on providing an effective marketing mechanism, which ensures transparent price determination. However, to establish transparent price formulation it is essential that the market is considered efficient. Although, the efficiency of the South African white maize market (Section 2.4.3) is still being questioned by some producers, even if conclusive evidence[97] exists that the market is weak form efficient. This implies that prices do not always reflect all possible information and may be slow to adjust to new information entering the market, allowing market participants to apply a hedging strategy more effectively by inter alia making use of technical analysis.

Consequently, Chapter 3 elaborated on implementing technical analysis as an analysis technique to aid in price risk management decisions. Firstly, technical analysis relies on three fundamental assumptions, including the market discounts everything, history repeats itself and trends exist (Section 3.3). The last mentioned assumption forms one of the main focus points of this study, since determining the current direction of these trends are complicated by market prices moving either sideways (trading market) or upwards or downwards (trending market). Several statistical methods to determine the primary tendency of market prices exist, where the researcher of this study examined the functioning of the Aroon (Section 3.4.1),

[97] See studies conducted by McCullough (2010:131), Moholwa (2005:21), Scheepers (2005:61), Viljoen (2003:206) and Wiseman *et al.* (1999:332-333).

Directional Movement Index (DMI) (Section 3.4.2) and the Chande Momentum Oscillator (CMO) (Section 3.4.3).

The accuracy and applicability of the different individual indicators, which are classified as leading and lagging indicators, accentuates the importance of determining the primary tendency of the prices in the market at a specific time. The proposed approach is to apply leading indicators in a trading market and lagging indicators in a trending market. The indicators examined in Chapter 3 include the Relative Strength Index (Section 3.5.1.1), the Stochastic oscillator (Section 3.5.1.2) and the Commodity Channel Index (Section 3.5.1.3) as leading indicators. Also, the lagging indicators examined included the Moving Averages (Section 3.5.2.1), Bollinger bands (Section **Error! Reference source not found.**), and the Moving verage Convergence Divergence (Section 3.5.2.3). Given the accuracy and simplicity of interpreting the indicator's calculated value, this study made use of the DMI to determine the primary tendency of the white maize market (Section 4.3.1). Results showed that prices varied between a trending and trading market as illustrated by Figure 4.2. This highlighted the need to take both types of markets into account when making use of technical analysis in an attempt to improve hedging levels.

To further ensure the accuracy of these indicators in assisting a producer in the hedging decision–making process, it is essential that the correct combination of technical indicators is applied in the specified type of market. Applying these indicators in the wrong type of market may lead to false signals generated, which in turn can ultimately result in a significantly low hedging level or even losses. This was confirmed in Chapter 4, where the individual indicators generated a significantly high number of selling signals, which also varied considerably, as well as demonstrating inconsistencies in the average hedge levels achieved each season. This may have been due to the implementation of wrong indicators in the market, leading to false selling signals being generated.

Consequently, Chapter 4 attempted to diminish this constraint by constructing a composite indicator (Composite Indicator A1) that includes both leading and lagging indicators which may assist in generating more accurate sell signals and ultimately increase the average hedge level (Section 4.3.3). Even though the results of Composite Indicator A1 (Section 4.3.3.2) seemed to surpass the individual indicators, the findings were still not the most desirable. The amount of sell signals generated was still high and varied significantly. Also, the hedge levels achieved were inconsistent throughout seasons. These findings may be due to the inconsistency in the calculation of the RSI, given that the EMA and MACD's calculations were made on the Stochastic oscillator's formula in order to obtain a value between 0 and 100 for these indicators.

In an attempt to improve the results obtained by Composite Indicator A1, Composite Indicator A2 (Section 4.3.3.4) was constructed by applying the Stochastic oscillator's formula to the RSI. However, the results proved to be inferior to Composite Indicator A1. This may have been as a result of the change in the statistical characteristics of the indicators when applying the Stochastic oscillator's formula to the indicators calculations.

This led to the construction of Composite Indicator B (Section 4.3.3.6) in an attempt to identify selling signals without changing the statistical properties of the individual indicators. The results of Composite Indicator B seemed to surpass the other indicators. However, the comparison made between the indicators was indefinite and allowed for subjective judgment. Therefore, a more exact and objective comparison was implemented in the study by means of assigning rankings to each indicators based on several criteria (Section 4.3.3.7).

From the comparison it was evident that Composite Indicator B prevailed above the other indicators. Composite Indicator B managed to achieve the highest hedge level for the most number of seasons; the lowest average sell signals generated over the entire period; as well as the highest average hedge level as a percentage of the maximum price over the entire period. Furthermore, the MACD, Composite Indicator A1 and Composite Indicator A2 followed Composite Indicator B respectively. These results validates the use of a composite technical indicator in the South African white maize market to identify and realise higher hedging levels more accurately.

5.3 Concluding statement and recommendations

Price risk in the white maize market has shown to be significantly higher compared to any other agricultural commodity traded in South Africa. To ensure profitable and sustainable maize production, producers are necessitated to manage price risk. So as to more accurately manage this price risk, the researcher provides a practical and applicable method in this study to ensure that maize producers can identify accurate sell signals with ease and confidence. The development of this composite indicator method may improve a maize producer's willingness to adopt price risk management instruments which may ultimately result in more advantageous hedging levels achieved by producers.

Additionally, several recommendations may improve the results obtained from this study. Firstly, the researcher of this study only made use of the default periods used in the calculations of the technical indicators. Other time periods may prove to be more optimal, which may further enhance the accuracy and applicability of the composite indicator. Different time periods may, more specifically, enhance the accuracy and applicability of trend identifying indicators and/or lagging indicators by decreasing the lag effect of some of these indicators in identifying trend reversals or sell signals, respectively. Secondly, the results of this study showed no significance in the adjustment of the weights assigned to the individual indicators in the construction of the composite indicator. It may be valuable to examine the underlying reason for the weights' insignificant role in the construction of the composite indicator. Possible reasons for the insignificance of the weights include the large amount of technical indicators used in the composite indicators, and the large number of ranges defined in the DMI. Thirdly, it may be valuable to examine the performance of the best performing individual indicators as another composite indicator, as better result than the given composite indicators may arise.

Testing the validity of a composite indicator in agricultural markets other than the white maize market will be an interesting future study. Furthermore, these tests can be expanded to test the validity of a composite indicator in other asset classes, including foreign exchange, equities, shares and assets, among others. The composite indicator can also be expanded and adjusted to generate buy signals as well. This may improve the applicability of the composite indicator to be implemented by several market participants, and not only producers.

Appendix

Table A.1: SAFEX contract specification: White maize

Specifications	
Code	WMAZ/YMAZ
Underlying Commodity	“Maize” means white/yellow maize from any origin, of the grade “WM1” (“YM1”) 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.
Trading Hours	09:00–12:00.
Contract Size	100 metric tonnes.
Contract Months	March, May, July, September, and December.
	All other calendar months are introduced 40 business days preceding the new month. Once the month is introduced it is traded in the same fashion as the five hedging months.
Expiration Date and Time	12:00 on the sixth last business day of the listed expiry month. Physical deliveries 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/tonne.
Minimum Price Movements	Twenty cents per tonne.
Initial Margin	R12 500/contract up to first notice day.
	At extended price limits, requirements increased to R25 000/contract.
	R25 000/contract up to expiry day.
	R30 000/contract up to last delivery day.
	R4 000/contract for calendar spreads.
	R6 000/contract for white spreads.
Expiry Valuation Method	Closing futures price as determined by the clearing house.
Booking Fees Charges	Futures: R13.00/contract (incl. VAT).
	Options: R6.50/contract (incl. VAT).
	Physical delivery: R200.00/contract (incl. VAT).
Maximum Daily Price Movement	R80/tonne (R120/tonne at extended limits).
Maximum Position limits	Position limits apply to White maize as per Derivative Directives.

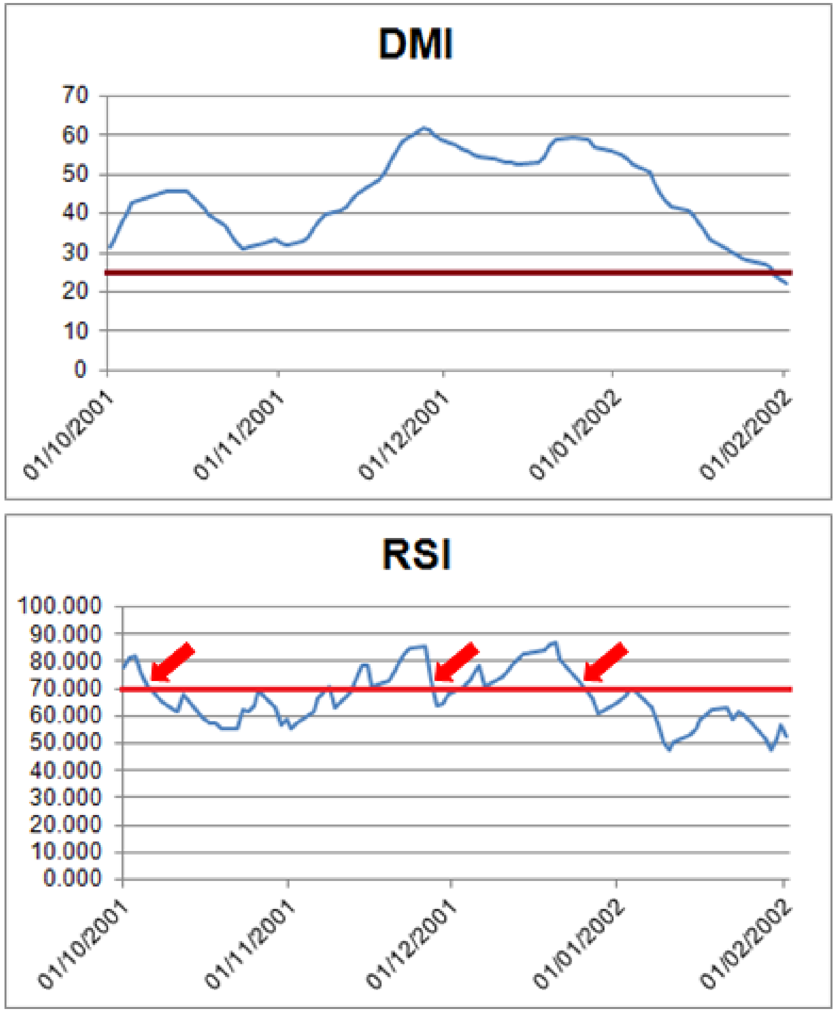
Source: JSE (2013a:9–10); JSE (2013d:1-4); JSE (2014:1).

Table A.2: Market anomalies

Anomaly	Description
Day–of–the–Week Effect	Monday returns significantly lower than returns observed the rest of the week, with Fridays returns usually the highest. Also known as the weekend effect.
Holiday Effect	Returns are affected by public holidays.
Turn–of–the–Month Effect	Returns in the beginning of the month are higher than at the end of the previous month.
Time–of–the–Year effect	Returns are higher during certain months of the year compared to other months.
January Effect	Small caps' stocks outperform large caps during the first few weeks in January. Related to the size effect.
Maturity Effect	Volatility of a futures contract increases as the contract nears maturity.
Size Effect	Small caps tend to outperform large caps; that is small caps' returns tend to be higher than large caps' returns.

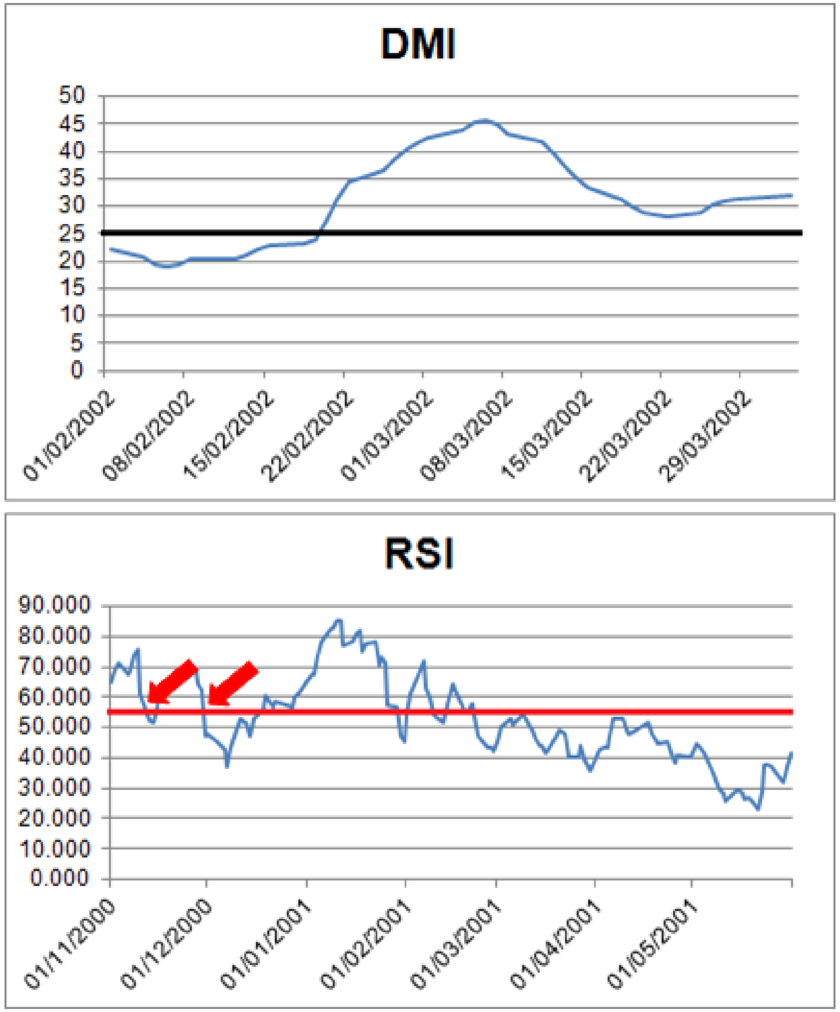
Source: Compiled by author; Latif *et al*. (2011:3–8); Milonas (1986:443); Thaler (1987:173); Viljoen (2003:116–124).

Figure A.1: RSI sell signals in a trending market



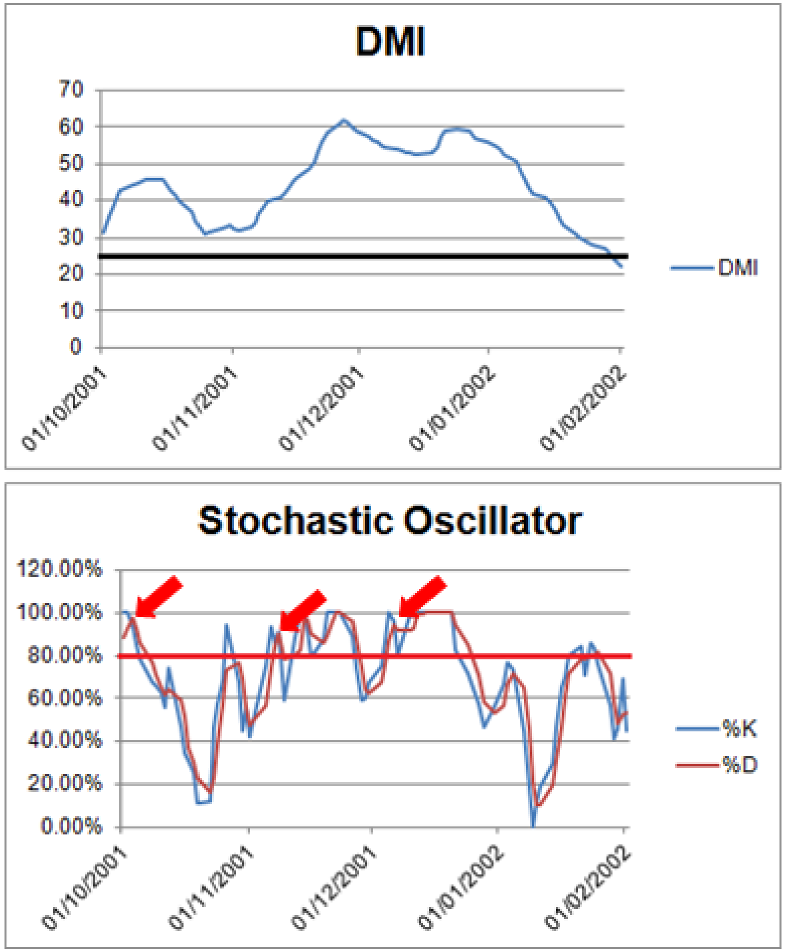
Source: Compiled by author

Figure A.2: RSI sell signals in a trading market



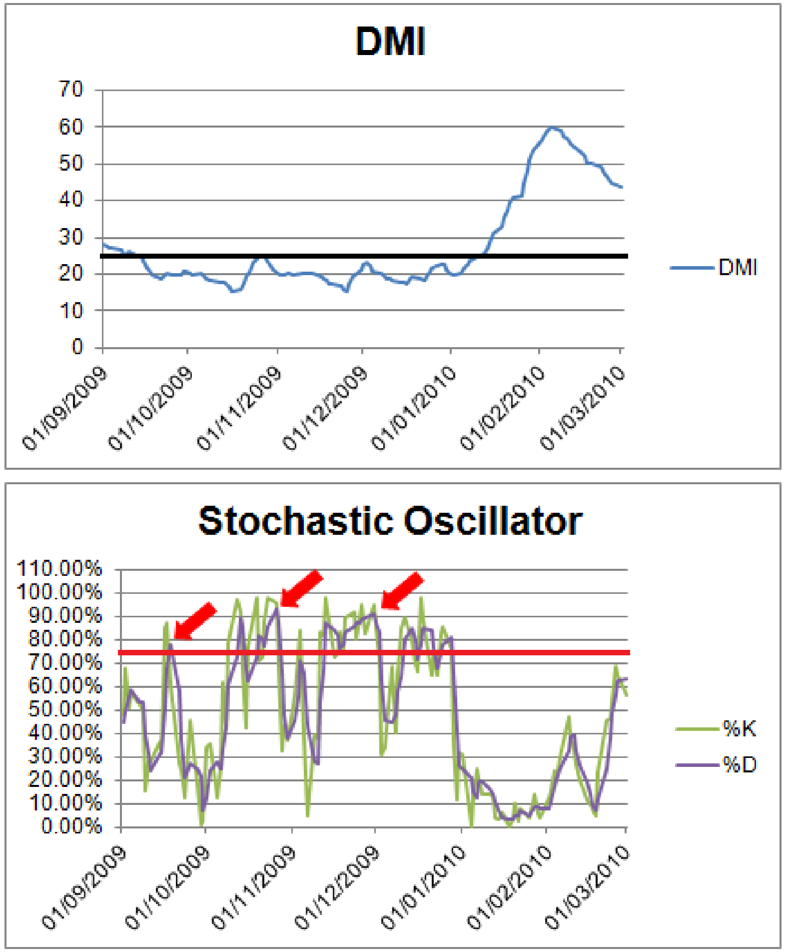
Source: Compiled by the author.

Figure A.3: Stochastic oscillator sell signals in a trending market



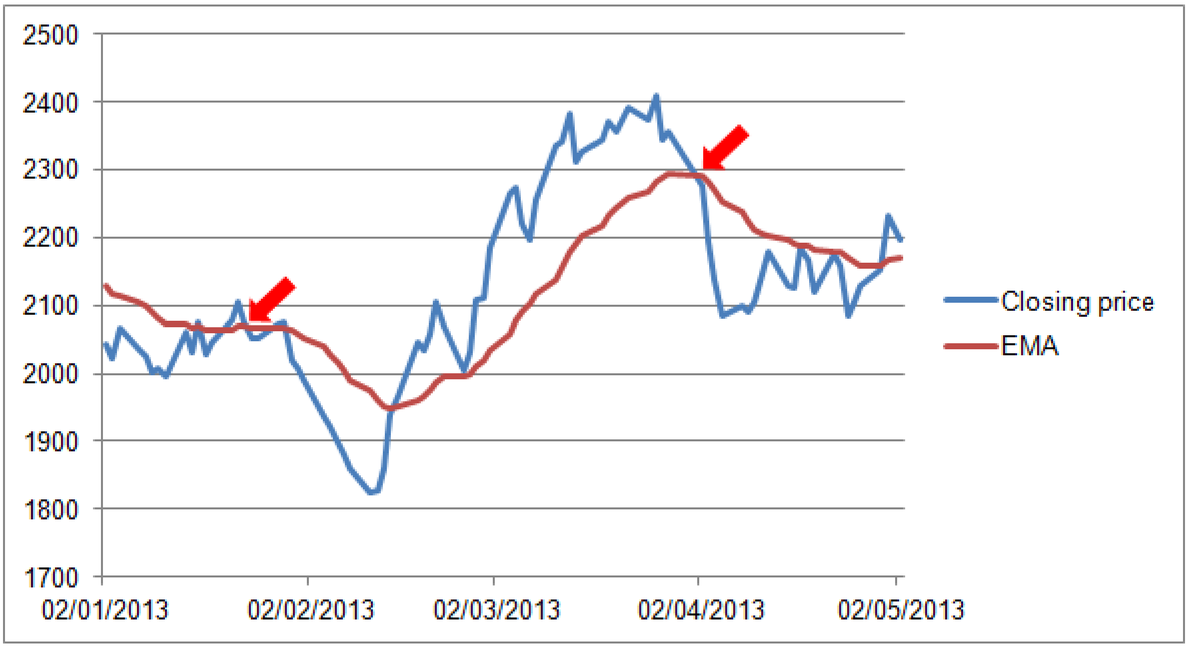
Source: Compiled by the author.

Figure A.4: Stochastic oscillator sell signals in a trading market



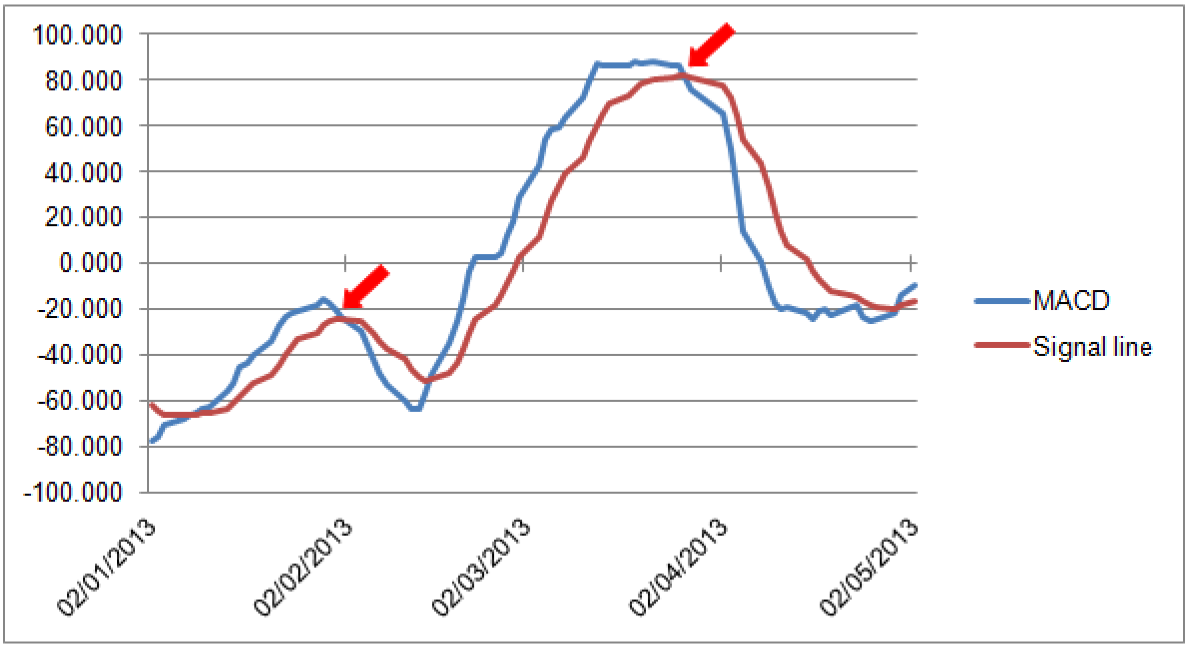
Source: Compiled by the author.

Figure A.5: EMA sell signals



Source: Compiled by the author.

Figure A.6: MACD sell signal



Source: Compiled by the author.

Proof of language editing

Acknowledgement of Language Review and Reference Editing

Date: 27 November 2013

To whom it may concern

This serves to confirm that I performed the tasks of **language review and reference editing** for **Susari Geldenhuys** on her dissertation, entitled: **Timing a hedge decision: The development of a composite technical indicator for white maize** for submission **November 2013**. A final document with comments for correction before submission was provided by me to **Ms Geldenhuys on 25 November 2013.**

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References

Achelis, S.B. 2001. Technical analysis from A to Z. 2nd ed. New York: McGraw–Hill.

Alexander, P. 1997. Beginners guide to computer assisted trading; how to successfully trade stocks, commodities, and funds with your PC. Greenville: Traders Press.

Appel, G. 2005. Technical Analysis: Power Tools for Active Investors. Upper Saddle River: Financial Times Prentice Hall.

Armah, P. & Shanmugam, V.P. 2013. Price Hikes in US Agricultural Commodity Futures Markets: An Empirical Efficiency Test. *Journal of food distribution research*, 44(1):66–74.

Asteriou, D. & Hal, S.G. 2011. Applied Econometrics: A Modern Approach Using Eviews and Microfit. England: Palgrave Macmillan.

Aulton, A.J., Ennew, C.T. & Rayner, A.J. 1997. Efficiency Tests of Futures Markets for UK Agricultural Commodities. *Journal of agricultural economics*, 48(3):408–424.

Beck, S.E. 1994. Cointegration and Market Efficiency in Commodity Futures Markets. *Applied economics*, 26(3):249–257.

Bernstein, J. 2000. How the futures market work. 2nd ed. New Jersey: Prentice Hall.

BFAP (Bureau for Food and Agricultural Policy). 2012. BFAP Baseline: Agricultural Outlook 2012 – 2021.

Bollinger, J. 1983. Bollinger on Bollinger bands. New York: McGraw-Hill.

Bown, A.N., Ortmann, G.F. & Darroch, M.A.G. 1999. Use of maize marketing alternatives and price risk management tools by commercial maize farmers in South

Africa. / Gebruik van mieliebemarkingsalternatiewe en prysrisikobestuursmiddel deur mielieboere in Suid–Afrika. *Agricultural economics research, policy and practice in Southern Africa,* 38(3):275–301.

Brown, K.C. & Reilly, F.K. 2009. Analysis of Investments and Management of Portfolios. 9th ed. Canada: South–Western, Cengage Learning.

Cass, L. 2009. Maize Marketing Strategies: The Trade–Off between Risk and Profit for a Mpumalanga Maize Farm. Pretoria: University of Pretoria. (Thesis – MAgric).

Chabane, N. 2002. An Evaluation of the Influences on Price and Production in the Maize Market following Liberalisation. Paper presented at the TIPS Forum 2002: Global Integration; Sustainable Development and The Southern African Economy, Johannesburg, RSA, 1 January. http://www.tips.org.za/files/566.pdf Date of access: 15 March 2013.

Chande, T.S. 1994. The New Technical Trader: Boost Your Profit by Plugging into the Latest Indicators. New York: John Wiley and Sons, Inc.

Chande, T.S. 1995. The Time Price Oscillator. *Technical analysis of stocks and commodities,* 13(9):369–374.

Chande, T.S. & Kroll, S. 1994. The New Technical Trader: Boost Your Profit by Plugging Into the Latest Indicators. New York: John Wiley & Sons, Inc.

Chicago Mercantile Exchange (CME). 2013. Products/First Day of Trading. http://www.cmegroup.com/company/history/cmegroupinformation.html Date of access:13 May 2013.

Colby, R.W. 2003. The Encyclopedia of Technical Market Indicators. 2nd ed. New York: McGraw–Hill.

Coopers & Lybrand. 1995. The financial jungle – a guide to financial instruments. 2nd ed. London: BPC Wheatons Ltd.

Credit Suisse. 2012. Technical Analysis Explained. https://www.credit–suisse.com/legal/pb_research/technical_tutorial_en.pdf Date of access: 5 May 2013.

Department of Agriculture, Forestry and Fisheries see South Africa. Department of Agriculture, Forestry and Fisheries.

De Swardt, S.J.J. 1983. Agricultural Marketing Problems in the Nineteen Thirties. *The South African journal of economics,* 51(1):1–28.

Dictionary.com Unabridged. 2013. Psychology. http://dictionary.refernece.com/browse/psychology Date of access: 5 May 2013.

Dorfman, J. H. & Karali, B. 2008. Do maize producers hedge optimally or by habit? A Bayesian partial–adjustment model of maize producer hedging. Proceedings of the NCCC–134 conference on applied commodity price analysis, forecasting, and market risk management, St. Louis, MO, 21–22 April 2008. http://www.farmdoc.uiuc.edu/nccc134 Date of access: 16 April 2013.

Fama, E.F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *Journal of finance*, 25(2):383–417.

Fedderke, J. & Joao, M. 2001. Arbitrage, Cointegration and Efficiency in Financial Markets in the Presence of Financial Crises. *The South African journal of economics*, 69(3):366–384.

Frankfurter, G.M. 2007. Market Efficiency cum Anomalies, or Behavioural Finance? Homo oeconomicus, 24(1):81–93.

Geyser, J.M. 2013. Short and Long of Futures Markets: SAFEX, Grain Hedging, Speculation. Noordheuwel, Krugersdorp: Kejafa Knowledge Works.

Geyser, M. & Cutts, M. 2007. SAFEX maize price volatility scrutinised. *Agricultural economics research, policy and practice in Southern Africa*, 46(3):291–305.

Goodwin, B.K. & Schroeder, T.C. 1994. Human Capital, Producer Education Programs, and adoption of Forward Pricing Methods. *American journal of agricultural economics*, 76(4):936–947.

Groenewald, J.A. 2000. The Agricultural Marketing Act: A Post–Mortem. *The South African journal of economics*, 68(3):364–402.

Groenewald, J.A., Gudeta, A.Z., Fraser, G., Jari, B., Jooste, A., Jordaan, A., Kambewa, E.V., Klopper, J., Magingxa, L., Obi, A., Pote, P.P.T., Stroebel, L., van Tilburg, A. & van Schalkwyk, H.D. 2003. Agricultural Marketing in the New Millennium. First National Bank.

Gultekin, M.N. & Gultekin, N.B. 1983. Stock market seasonality: International Evidence. *Journal of financial economics*, 12(4):469–481.

Hasbrouck, J. 1995. One Security, Many Markets: Determining the Contributions to Price Discovery. *Journal of finance*, 50(4):1175–1199.

Hull, J.C. 2012. Options, Futures and Other Derivatives: Global Edition. 8th ed. Boston: Pearson Education, Inc.

Jecheche, P. 2011. Basics of futures and forward contracts discussed from a risk management perspective. *Journal of comprehensive research*, 9:1–19.

Jordaan, H. & Grové, B. 2007. Factors affecting maize producers adoption of forward pricing in price risk management: The case of Vaalharts. *Agricultural economics research, policy and practice in Southern Africa*, 46(4):548–565.

Jordaan, H., Grové, B., Jooste, A. & Jooste, Z.G. 2007. Measuring the price volatility of certain field crops in South Africa using the ARCH/GARCH approach. *Agricultural economics research, policy and practice in Southern Africa*, 46(3):306–322.

JSE (Johannesburg Stock Exchange). 2005. Agricultural Derivatives celebrates 10 years of providing price risk management! http://www.jse.co.za/Libraries/SAFEX_AP_–_About_Safex_APD_–_Recap_of_the_last_10_years/Ten_years_later_APD.sflb.ashx Date of access: 8 October 2013

JSE (Johannesburg Stock Exchange). 2010. Commodities derivative market dealer examination material. Johannesburg: South African Institute of Financial Markets.

JSE (Johannesburg Stock Exchange). 2013a. Exchange traded agricultural derivatives in South Africa. http://www.jse.co.za/libraries/brochures/agricultural_commodities.sflb.ashx Date of access: 18 March 2013.

JSE (Johannesburg Stock Exchange). 2013b. Monthly Volumes. http://www.jse.co.za/Markets/Commodity–Derivatives–Market/Commodity–Derivatives–Market–data–and–price–info.aspx#volumes Date of access: 26 May 2013.

JSE (Johannesburg Stock Exchange). 2013c. Commodity Derivatives market history. http://www.jse.co.za/Markets/Commodity–Derivatives–Market/Commodity–Derivatives–market–history.aspx Date of access: 28 May 2013.

JSE (Johannesburg Stock Exchange). 2013d. Grain Contract Specifications. http://www.jse.co.za/Products/Commodity–Derivatives–Market/Commodity–Derivatives–Market–Product–Detail/Grain_Futures_Options.aspx Date of access: 08 April 2014.

JSE (Johannesburg Stock Exchange). 2014. Initial Margin Requirements – Grain Futures. http://www.jse.co.za/Markets/Commodity–Derivatives–Market/Initial–Margin–Requirements.aspx Date of access: 08 April 2014.

Keim, D.B. 2006. Financial Market Anomalies. http://finance.wharton.upenn.edu/~keim/research/NewPalgraveAnomalies(May302006).pdf Date of access: 11 April 2013.

Kleinman, G. 2001. Commodity futures and options: A step–by–step guide to successful trading. London: Prentice Hall.

Krugel, L.J. 2003. White maize futures contracts in South Africa. Potchefstroom: Potchefstroom University for Christian Higher Education. (Dissertation – MCom).

Lambert, D.R. 1982. Commodities Channel Index: Tools for Trading Cyclical Trends. *Technical analysis of stocks and commodities,* 1(5):120–122.

Larson, D.F., Anderson, J.R. & Varangis, P. 2004. Policies on Managing Risk in Agricultural Markets. The World Bank research observer, 19(2):199–230.

Latif, M., Arshad, S., Fatima, M. & Farooq, S. 2011. Market Efficiency, Market Anomalies, Causes, Evidences, and Some Behavioral Aspects of Market Anomalies. *Research journal of finance and accounting,* 2(9/10):1–13.

Leng, H.M.J. 2002. The South African share index futures and share markets: efficiency and causality revisited. *Journal for studies in economics and econometrics,* 26(3):1–18.

Mahalik, M.K., Acharya, D. & Babu, M.S. 2009. Price Discovery and Volatility Spillovers in Futures and Spot Commodity Markets: Some Empirical Evidence from India. Paper Presented to Fourth Annual International Conference on Public Policy and

Management: Quantitative Approaches to Public Policy. August 9–12. http://www.igidr.ac.in/pdf/publication/PP–062–10.pdf Date of access: 26 May 2013.

Marshall, J.F. 1989. Futures and Option Contracting Theory and Practice. Cincinnati: South–Western Publishing Co.

Marx, J., Mpofu, R.T., De Beer, J.S., Nortjé, A. & Van De Venter, T.W.G. 2010. Investment Management. 1st ed. Hatfield, Pretoria: Van Schaik Publishers.

McCullough, K. 2010. Testing the Efficiency of the South African Futures Market for White maize: 1996–2009. Kwazulu–Natal: University of Kwazulu–Natal. (Dissertation – MCom).

McFall Lamm, R. 2003. Asymmetric returns and optimal hedge fund portfolios. *Journal of alternative investments*, 6(2):9–21.

McKenzie, A.M. & Holt, M.T. 2002. Market Efficiency in Agricultural Futures Markets. *Applied economics,* 34(12):1519–1532.

Meyers, T.A. 1994. The Technical Analysis Course: A Winning Program for Investors and Traders. 2nd ed. New York: McGraw–Hill

Milonas, N.T. 1986. Price variability and the maturity effect in futures markets. *Journal of futures markets*, 6(3):443–460.

Moholwa, M.B. 2005. Testing for Weak–Form Efficiency in the South African Futures Market for White and Yellow Maize. Michigan: Michigan State University. (Dissertation – MSc).

Monk, M.J., Jordaan, H. & Grové, B. 2010. Factors affecting the price volatility of July futures contracts for white maize in South Africa. *Agricultural economics research, policy and practice in Southern Africa*, 49(4):446–458.

Murphy, J.J. 1986. Technical Analysis of the Futures Markets: A Comprehensive Guide to Trading Methods and Applications. New York: New York Institute of Finance.

Murphy, J.J. 1996. The Visual Investor: How to Spot Market Trends. New York: John Wiley & Sons, Inc.

Nikolova, A. 2003. Testing the Efficiency of the South African Futures Market for White maize from 1997–2002. Kwazulu–Natal: University of Natal (Dissertation – Bcom).

Pennings, J.M.E & Meulenberg, M.T.G. 1997. The Hedging Performance in New Agricultural Futures Markets: A Note. *Agribusiness*, 13(3):295–300.

Phukubje, M.P. & Moholwa, M.B. 2006. Testing for Weak–Form Efficiency in South African Futures Markets for Wheat and Sunflower Seeds. Agricultural economics research, policy and practice in Southern Africa, 45(2):198–213.

QMS (Quantitative Micro Software). 2007. Eviews user guide 1.

Reuters. 1999. An Introduction to Technical Analysis. Asia: John Wiley & Sons Pte Ltd.

Roehner, B.M. 2002. Patterns in Speculation. Cambridge: Cambridge University Press.

Roffey, C. 2008. Essential Decisions for Investors, Traders, Analysts and Portfolio Managers in Shares, Forex, Indexes and Metals. South Africa: Kethern Investments.

Rogalski, R. 1984. New Findings Regarding Day–of–the–Week Returns over Trading and Non–Trading Periods: A Note. *Journal of finance*, 34(5):1603–1614.

Santos, J.M. 2009. Grain Futures Markets: What Have They Learned?. Proceedings of the NCCC–134 Conference on Applied Commodity Price Analysis, Forecasting, and

Market Risk Management. St. Louis, MO. http://ageconsearch.umn.edu/bitstream/53040/2/confp06-09.pdf Date of access: 27 June 2013.

Samuelson, P. 1965. Proof that properly anticipated prices fluctuate randomly. *Industrial management review*, 6(1):41–49.

Scheepers, D. 2006. Applications and portfolio theory in the South African agricultural derivatives market. Pretoria: University of Pretoria. (Dissertation – MSc).

South Africa. 2013. http://www.info.gov.za/aboutsa/holidays.htm Date of access: 30 June 2013.

South Africa. Department of Agriculture, Forestry and Fisheries. 2012. http://www.nda.agric.za/docs/stratplan2012/201213–201617.pdf Date of access: 13 May 2013.

Srinivasan, P. & Bhat, K.S. 2009. Spot and Futures Markets of Selected Commercial Banks in India: What Causes What? *International research journal of finance and economics*, 31(1):28–40.

Stockil, R.C. & Ortmann, G.F. 1997. Perceptions of risk among commercial farmers in Kwazulu–Natal in a changing economic environment. *Agricultural economics research, policy and practice in Southern Africa*, 36(2):139–156.

Teweles, R.J. & Jones, F.J. 1974. The Futures Game. 1st ed. New York: McGraw–Hill Book Company.

Thaler, R. 1987. Anomalies: Seasonal Movements in Security Prices II: Weekend, Holiday, Turn of the Month, and Intraday Effects. *The Journal of economic perspectives,* 1(2):169–177.

Ueckermann, E.M., Blignaut, J.N., Gupta, R. & Raubenheimer, J. 2008. Modelling South African grain maize producers' preferences to adopt derivative contracts using discrete choice models. *Agricultural economics research, policy and practice in Southern Africa,* 47(2):222–239.

Van Der Wath, N. 2011. Tools for analysing the SA maize market. Paper presented at the Biennial Conference of the Economics Society of South Africa, Stelenbosch, RSA, 5–7 September. www.essa2011.org.za/fullpaper/essa2011_2260.pdf Date of access: 15 March 2013.

Van Zyl, J. 1986. ’n Statistiese ontleding van die vraag na mielies in Suid–Afrika. *Agricultural economics research, policy and practice in Southern Africa*, 25(3):49–55.

Viljoen, C. 2003. Price Discovery, Price Behaviour, and Efficiency of Selected Grain Commodities Traded on the JSE Securities Exchange. Grahamstown: Rhodes University. (Thesis – Phd).

Vink, N. 2012. The long–term economic consequences of agricultural marketing legislation in South Africa. *South African Journal of Economics*, 80(4):553–566.

Wang, H.H. & Ke, B. 2002. Efficiency Tests of Agricultural Commodity Futures Markets in China. *Australian journal of agricultural and resource economics*, 49(2):125–141.

Whistler, M. 2004. Trading pairs: Capturing profits and hedging risk with statistical arbitrage strategies. Hoboken, NJ: John Wiley & Sons.

Wilder, J.W. 1978. New Concepts in Technical Trading Systems. Greensboro, NC: Trend Research.

Wiseman, J.A., Darroch, M.A.G. & Ortmann, G.F. 1999. Testing the efficiency of the South African futures market for white maize / Toetsing van die doeltreffendheid van die

Suid–Afrikaanse termynkontrakmark vir witmielies. *Agricultural economics research, policy and practice in Southern Africa*, 38(3):321–335.

Wouters, T.I.M. 2006. Style Investing: Behavioral Explanations of Stock Market Anomalies. Groningen: Rijksuniversiteit Groningen. (Thesis – Phd).

Yang, J. & Leatham, D.J. 1998. Market Efficiency of US Grain Markets: Application of Cointegration Tests. *Agribusiness*, 14(2):107–112.

List of Acronyms

ADX	**Average Directional Movement**
AMD	**Agricultural Markets Division**
APD	**Agricultural Products Division**
ASX	**Australian Securities Exchange**
CBOT	**Chicago Board of Trade**
CCI	**Commodity Channel Index**
CME	**Chicago Mercantile Exchange**
CMO	**Chande Momentum Oscillator**
DI	**Directional Movement**
DMI	**Directional Movement Index**
ECM	**Error Correction Model**
EMA	**Exponential Moving Average**
EMH	**Efficient Market Hypothesis**
JSE	**Johannesburg Stock Exchange**
KCBT	**Kansas City Board of Trade**
LIFFE	**London International Financial Futures Exchange**
MA	**Moving Average**
MACD	**Moving Average Convergence/Divergence**
MGEX	**Minneapolis Grain Exchange**

RSI	**Relative Strength Index**
SAFEX	**South African Futures Exchange**
SMA	**Simple Moving Average**
TR	**True Range**
VECM	**Vector Error Correction Model**