The effect of Chicago Board of Trade prices and fundamental factors on South African yellow maize prices

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DEDICATION

To my beloved parents,

Andries and Santie Martinson.

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ABSTRACT

Maize traders on the South African Futures Exchange (SAFEX) strive to determine future price movements by tracking the following influential price indicators: domestic fundamental factors, the USA yellow maize prices, and the ZAR/USD exchange rate. This study investigates whether there were certain periods where the CBOT yellow maize prices influenced the SAFEX yellow maize prices more than in other periods, as well as whether fundamental factors can be used as a price indicator in the periods where CBOT had a less significant effect on the SAFEX prices. Therefore, this study examined the approach of determining the future price movements of yellow maize prices in South Africa by establishing the volatility spill-over effect between the two markets in two seasonal regimes and comparing the results.

After an extensive empirical study and a supporting literature overview of the fundamental factors that influence the South African and USA maize markets, the volatility spill-over effect between SAFEX and CBOT was determined. This led the study to conclude the following: There are certain periods where the CBOT yellow maize prices influenced the SAFEX yellow maize prices more than in other periods. Consequently, in the periods where CBOT did have a less significant influence on the SAFEX prices, fundamental factors could be used as an alternative price indicator. Traders on the SAFEX market can therefore use the CBOT yellow maize prices as a reliable price indicator in the South African harvesting season; whereas, in the planting season, the CBOT prices in collaboration with fundamental analysis should be used.

<u>*Keywords:*</u> *Yellow maize, SAFEX, CBOT, Markov switching auto-regressive model, co-movement, Pearson correlation coefficient, covariance coefficient, Granger causality test, Sims causality test, Johansen cointegration, VEC model, stationary data.*

OPSOMMING

Mieliehandelaars op die Suid-Afrikaanse Effektebeurs (SAFEX) streef daarna om toekomstige prysbewegings te bepaal deur na die volgende invloedryke prys-aanwysers te kyk: binnelandse fundamentele faktore, die VSA-geelmieliepryse, en die ZAR/VSD-wisselkoers. Hierdie studie ondersoek die waarskynlikheid van periodes waar die CBOT-geelmieliepryse ’n groter invloed op SAFEX-geelmieliepryse sal hê, asook die waarskynlikheid dat fundamentele faktore gebruik kan word as prys-indikators in die periodes waar CBOT-geelmieliepryse ’n mindere invloed het. Die studie sal daarom ’n benadering bepaal wat deur mieliehandelaars gebruik kan word om toekomstige prysbewegings van geelmieliepryse in Suid-Afrika te bepaal. Die studie het ondersoek ingestel na hoe om toekomstige geelmieliepryse (van Suid-Afrika) te bepaal wanneer handel gedryf word, deur die wisselvalligheid-oorspoel-effek tussen die twee markte in twee seisoene te vergelyk.

Na ’n omvattende empiriese studie en ’n ondersteunende literatuuroorsig van die fundamentele faktore wat ’n invloed op die Suid-Afrikaanse en die VSA-mieliemarkte het, is die wisselvalligheid-oorspoel-effek tussen SAFEX en CBOT bepaal. Dit het die studie gelei tot die volgende gevolgtrekking: Daar is sekere periodes waar SAFEX-geelmieliepryse grootliks deur die CBOT-pryse beïnvloed word, en ander periodes waar die CBOT-geelmieliepryse ’n mindere effek het. Gevolglik, in die periodes waar die CBOT-geelmieliepryse die SAFEX-geelmieliepryse minder beïnvloed, kan die fundamentele faktore as ’n alternatiewe prys-indikator gebruik word. Mieliehandelaars in die SAFEX-mark kan daarom die CBOT-geelmieliepryse as ’n betroubare prys-indikator in die Suid-Afrikaanse oes-seisoen gebruik, maar in die plantseisoen kan die CBOT-geelmieliepryse in samewerking met die fundamentele faktore as prys-indikator gebruik word.

Sleutelwoorde: *Geelmielies, SAFEX, CBOT, Markov skakel outoregressiewe model, samebeweging, Pearson korrelasiekoëffisiënt, kovariansie-koëffisiënt, Granger kousaliteit-toets, Sims kousaliteit-toets, Johansen koïntegrasie, Vektor-foutaanpassingsmodel, stasionêre data.*

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CHAPTER 1

Introduction

"A man should look for what is, and not for what he thinks should be"

(Albert Einstein)

1.1 INTRODUCTION

In 1996, the Marketing of Agricultural Products Act was passed, which paved the way for grain producers and traders (market participants) to trade in a free market environment. The free market environment implies that market participants can respond to supply and demand forces when trading grain (Department of Agriculture, Forestry and Fisheries, 2003:124). In a free market environment, producers compete with each other and with foreign producers in order to maximise their own profits. As a result, individual producers have no alternative but to take the best price possible, be it the local price or the international price (Department of Agriculture, Forestry and Fisheries, 2003:124).

This interactive relationship between the local price and international price is referred to as the import/export parity and the method used to calculate the prices at which producers can sell their product locally or internationally is known as an import/export parity calculation. For instance, if grain millers can buy imported maize (including costs such as transport, insurance, and the exchange rate) cheaper than locally-produced maize, they will do so until local producers are able to supply maize at the same price or cheaper. This is called the import parity price. The opposite is also true, where South African maize producers will sell their maize to foreign millers at a better price than local millers are prepared to pay. This is known as the export parity price (Department of Agriculture, Forestry and Fisheries, 2003:125). Consequently, it is highly unlikely that the price of maize on the domestic market will go higher than the import parity price, as millers will then merely increase imports, which implies that the import parity price is regarded as the maximum price. In the same manner, the export parity price is regarded as the lowest/minimum price. The domestic price of maize will usually fluctuate between export and import parity prices. Whether the domestic price of maize goes up to the maximum level of the import parity price depends on the relative scarcity of maize in the domestic market. If there is a domestic shortage caused, for instance, by drought, the grain prices will move to import parity, but if there is an excess of produce, the supply prices will decrease to the export parity price level (Department of Agriculture, Forestry and Fisheries, 2003:125).

It is clear from the discussion above that in the free market environments there is active interaction between the domestic and international grain prices. This is also illustrated by the market relationship between the South African and USA yellow maize markets, due to the fact that the yellow maize prices of a smaller producing country (South Africa) are highly affected by the prices in the larger producing country (the USA) (Meyer *et al.,* 2006:1). Consequently, the agricultural commodity prices in the smaller grain market (SAFEX) can be calculated as a function of the agricultural commodity prices in the dominant grain market (CBOT), the exchange rate and the transaction costs (Meyer *et al.,* 2006:1). As a result, the SAFEX yellow maize prices may be influenced by a volatility spill-over effect[2] between the CBOT and SAFEX yellow maize markets, which implies that SAFEX yellow maize prices may follow similar volatility patterns as the CBOT yellow maize prices (Meyer *et al.,* 2006:1). In determining the intensity of the volatility spill-over effect between the two markets, maize traders on SAFEX could make better trading decisions with regard to their analysis of price indicators. However, the intensity of the volatility spill-over effect between SAFEX and CBOT could differ during the planting and harvesting season, due to fundamental factors (internationally and domestically) that influence the supply and demand of maize differently in each season (Geyser & Cutts, 2007a:30).[3]

The influence of fundamental factors on the supply and demand of maize, and ultimately the volatility spill-over from one market to the other, is significantly seasonally related. The reason is

[2] Volatility spill-over effect refers to an event that causes volatility in one region, resulting in an interdependent reaction of volatility in another region (Gallo, 2007:2).

[3] See Section 2.4 and 2.5 for a discussion on USA and South African fundamental factors.

that in the planting season the maize consumption is greater than the maize stock levels; however, in the harvesting season, the situation changes and the maize stock levels become greater than the local consumption (Department of Agriculture and Land Reform, 2008:6). This cycle continues throughout each season in South Africa: From October to March, consumption is more than the maize stock levels, and from April to September, the opposite effect occurs. In the case of the USA, the growing season is from March to October, which indicates that the volatility of maize prices is at a high and from November to February the opposite effect occurs (Seeley, 2009:11).

For the purpose of this study, the focus will be on yellow maize[4] that is produced and traded in South Africa (SAFEX) and the USA (CBOT). In South Africa, maize is a very important agricultural commodity as it is the staple food of the mainstream of the South African residents. Yellow maize is primarily used for animal feed, whereas white maize is mainly used for human consumption (Department of Agriculture, Forestry and Fisheries, 2011a:1). During the 2011/2012 production season, the summer grain crops in South Africa were located mainly in the Free State (43%), North West (27%) and Mpumalanga (18%) provinces (Department of Agriculture, Forestry and Fisheries, 2011b:2). The final crop harvested for South African maize production during the 2011 season was 10,360 million tons (6,052 million tons of white maize and 4,308 million tons of yellow maize). The estimated area planted for summer rainfall maize during the 2012 season was 2,630 million ha (1,590 million ha for white maize and 1,040 million ha yellow maize), which equals a ratio of 60:40 (Department of Agriculture, Forestry and Fisheries, 2011b:1).[5] Both white and yellow maize are traded in the South African Futures Exchange (SAFEX, 2010c).[6]

In the United States of America (USA), yellow maize is more generally referred to as corn and is traded on the Chicago Board of Trade (CBOT).[7] More than 80% of the USA's yellow maize is

[4] The reason why yellow maize is the focus in this study is because the USA produces mainly yellow maize.
[5] These estimates were the latest result during the time of completion of this study.
[6] See section 2.3.4 for a discussion on the history of the South African Futures Exchange (SAFEX).
[7] See section 2.3.3 for a discussion on the history of the Chicago Board of Trade (CBOT).

produced in the Corn Belt States, with Iowa leading all states and Illinois ranking second. The Corn Belt also includes parts of Indiana, Minnesota, South Dakota, Nebraska, Kansas, Missouri and Ohio. The expected USA yellow maize production was estimated at 12,358 million bushels (313910,572 million tons)[8] for the 2011/2012 season (WAOB, 2012:12). The estimated area planted for maize was 91,9 million acres (37,2 million ha)[9] for the 2011/2012 season (WAOB, 2012:12). The world production in maize for 2012 was approximately 819,23 million tons and accumulated by the following figures: USA 332,55 million tons, China 163,97 million tons, European Union (EU) 56,95 million tons, Brazil 56,10 million tons, Mexico 20,37 million tons, Argentina 23,30 and South Africa 13,42 million tons (WAOB, 2012:22).[10]

1.2 PROBLEM STATEMENT

1.2.1 Motivation

There are periods where the CBOT and SAFEX maize prices have the same volatility movements and periods where they differ (Geyser & Cutts, 2007a:30). The period where the CBOT and SAFEX price volatility movements differ, could be due to fundamental factors that are regarded as a superior price indicator on SAFEX in the South African planting season.[11] In addition, during the periods where the CBOT and SAFEX price volatility movements are more correlated, the USA yellow maize prices are regarded as a superior price indicator on SAFEX in the South African harvesting season (Geyser & Gutts, 2007a:295). The USA is the leading producer in grain; therefore, the price fluctuations on CBOT can result in similar price fluctuations on SAFEX (Geyser & Gutts, 2007a:295). The yellow maize price parity between SAFEX and CBOT will be investigated in an attempt to improve the knowledge regarding commodity trading strategies. By knowing the volatility spill-over effect intensity in each season, the decision-making can be enhanced and maize traders on the SAFEX market can ensure maximum profits.

8 1 hectare = 2.4710 Acres (WAOB, 2012:38).
9 1 metric ton equals 39.3679 bushels of corn, sorghum or rye (WAOB, 2012:38).
10 These estimates were the latest result during the time of completing this study.
11 See sections 2.4 and 2.5 for a discussion on USA and South African fundamental factors.

1.2.2 Research question

With regard to South African yellow maize prices, are there certain periods where the CBOT yellow maize prices influence the SAFEX yellow maize prices more than in other periods? Furthermore, can fundamental factors be used as a price indicator in the periods where CBOT has a less significant effect on the SAFEX prices?

1.3 GOAL

The main goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This goal can be divided into two sub-objectives; firstly, to provide a broad discussion on the fundamental factors that influence the South African and USA yellow maize markets. Secondly, to determine and measure the intensity of the volatility spill-over effect between the two markets in the planting and harvesting seasons, respectively. These results can provide valuable insight into the decision-making process of yellow maize trader and derivative trader.

1.4 RESEARCH METHOD

This study will consist of a literature study, as well as an empirical investigation. Past literature studies will be used to provide insight into the most relevant fundamental factors that are used in price analyses. It will also be used as references in order to investigate the phenomenon of the cointegrated spill-over effects between two international markets.

The aim of the empirical study is to identify and measure the volatility spill-over effect between SAFEX and CBOT. The identification procedure will make use of the Markov Switching Vector Autoregressive (MS-VAR) model to emphasise the existence of immense price volatility in the two markets. Due to the high price volatility, it will be impossible to indicate the planting and harvesting seasonal regimes for each market.[12] A visual inspection of the price volatility and MS-VAR graphs will indicate possible confluence between SAFEX and CBOT yellow maize

[12] The original reason for estimating the MS-VAR model was to indicate the seasonal periods in each market empirically.

prices. Thereafter, the SAFEX and CBOT yellow maize price data will be divided into new datasets as follows: the South Africa planting season and USA harvesting season (October to March) will be referred to as time period 1. In addition, time period 2 will represent the harvesting season of South African and planting season of the USA (April to September) (Department of Agriculture and Land Reform, 2008:6). The division of the SAFEX and CBOT yellow maize price data is necessary in order to examine the volatility spill-over effect in different seasons more elaborately.

After establishing the presence of intense volatility in the SAFEX and CBOT yellow maize prices, these datasets will be divided into two periods, as mentioned above. The following measuring criteria will then be applied for both periods, which will be compared to each other in order to achieve a better understanding of the interactive relationship between the SAFEX and CBOT yellow maize price volatility spill-over. Firstly, the Granger (1969) and Sims (1972) causality tests will be estimated in order to establish the direction of causality flow between the two markets, for each period. These tests will indicate whether SAFEX Granger causes CBOT or vice versa. The Granger causality test will be estimated first and the Sims test secondly in order to clarify and verify the results of the Granger causality test. The following section on measuring the volatility spill-over effect will determine the co-movement between the SAFEX and CBOT yellow maize prices in each period.

The co-movement will be examined by estimating the covariance and Pearson correlation coefficient. In the final step, the co-movement analysis will be extended by estimating the Johansen (1991) cointegration test and a VEC model, which will provide more insight into the long-run cointegration relationship between the two markets. All of the methods that will be employed will provide more insight to the volatility spill-over effect between SAFEX and CBOT in the two different seasons.

1.5 CHAPTER LAY-OUT

1.5.1 Chapter 2: South African and USA maize markets and fundamental factors

The objective of Chapter 2 will be to elaborate on the fundamental factors that influence yellow maize prices on SAFEX and CBOT. This chapter will commence with a discussion on the history and uses of maize (section 2.2), and will continue with a discussion on the relationship between spot and future maize prices (section 2.3). Thereafter, how the exchange markets like the Chicago Board Of Trade (CBOT) (section 2.3.3) and the South African Futures Exchange (SAFEX) (section 2.3.4) came to be, will be discussed. This chapter will conclude with a discussion on price factors that have a significant influence on the CBOT (section 2.4) and SAFEX (section 2.5) markets. This includes both the supply and demand side factors in the USA maize market and in the South African maize market.

1.5.2 Chapter 3: The integration between two international markets (volatility spill-over)

The objective of Chapter 3 will be divided into two sections, which entail examining the price volatility of yellow maize prices in SAFEX and CBOT (section 3.2) and the volatility spill-over effect between SAFEX and CBOT (sections 3.3 to 3.5). Firstly, this chapter will commence by discussing the Markov Switching Vector Autoregressive (MS-VAR) model, which will be used to emphasise the intensity of the price volatility in the two markets (section 3.2). Secondly, the chapter will examine the presence of co-movement between the two markets. This entails the determination of the direction of causality (section 3.3), and examining the co-variance and the Pearson correlation (section 3.4) for each market and period. This section will then continue by examining the extent of the volatility spill-over effect between SAFEX and CBOT by estimating a Johansen (1991) cointegration test and a VEC model for each period (section 3.5). The Johansen (1991) cointegration test and VEC model will provide insight regarding the long-run cointegration relationship between the two markets and the influential capabilities of the markets.

1.5.3 Chapter 4: Methodology and results

The objective of Chapter 4 will be to review the results found after performing the empirical analysis discussed in Chapter 3, which entails the price volatility results of yellow maize prices in SAFEX and CBOT (sections 4.2 and 4.3), and the volatility spill-over effect results between SAFEX and CBOT (sections 4.4 to 4.7). The findings of the first section on price volatility indicate that there is some form of price volatility interaction between SAFEX and CBOT, which leads this study to the point where the intensity of the volatility spill-over effect should be measured. The second section will indicate that, although there is a volatility spill-over effect from CBOT to SAFEX and a confluence of yellow maize prices, the difference in the volatility spill-over effect from CBOT to SAFEX in each period is significantly small.

1.5.4 Chapter 5: Summary, Conclusion and recommendations

Chapter 5 concludes the study by reconciling the problem statement and the final results to a logical conclusion to this study. Recommendations for future studies will also be provided.

CHAPTER 2

South African and USA maize markets and fundamental factors

"*Chimango ndi moyo* - maize is our life" Malawians of the late twentieth century

(McCann, 2001:246)

2.1 INTRODUCTION

The main goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This chapter will commence with a discussion on the fundamental factors that affect the maize prices in the South African and USA maize markets. In order to fully understand the relationship between the two markets, it is necessary to first have knowledge of the history and uses of maize (section 2.2), as well as the relationship between spot and futures maize prices (section 2.3). Since the price of maize is determined by the buyers and sellers of this commodity, the history of CBOT (section 2.3.3) and of SAFEX (section 2.3.4) will be discussed in the first part of this chapter. In the second part of this chapter, a broad description on price factors that have a significant influence on the CBOT and SAFEX markets will be discussed, respectively. This includes both the supply and demand side factors in the USA maize market (section 2.4) and in the South Africa maize market (section 2.5).

2.2 THE HISTORY AND USES OF MAIZE

Maize or *Zea mays,* as it is known scientifically, originated around seven thousand years ago somewhere around central Mexico. "Maize" literally means "that which sustains life", and around 1500 AD the Aztec and Mayan civilizations referred to maize as flesh and blood itself. In the fifteenth and sixteenth centuries, the Spaniards and other Europeans exported maize from America to Europe, which was the starting point of maize production all around the world (Schmitt, 2005:4). By the late-nineteenth and early twentieth century, the mining industry in South Africa was booming. This caused the demand for and supply of maize to increase as the mine labour force increased. The main area used for maize production was called the "maize triangle", which consists of the Transvaal, the Eastern Orange Free State, and Lesotho (McCann, 2001:260). The majority of maize produced in South Africa is white maize, which is used for human consumption and is the staple food of South Africa (Seeley, 2009:9). As such, South Africa is one of the largest producers of white maize in the world. Although local farmers also produce yellow maize, more or less 60 percent of local production consists of white maize (Krugel, 2003:2). Yellow maize is used for animal feed and is also an important raw material for various industrial products. Every year, animals like hogs, cattle, sheep and poultry feed on more than half of the local produce of yellow maize. The remaining half is used in the industrial production of sweeteners, corn oil, beverage and industrial alcohol, and ethanol (Seeley 2009:9; Department of Agriculture, Forestry and Fisheries, 2009a:9; McCann, 2001:248).

2.3 RELATIONSHIPS BETWEEN SPOT AND FUTURES PRICES

2.3.1 Introduction

SAFEX and CBOT are commodity derivatives markets that provide the opportunity to effectively manage price risk for commodities. On both these markets, derivative instruments like futures[13] and options[14] contracts are used to manage price risk and thereby minimise exposure to unfavourable price movements (SAFEX, 2010c:1). The following section will discuss the relationship between spot and futures prices, which will be followed by a discussion on the history of CBOT (sections 2.3.3) and SAFEX (section 2.3.4), respectively.

2.3.2 Relationship between spot and future prices

The price of a derivative is linked to the supply of and demand for an underlying asset. The magnitude of price exposure and the importance of derivatives can be determined by a diversity of factors that influence the supply and demand for yellow maize, which include:

[13] A futures contract is a legally binding agreement that gives the investor the right to buy or sell an underlying commodity at a fixed price on a future date (Krugel, 2003:77).

[14] An option contract gives the investor the right, but not the obligation, to buy or sell a specific amount of a given commodity, at a specified price during a specified period of time (Krugel, 2003:77).

- supply and demand factors at an international level;
- supply and demand at a domestic level; and
- the ZAR[15]/US$ exchange rate, because it affects the import and export parity.

Future expectations can be added as an additional factor to the list above because it has a significant effect on commodity prices. The study of Strong (2002:420) argues that the total basis value for a commodity is the difference between a futures price and the cash price, at a specific location, for an underlying asset. The total basis can be divided into two sections, namely a carry[16] and a value basis[17]. The basis of a commodity will differ since the cash price of a commodity differs from one location to another, because each location differs in market imperfections, such as storage and transportation costs. Therefore, basis risk is defined by the difference in cash prices of a commodity from one location to another, for reasons other than storage and transportation cost (Kleinman, 2001:21).

Depending on the link between the cash price and the futures price, the basis can have a positive or negative value (Heymans, 2008:22). The basis will be negative where the futures price is higher than the cash price and is also called a contango market. Conversely, the basis is positive where the futures price is lower than the cash price and is referred to as a backwardation market (Kolb, 1997:64; Strong, 2001:410, 421). The study of Kolb (1997:65) stated that on the date of delivery the basis should be zero as the futures price is equal to the cash price. A contango market is also known as a normal market, which arises when the price of the 'nearby' futures contract is lower than a futures contract with an expiration date in the distant future. The basis of such a 'nearby' contract will increase from its negative value to zero at expiration, because the cash price of the underlying commodity is lower than the futures price (Kolb, 1997:65). On the other hand, a backwardation market is known as an inverted market, which arises when the price of a nearby futures contract is higher than a futures contract with

[15] The South African Rand.

[16] Carry basis can be defined as the difference between the theoretical future price and the spot price of an underlying asset, equal to the net cost of carry (Watsham, 1998:88).

[17] Value basis is defined as the difference of the theoretical future price and becomes the market price (Watsham, 1998:88).

an expiration date in the distant future. At the expiration date, the basis of the ‘nearby’ futures contract will have decreased for its positive value until zero (Kolb, 1997:65). Nonetheless, for the basic concept to apply, the underlying factors that influence the price of futures contracts must be examined.

Agricultural commodities are traded not only for financial benefits, but also for consumption and production purposes (Watsham, 1998:93). The futures contract prices can, therefore, not be derived only from the availability of the underlying commodity (Heymans, 2008:23). It will therefore be unfeasible to rely on the arbitrage process to ensure that commodity futures contracts trade below the price of the commodity, plus the net carry cost (Watsham, 1998:86). Assume a potential consumer that is interested in an underlying commodity with the intension of not consuming it, but for selling the futures contract short.[18] The objective then would be fiscal delivery and it is expected that the activities of commodity consumers will ensure that the futures price does not exceed the price of the commodity plus the net carry cost. Such a futures contract will be priced less than the price of the commodity plus the net carry cost to an extent where it is well-situated for the commodity holder to have the commodity in his ownership, in order to facilitate the production process (Heymans, 2008:24). The futures price of an agricultural commodity can be illustrated as follows (Watsham, 1998:94):

$$F = P + (C - Y)\,, \tag{2.1}$$

where:

- F is the futures price;
- P is the price of the commodity;
- C is the net carry cost; and
- Y is the monetary value.

The monetary value (Y) is given to the convenience yield, which is an adjustment to the carry cost in the non-arbitrage pricing formula for forward prices, in markets with trading constraints.

[18] The short seller profits from a decline in the price of an underlying asset between the sale and the repurchase. A short seller will incur a loss if the price of the assets rises (Investopedia, 2011).

From Equation 2.1 it is clear that a commodity futures contract is priced differently than non-consumed commodities. It is, therefore, necessary to acknowledge that there are differences in the futures and spot prices of a stock. The general differences between the spot and futures prices for different futures contracts can be listed as follows (Shawky *et al.,* 2003:936):

- Both the spot and futures returns have means that are not significantly different from zero.
- The volatility in the spot price is two to fifteen times higher than the futures price.
- The spot price series display a statistically significant level of positive skewness[19], whereas the futures price and return series do not consistently show such behaviour.

In addition, option and futures contracts are traded on exchange markets like the Chicago Board Of Trade (CBOT) and the South African Futures Exchange (SAFEX), which will be discussed briefly in the sections 2.3.3 and 2.3.4, respectively.

2.3.3 The history of the Chicago Board of Trade (CBOT)

CBOT was founded in 1848 and has developed into one of the largest agriculture exchanges in the world. In the 1830s, the city of Chicago started to expand, with extensive growth in grain trading. In March 1848, a group of 25 businessmen held a meeting in the office of WL Whiting, where an agreement was reached that merchandising should be more organised and standardised than it was at that time. During the second meeting, the CBOT was officially organised. In the following year, the board was granted a charter that gave official authority to its acts. A common meeting ground for buyers and sellers was established where they could do their trades, which also ensured farmers receiving better prices for their goods and merchants receiving improved quality products (Webb, 2000:54). In 1865, the CBOT introduced futures contracts that formalise grain trading by standardised agreements.

By the late nineteenth century, the use of futures trading was becoming more popular and grew extensively. One of the main functions of CBOT was and still is to maintain futures markets for wheat, maize, oats, rye, barley, provisions, as well as stocks and bonds (CTIS, 2008:1). In the

[19] Positive skewness in the wholesale electricity prices reflects the possibility of large upward swings in the marginal production costs (Shawky *et al.,* 2003:936).

1870s, the CBOT handled approximately 60 million bushels of grain. During 2008 it was noted that approximately 400 million bushels of grain are traded annually, which ranks CBOT first among the world's commodity exchanges (CTIS, 2008:1). CBOT also has several types of memberships, such as merchants, exporters, bankers, millers, elevator owners, cooperative farm groups, brokers, and insurance companies. Furthermore, the Board of Trade broadcasts quotations from CBOT several times a day by radio. Most farmers are, therefore, frequently informed of the market and can operate accordingly (Webb, 2000:54; CTIS, 2008:1).

2.3.4 The history of South African Futures Exchange (SAFEX)

Prior to 1987, there were no futures contracts available on commodities (except for gold) in South Africa. This was because prices were not determined by market forces, but by the South African government. South African investors that wanted to trade in the commodity futures market with supply and demand forces had to look for opportunities in foreign markets.

In South Africa, financial futures trading began in April 1987, when Rand Merchant Bank began trading contracts based on the Johannesburg Stock Exchange (JSE) Actuaries, All-Share, All-Gold, and Industrial indices. In May 1988, the JSE, a group of banks, and discount houses came together to define and design a formal futures exchange to standardise grain trading in South Africa. In September of that year, the JSE and 21 banks subscribed to the prospectus and became founding members of the South African Futures Exchange (SAFEX) and shareholders of the SAFEX Clearing Company (SAFEX, 2010a:1). On 10 August 1990, SAFEX was licensed as the official derivative exchange for South Africa, which was done according to the Financial Markets Control Act of 1990. This led to the opening of the SAFEX Agricultural Derivatives Division on January 1995, which was followed by the initiation of options on agricultural products in March 1998. In July 2001, SAFEX was bought out by the Johannesburg Securities Exchange (JSE), which was accompanied by the separation of SAFEX into two divisions, namely the SAFEX Financial Derivatives division and SAFEX Agricultural Derivatives division of the JSE (SAFEX, 2010a:1).

2.3.5 Summary

The formal platforms provided by SAFEX and CBOT lead to some substantial benefits. The connection between the buyers and sellers is transparent in the process of price discovery and all the transactions are supervised by the clearing houses. In addition, farmers can benefit from this platform by enabling them to manage production risks such as changes in the weather, seasonal conditions, and farm management, which helps to decrease price risks (SAFEX, 2010c:1). Now that the history of CBOT and SAFEX is known, the following discussion will continue by providing a discussion of the different price factors that influence maize prices on CBOT and SAFEX in sections 2.4 and 2.5, respectively. Both sections will be followed by the influential supply and demand factors of each respective market.

2.4 PRICE FACTORS ON CBOT

2.4.1 Introduction

This section will consist of a discussion of underlying factors that have a significant influence on maize prices. The factors influencing the USA market will be listed in sections 2.4.3 and 2.4.4 for supply and demand factors, respectively, which will be followed by a discussion of the South African maize market in section 2.5. This section will commence by providing a brief discussion of the USA maize market.

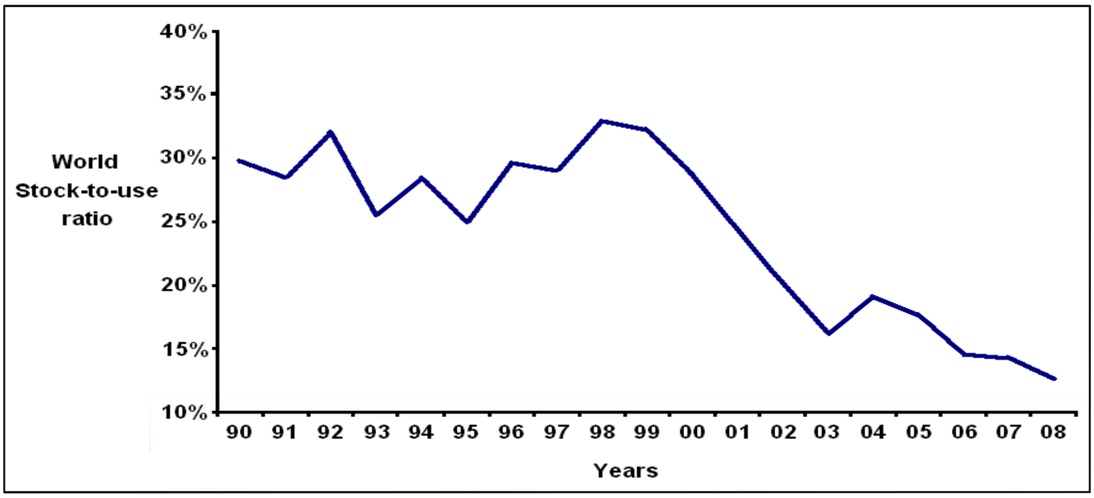
2.4.2 The United States of America's (USA) maize market

The maize production in the USA reached a record high of 13 billion bushels in 2009 (Robinson, 2010:22). USA framers produced just under half of the world's maize in the 2009 season (Seeley, 2009:9). The study by Seeley (2009:9) indicated that maize planted in the USA is located mostly in the area called the Corn Belt, which includes the following states: Michigan, Minnesota, South Dakota, Wisconsin, Ohio, Illinois, Indiana, Iowa, Missouri, Kansas, and Nebraska, which consist of approximately 32 million hectares. In these areas, the planting season for maize is from April to May (Farnham, 2001:2), while the harvesting is from October to November (Seeley, 2009:11). Each year's planting and harvesting season can present its own challenge, testing the farmer's ability to compensate and adjust his/her day-to-day decision-making process. The supply and demand factors that require consideration in a farmer's decision-making process will be discussed in the following sections.

2.4.3 Factors influencing the supply of USA maize

There is a continuously fluctuating cycle of maize levels during the year (Gyser & Gutts 2007:292b). The study of Kirsten *et al.* (2009:34) found that a larger supply of maize will decrease the price, especially during the harvest season. Underlying factors that have an influence on this cycle and on the supply of maize include weather and diseases, low water supply, high input costs, the shortage of farmland as well as a farmer's knowledge of farming. Over the last decade, the growth in supply became sluggish, while the growth in demand increased. For instance, the world demand for bio-fuels produced from maize increased and undesirable weather conditions, increased inflation, and rising energy prices contributed to the amplification of production costs (Trostle, 2008:1). Furthermore, maize is very price-inelastic, which means that the amounts demanded and supplied change proportionally less than the price. A reason for this price inelasticity could be the constant weather change that has immense effects on maize production (Gyser & Gutts, 2007b:295).

Figure 2.1: Diminishing world stock-to-use ratio of maize



Source: Hill (2009:6).

As illustrated in Figure 2.1, the world stock-to-use ratio[20] has been declining since 1998 to 13 percent in 2008. The world stock-to-use ratio shows that there is a shortage of production, which can be associated with a limited supply of water, temperature, high input costs, limited farmland, and a farmer's knowledge, and these factors will be discussed in the following paragraphs.

2.4.3.1 Water supply

Trostle (2008:6-7) states that the capability to attain extra water for agricultural utilisation has become increasingly complex due to overly expensive and complicated irrigation systems, as well as ever deepening water tables. Since the required annual rainfall a farmer needs is 500 to 750mm, and the average annual rainfall is about 450mm, depending in which area a farm is situated, modern-day farmers find it increasingly difficult to farm economically (Department of Agriculture, Forestry and Fisheries, 2008:2). Fortunately, maize can be planted under irrigation, although it is very expensive. It is, however, more efficient because it takes a shorter period to produce (Department of Agriculture, Forestry and Fisheries, 2008:2). Dowgert (2010:1) reports that 17 percent of cultivated land in the USA is irrigated, generating approximately 50 percent of the total USA crop revenue. To emphasise the impact of irrigation, approximately 80 percent of the world's total cultivated land area (1,260 million ha) is classified as dry land and is fed by rain. However, only 60 percent of the world's food supply is cultivated on this area. The remaining 20 percent of the world land area (277 million ha) is under irrigation, accounting for the remaining 40 percent of world food supply (Dowgert, 2010:1). Not having enough rain water therefore poses a serious threat to the world's food security. However, temperature (section 2.4.3.2), inputs costs (section 2.4.3.3), limited farmland (section 2.4.3.4), and the farmer's knowledge (section 2.4.3.5) also have a significant impact on a farmer's production abilities, which will be discussed in the following sections.

[20] The stock-to-use ratio can be calculated by dividing the current year's ending stock by the current year's use (Hill, 2009:6).

2.4.3.2 Temperature

Temperature levels have a significant influence on maize production. Temperatures of more than 32˚C can cause maize production to decrease, while temperatures below 0˚C can have harmful effects on maize yields at any stage of the growth phase. The most favourable temperature is between 19 and 25˚C (Department of Agriculture, Forestry and Fisheries, 2008:2).

2.4.3.3 Input costs

A number of raw materials are required for the successful production of maize. An increase in the price of these inputs is therefore of great concern for farmers. According to Trostle (2008:29), the continual increase in input costs and the lack of credit facilities are the main reasons for farmers to produce fewer crops. Input costs can be divided into two groups, namely variable- and capital costs (NAMC, 2007:10). Variable costs comprise the cost of seed, fertiliser, fuel, maintenance and repairs, licenses and insurance, permanent labour, interest on production credit, banking fees, water and electricity, telephone as well as auditing costs. Capital costs, on the other hand, consist of costs of machinery and equipment, depreciation, and fixed improvements (Department of Agriculture, Forestry and Fisheries, 2008:2). This study will only focus on the more basic input costs[21], which include the following:

- Seeds: Seeds differ in cultivars for a variety of maize producing areas. Some cultivars differ in yield potential, length of growing season, prolificacy and percentage grain moisture. Furthermore, each cultivar differs in price and every farmer should determine what cultivar suites the soil the best at the lowest possible price (Department of Agriculture, Forestry and Fisheries, 2008:2).
- Irrigation[22]: Irrigation is a great addition to the cultivating of maize, but is very expensive to set up. A lot of water is required to ensure the ongoing benefits of irrigation, which includes higher yields in a shorter production periods (Department of Agriculture, Forestry and Fisheries, 2008:20).

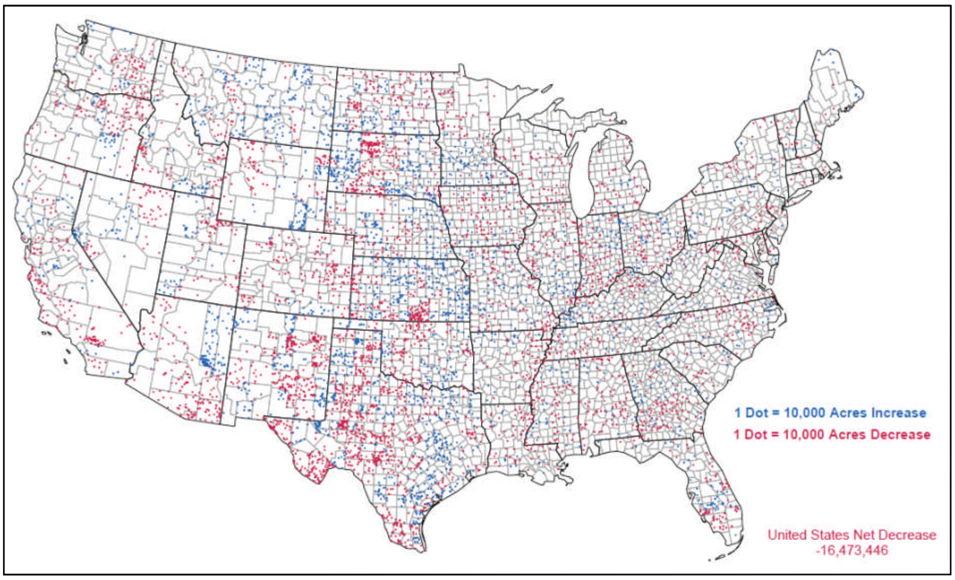
[21] Due to the large quantity of input costs and the goal of this study, only the basic input costs will be discussed.
[22] See also section 2.4.3.1.

- Soil requirements: Requirements can vary over different areas, with soil tillage as the most important and common requirement for maize. Soil tillage refers to the changing of the soil's structure, hydraulic properties, and stability. This allows the maize to grow and produce optimally (Du Plessis, 2003:12). Furthermore, the physical properties of good soil should include the facilitation of good internal drainage, enhancing the balanced quantities of plant nutrients and chemical properties, and it must be ploughed easily. Preparing the soil to its desired condition also includes the use of fertilization to add nutrients, which forms one of the most basic input costs (Department of Agriculture, Forestry and Fisheries, 2008:2).
- Weed and pest control: Weed and pest control is necessary to avoid great losses in production. Weed control is essential in the first six to eight weeks after planting. If weed control is not applied during this early stage of the maize's lifecycle, the maize will suffer a great deal as the weed will use most of the nutrients and water in the soil. If weeds are present during harvesting, they can pollute the grain and can cause the downgrading of seeds due to transmitted odours (Department of Agriculture, Forestry and Fisheries, 2008:2).
- Fuel: Fuel is a great expenditure when it comes to farming, because the day-to-day activities are performed by tractors and other automobiles. These activities include the (Department of Agriculture, Forestry and Fisheries, 2008:2):
    - Preparation of soil – the soil is usually disked (prepared) about three to four weeks before planting;
    - Planting of seeds;
    - Harvesting; and
    - Fertilisation.

2.4.3.4 Limited farmland

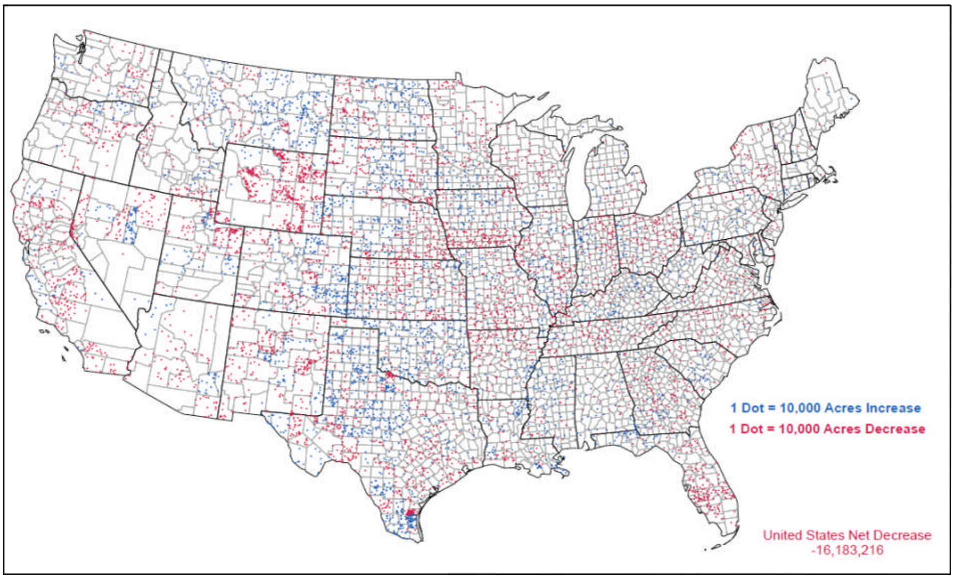
Another factor that greatly influences the supply of maize is the availability of farmland. Due to the need for a particular type of soil for agricultural purposes, it is essential for a country to examine potential areas that could promote high yields (FAO, 1976:1). The Food and Agricultural Organization (FAO) of the United Nations defines good agricultural land as the physical environment, including climate, relief, soils, hydrology and vegetation, to the extent that these influence the potential for land use (FAO, 1976:1). Figures 2.2 and 2.3 illustrate the increase and decrease in cultivated land area in North America. The increase of farm land is illustrated with blue dots (1 dot equals 10 000 acres increase) and the decrease of farm land with red dots (1 dot equals 10 000 acres decrease). The net decrease, from 1997 to 2002, was 16 473 446 acres, while a further decrease of 16 183 216 acres occurred from 2002 to 2007. The total net decrease of land for farming purposes in the USA over ten years was 32 656 662 acres (US Department of Agriculture, National Agricultural Statistics Service, 2002:1).

Figure 2.2: Land in farms: Change in acreage (1997 to 2002)



Source: US Department of Agriculture, National Agricultural Statistics Service (2002:1)

Figure 2.3: Land in farms: Change in acreage (2002 to 2007)



Source: US Department of Agriculture, National Agricultural Statistics Service (2007:1)

2.4.3.5 Farmer knowledge

The knowledge of farming also plays a significant role in the supply of maize. Sir Francis Bacon (1561-1626) said "Knowledge is power". This is imperative for farming, because when producing grain, a farmer has to comply with a number of factors. The appropriate knowledge is necessary for every phase of farming, which includes buying the correct quality/quantity seeds, preparing the soil for harvesting, and selling the grain on the market. A farmer's knowledge about farming has to be diverse in aspects like growth and development[23], planting and fertility needs[24], weed control[25], insects and diseases, harvesting[26], and storage (Boshoff, 2008:11). However, in addition to the above topics, the farmer must also be informed about the following aspects (Pannar, 2007:4)

- Maize cultivar selection: It is important to make the right choice when it comes to the seeds that are planted. Choosing the suitable cultivar guarantees higher returns, cheaper and more effective planting (KZN-AGRI, 2006:2; Pannar, 2007:4). The yield and the yield reliability are the first aspects to observe when choosing the most appropriate cultivar. Furthermore, a farmer must consider other factors like disease resistance and the quality of the seeds (KZN-AGRI, 2006:1; Myers, 2005:13).
- Soil preparation: Production consistency can be improved by the correct soil preparation. The first step should be to make use of natural water supplied by rainfall and to be proactive by applying the correct soil cultivation practices, which will minimise the runoff losses (KZN-AGRI, 2006:3; Pannar, 2007:3). Ploughing with a mouldboard plough or chisel plough helps with the preparation of soil, which includes breaking up the limiting layers, destroying weeds, providing a suitable seedbed, and breaking the soil surface. Furthermore, ploughing will prevent wind and water erosion as well as helping to obtain maximum rainfall infiltration (KZN-AGRI, 2006:3; Myers, 2005:13: Pannar, 2007:3).

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[23] Growth and development refer to the different development stages as well as the related crop management inputs (Boshoff, 2008:11).

[24] Planting and fertility needs refer to soil requirements and preparation, yield potential, cultivar choice, planting dates, row width, plant density, planting depth and planting techniques, and macro-nutrients (Boshoff, 2008:11

[25] Proactive weed control is essential for maize production. Weed and insect control can be achieved by both mechanical and chemical preparation (Putnam *et al*., 1990:18; Schneiter, 1997:35).

[26] The visible sign of the maturing maize plant is when the leaves are dying back, starting from the lower leaves ongoing to the upper leaves. Harvesting generally starts when a black layer at the tip of the kernel appears (Department of Agriculture, Forestry and Fisheries, 2008:2).

- Planting depth and planting techniques: For every soil type and area, different planting depths are required. Generally, planting commences shallower in heavier soils than in sandy soils. Planting depth can vary from 5 to 10 cm, depending on the soil type and planting date (Department of Agriculture, Forestry and Fisheries, 2008:2). Furthermore, optimal yield can be obtained by using a planter, because seeds should be spread out evenly and good depth control should be managed (KZN-AGRI, 2006:4; Myers, 2005:13; Pannar, 2007:5).
- Yield potential: A farmer should do effective planning to obtain the ultimate yield potential. The plant density, cultivar and fertilisation programmes contribute to the success of a season and cannot be utilised before the yield potential has been determined (Pannar, 2007:2).

To summarise, the factors that influence the supply of USA maize are mostly caused by limited water supply, high input costs and limited farmland available. As shown above, there is a shortage of maize production in comparison with demand for maize. Therefore, the influential demand factors on USA maize must also be examined to understand the reasons for the higher demand of USA maize, which will be discussed in the following section.

2.4.4 Factors influencing demand for USA maize

The growing demand for food along with the increasing need for energy consumption, like bio-gas or transport fuel (section 2.4.4.3), cause prices for agricultural commodities to rise (Zeller & Häring, 2007:157). This growing demand for food stems from the continued growth of the world's population (section 2.4.4.2), especially in developing countries (Trostle, 2008:29). Since maize products are used as feed for farm animals, and farm animals are another source of food around the world, demand for feed for the livestock sector also increased over the past few decades. Additional to population growth (section 2.4.4.2) and the increase in the production of bio-fuel (section 2.4.4.3) as factors that influence the demand for USA maize, are other factors like dietary preferences also influencing the demand for USA maize, which will be discussed in the following section.

2.4.4.1 Dietary preferences

According to the International Fund for Agricultural Development (IFAD, 2008:5), the structure demand for food commodities is gradually changing, because most diets are altering from starchy foods towards meat and dairy products. Evidence reported by IFAD (2008:5) indicated that it takes almost seven to eight kilograms of grain to generate one kilogram of beef and five to seven kilograms of grain to produce one kilogram of pork. These results justified the substantial increase in the demand for feed grains to feed farm animals.

Table 2.1: How much meat can be produced by one ton of maize?

Maize inputs	Potential production of meat
1 ton of maize	**100 kg beef**
	250 kg pork
	333 kg chicken
	500 kg catfish

Source: IFAD (2008:9)

In addition, Table 2.1 illustrates that one ton of maize can produce around 100kg beef and up to 500kg of catfish. This production of meat is less than half of the weight of maize. Therefore, the maize production has to increase to ensure that meat production will satisfy human consumption. In China, the per capita meat consumption increased from 20kg to 50kg in the period from 1980 to 2008. Furthermore, dietary preference and the development of urbanisation contributed to the increase in food demand, particularly in developing countries **(**IFAD, 2008:5).

2.4.4.2 Population growth

To get an idea of the impact of these changes on maize producing countries, it is necessary to analyse the USA import and export situation over the last few seasons. Looking at the USA maize imports and exports in Table 2.2, it is clear that the USA farmers are great exporters of yellow maize. Most of the demand is from countries such as Japan, Taiwan and South Korea (US Department of Agriculture and Foreign Agricultural Service, 2010:19).

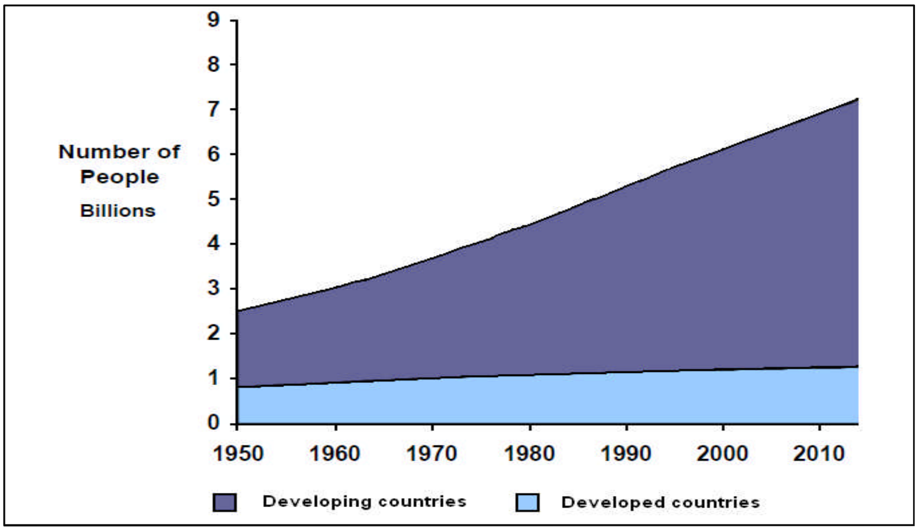
Table 2.2: Imports and exports of USA maize from 2008 to 2011 in thousand metric tons

Production season	Imports	Exports
2008-2009	344	46 965
2009-2010	203	50 472
2010-2011	254	50 802

Source: US Department of Agriculture and Foreign Agricultural Service (2010:48)

Table 2.2 also illustrates that between 2008 and 2009, the USA imported 344 thousand metric tons of maize, while exporting 46 965 thousand metric tons. Between 2009 and 2010, these figures changed to 203 thousand and 50 472 thousand metric tons, respectively. An increase of 3 507 thousand metric tons is seen in the export figure and a decrease of 141 thousand metric tons is seen in the import figure. During 2010 to 2011, the export and import figures increased by 330 thousand metric tons and 51 thousand metric tons, respectively. Although the import figure has increased from the 2009/10 season to the 2010/11 season, the import figure is still a great deal smaller than the export figure.

Figure 2.4: World population growth from 1950 to 2010



Source: Haub et al. (2010:4)

To conclude this section, food demand is intensifying because the global population has been increasing by approximately 78,5 million people every year **(**IFAD, 2008:5). Figure 2.4 illustrates that the world population was at 2,5 billon people in 1950 and grew to more than 6 billon people in 2010. The greatest majority of these people come from the developing countries of Africa and Asia (Haub *et al.,* 2010:8). Figure 2.4 also illustrates that the number of people in developing countries increases by far more than developed countries, contributing more than half of the world population. These figures put enormous pressure on USA maize producers and provide early signals for huge shortages to come if the population growth rate remains on this growth path.

2.4.4.3 Bio-fuel production increases

Bio-fuels mainly consist of some form of ethanol, whereas ethanol is created during a fermentation process where maize starch is the main ingredient. Therefore, the increased demand for ethanol causes an increased demand for maize, which causes a playoff between bio-fuel production and food security (Chakauya *et al.,* 2009:174). This huge demand playoff challenge lies ahead for developing countries, because achieving basic food security and economic development is difficult with increasing crude oil prices, for instance; especially between 1997 and 2008, where crude oil increased from $27 to more than $100. This increase in crude oil leads to an increased demand for a substitute product, which includes bio-fuels made from maize (Chakauya *et al.,* 2009:174).

Ethanol production from USA maize, from 1980 to 1990, had a very small effect on global markets. However, the study of Trostle (2008:18) reported that the production of ethanol increased substantially between 2003 and 2008, causing a major transformation in the structure of the USA maize markets. It also had a significant impact on the world's maize supply and demand balance. In the USA, maize used for ethanol increased from about 1 billion bushels to 3,1 billion bushels between 2002 and 2007. The USA maize used for ethanol production, therefore, increased from 10 to 24 percent. A reason why USA maize demand spiked is because the maize used by non-ethanol industries (like food feed, and other exports) did not decrease (Trostle, 2008:16). Therefore, the deficit of maize supply is being imported. Until now, the USA and European countries have been the main ethanol importers. Furthermore, the demand for ethanol is growing in Asia and Brazil, which cannot satisfy their supply needs. Therefore, export markets for USA ethanol may be needed in the near future (Renewable Fuels Association, 2010:23).

2.4.5 Summary

The demand for USA maize has increased over the last few years, which can lead to shortages in the near future. Some of the reasons for the increased demand for USA maize include the growing demand for animal feed to increase the production of meat and dairy products, the high global population growth rate, and the increasing demand for bio-fuels. Furthermore, some fundamental factors of the South African maize market also correspond with the USA maize market. Therefore, the fundamental factors that influence the South African maize market will be discussed in the following section.

2.5 PRICE FACTORS ON SAFEX

2.5.1 Introduction

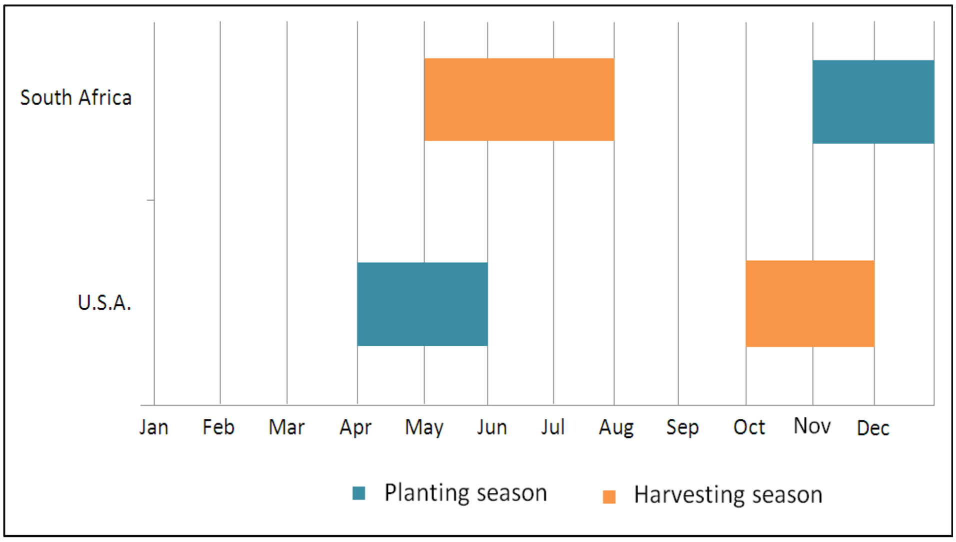
This section will list the fundamental facts of the South African maize market; followed by sections 2.5.3 and 2.5.4, which will briefly mention the supply and demand factors that have mostly influenced maize prices in the South African Maize market, respectively.

2.5.2 The South African maize market

The estimated planted area for maize in South Africa was 2,630 million ha for the summer rain fall crops, in the production 2012 season (Department of Agriculture, Forestry and Fisheries, 2011b:1). This planted area of maize is mainly situated in the Free State, North West Province and Mpumalanga (Department of Agriculture, Forestry and Fisheries, 2009a:1). South Africa is situated in the southern hemisphere, which means that the planting season is from November to December, and the harvesting season generally starts in May and ends in July, depending on where the farm is situated (Department of Agriculture and Land Reform, 2008:6). Figure 2.5 can be used to illustrate the comparison between the USA and South African maize seasons.

In addition, the difference in production seasons can be the reason for the strong correlation between the South African and USA maize markets (Gyser & Gutts, 2007b:299). The study of Meyer *et al.* (2006:378) tested the strength of the correlation between South African and world maize prices, while nearly half of the world's maize is produced by USA farmers. The results of the study by Meyer *et al.* (2006:378) showed that the South African maize price indicated an 11.2 percent increase in import parity if the world maize price would increase by 10 percent. Price volatility is also strongly influenced by fundamental factors and supply levels. Therefore, price volatility is higher when stock levels are low and *vice versa* (Kirsten *et al.,* 2009:34). For example, in times when maize is scarce, in the beginning of the season, South African maize prices move in the direction of the import parity price, which means that the SAFEX maize price is influenced more by CBOT prices. However, when there is a surplus of South African maize later in the season, South African maize could be exported. The SAFEX prices will then move in the direction of export parity, where fundamental factors have a greater influence on the SAFEX prices (Kirsten *et al.,* 2009:35).

Figure 2.5: Illustration of South African and USA maize seasons



Source: Compiled by author

Furthermore, SAFEX demonstrates more regular high price volatility than the other markets (Gyser & Gutts, 2007b:297), which emphasises the fact that the correlation between SAFEX and CBOT can sometimes be stronger over a certain period. From the discussion above, it is evident that there is a difference in the northern and southern maize markets. To improve the understanding of these two maize markets, the fundamental factors influencing the supply and demand of the South African market should also be examined. This leads to section 2.5.3, which will discuss the factors influencing the supply of maize in South Africa, which will be followed by a discussion on the factors influencing the demand for maize in South Africa (section 2.5.4).

2.5.3 Factors influencing the supply of South African maize

Most of the factors that influence the maize price in South Africa also influence the USA prices. Some of these factors include weather and limits in the supply of water (section 2.5.3.1), input costs (section 2.5.3.2), scarcity of arable farmland (section 2.5.3.3), politics (section 2.5.3.4), and knowledge of farming (section 2.5.3.5). Furthermore, demand for bio-fuels, inflation and rising energy prices can contribute to the increase of South African maize production costs (Trostle, 2008:1).

2.5.3.1 Water supply

Weather plays a significant role in South Africa's agricultural sector (Schmitt, 2005:9). South Africa is the fourth largest country in Africa, with an average rainfall of 450mm per annum, which differs drastically around the coast lines. Only 27 percent of the natural mean annual runoff (MAR)[27] is currently available as a trustworthy source for useable water. High variation in rainfall, high evaporation, and the location of water users have contributed to the decrease to 11 percent of unusable MAR. In addition, South Africa's available water resource consists of surface water (77%), groundwater (9%), and the re-use of return flows (14%), which emphasises the importance of irrigation in South Africa (United Nations, 2006:502).

In South Africa, approximately 6,3 percent of white maize and 14,9 percent of yellow maize are planted under irrigation. The quantity of white and yellow maize planted on dry land is estimated to be 93.7 percent and 85.1 percent, respectively (Department of Agriculture, Forestry and Fisheries, 2009a:11). It is therefore be derived that most of the South African maize production is dependent on rainfall. The study of Martin *et al.* (2000:1473) argues that many South African farms are subjected to climatic extremes that often lead to low crop production. Even rainfall forecasts can indirectly influence the South African crop estimation made every season.

[27] The mean annual runoff is the amount of water running over the land surface during the year (United Nations, 2006:502).

However, these estimations are not entirely correct, because they do not reveal the complete relationship between crop yields and other climatic variables (temperature, humidity, radiation and wind) during the growing season (Martin *et al.,* 2000:1473).

Martin *et al.* (2000:1473) argue that, in South Africa, seasonal crop forecasts are inferred by rainfall forecasts, but these forecasts do not capture the complete understanding of weather, which includes facts like temperature, humidity, radiation and wind. The study of Martin *et al.* (2000:1473) further states that predictors such as the Southern Oscillation Index (SOI) should rather be used instead of rainfall forecasts. The SOI would forecast better potential crops, because the historical crop yield corresponds with the SOI (Martin *et al.*, 2000:1473).[28]

To summarise: water and the proper temperatures[29] play a significant role in the production of maize in South Africa, because most of the maize crops are reliant on rainfall, with irrigation being too expensive. From this discussion, it is evident that rainfall forecasts are very unreliable (Martin *et al.,* 2000:1473), which increases volatility and, therefore, increases uncertainty (Gyser & Gutts, 2007:300b).

2.5.3.2 Input costs

In section 2.4.3.3, the influence of input costs on USA maize was already discussed, which is basically the same for South Africa; therefore, only labour and mechanisation will be discussed as additional input costs for South Africa.

- Labour and mechanisation: Farming in South Africa is more labour intensive, which implies that when a minimum wage increase is announced, such as in 2006, it has a significant effect on input costs and profitability. Such an increase is unfortunately not correlated with an increase in labour productivity (Van Wyk & Nell, 2007:180). Therefore, if labour costs become too high, a farmer may consider becoming more mechanisation intensive than labour intensive (Van Wyk & Nell, 2007:180).

[28] The Southern Oscillation is an up and down shift in air pressure at Darwin, Australia and the South Pacific Island of Tahiti (Rasmusson & Wallace, 1983:1195).

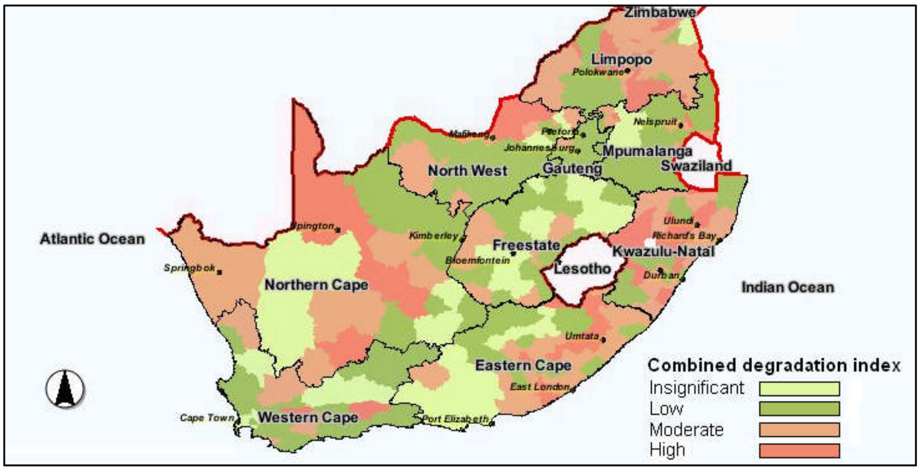
[29] See section 2.4.3.2

2.5.3.3 Limited farmland

South Africa has a restricted quantity of agricultural farmland and because of this shortage, it can lead to food scarcity if not managed effectively. Most of the soil limitations are due to limited soil depth or moderate erosion, which is caused by sandy texture or slopes (Collett, 2008:2). To elaborate on these limitations, Figures 2.6 and 2.7 can be used to illustrate the degradation of land and potential arable land in South Africa, respectively.

Figure 2.6 illustrates areas of degradation of both soil and vegetation, with high degradation situated mainly close to sloping environments, which include the Limpopo, North West, Northern Cape and Mpumalanga provinces. However, commercial farmland in the Western and Northern Cape is where most degradation is located, which is mainly due to wind and water erosion (State of Environment Affairs, 2010b:1).

Figure 2.6: Degradation of land in South Africa



Source: State of Environment Affairs (2010b:1)

Figure 2.7 further illustrates that there is a scatter of moderate to high arable land areas in the eastern part of the country (Mpumalanga and Gauteng). Low to marginal arable areas are located in the eastern half of South Africa and parts of the Western Cape. The State of Environment Affairs (2010a:1) indicated that 80 percent of South Africa’s land surface is used for agriculture and subsistence livelihood, which consists of 11 percent that has arable potential and 69 percent that is used for grazing.

Figure 2.7: Arable lands in South Africa

Source: State of Environment Affairs (2010a:1)

There is a problem for South Africa due to limited land surface. According to the international norm, the arable land required to feed a person is 0.4 ha, whereas South Africa has only 14 million ha arable land available, which can feed only 35 million people (Department of Environmental Affairs and Tourism, 2006:1). Furthermore, by examining the South African population figures and the cultivated land area, South Africa is trending on 2.5 ha per person, which is below the international norm (Collett, 2008:7). In the last few decades, a fraction of the agricultural land has also been used each year for something other than the producing of agriculture products (Trostle, 2008:6), which can have a negative effect on the supply of maize in the near future.

2.5.3.4 Politics and land repossession

Another factor influencing the supply of South African maize is politics. According to the Organisation of Economic Co-operation and Development (OECD, 2006:4-5), the South African government reduced their support for agriculture[30] since their first democratic elections in 1994. In addition, South Africa's support for agriculture producers, from 2000 to 2003, represents five percent of the gross farm receipts on average, with the average level being 31 percent. This figure is comparable with countries like Brazil, China and Russia (OECD, 2006:5). The OECD

---

[30] Government support can be measured by the OECD Producer Support Estimate (PSE) (OECD, 2006:5).

(2006:5) also reports that the South African government's main support is through Market Price Support, which includes direct production subsidies or input subsidies.

In an attempt to improve government's support in agriculture, the Broad-based Black Economic Empowerment Act (BBBEE) was established in 2003 (SA, 2004:1). This Act involved the empowerment of black farmers in South Africa and aimed to transfer at least 30 percent of all agricultural land in South Africa to previously disadvantaged persons, within the first five years of democracy (SA, 2004:1). The land repossession of agricultural land in South Africa to previously disadvantaged persons is a time-consuming process requiring thorough public consultation and careful preparation. The necessary institutional development is likely to take decades, which could have an declining effect on supply (Adams *et al.,*1999:1).

2.5.3.5 Farmer knowledge

Knowledge about farming also plays a noteworthy role in the supply of South African maize. For maize cultivar selection, soil preparation, planting techniques, and yield potential, see section 2.4.3.5. For the case of South Africa, growth and development and storage will be added to the discussion.

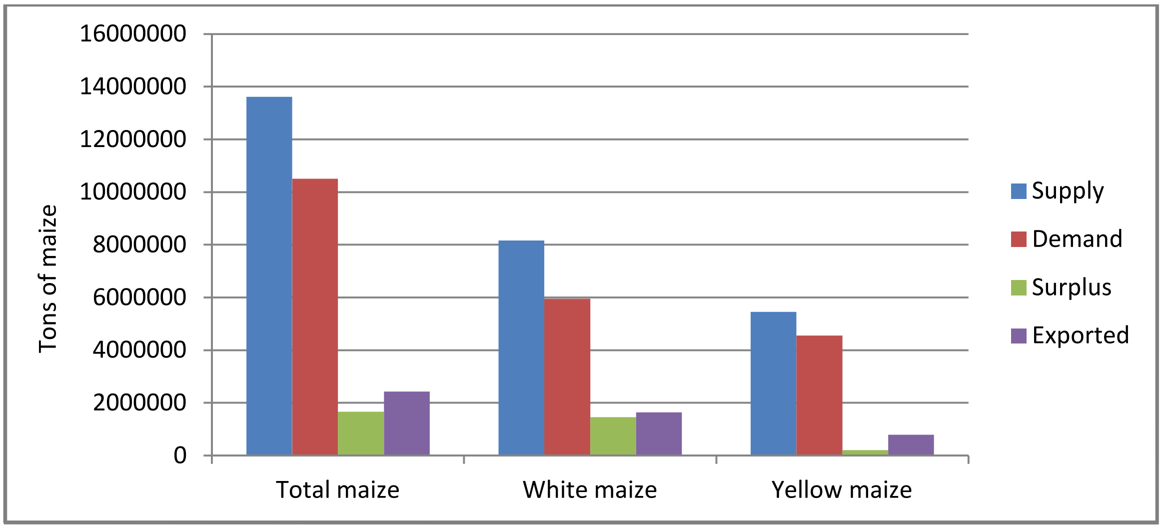
- Growth and development: South African farmers should be knowledgeable on the different development stages of maize, like the leaf development, flowering, and seed development stages. This is required in order to apply the correct attention, like weed control, fertilisation, moisture, disease control, ripeness, and harvesting, which should be managed within a precise timescale (Boshoff, 2008:11).
- Storage: Grain seeds in South Africa can be stored during the cold months at a moisture level of 10 percent or less. During the warmer periods, however, the storage moisture level should be at eight percent or less. The best method is to store the grain in silos where sufficient ventilation and moisture levels can be controlled. If grain seeds are not stored according to the above-mentioned guidelines, there is a possibility that the maize quality could decrease and become useless, which ultimately leads to supply and profit losses (Boshoff, 2008:11).

To summarise, although section 2.4.3.3 already discussed some of the factors that also influence the South African maize supply, this section elaborated on water supply, input costs, limited farmland, politics, and farmer knowledge as additional factors that influence the South African maize supply. In order to fully understand the South African maize market, it is necessary to also examine the demand side of South African maize, which will be discussed in the following section.

2.5.4 Factors influencing the demand for South African maize

South Africa produced more maize than the local demand during 2011 to 2012, resulting in the export of the remaining maize (Department of Agriculture, Forestry and Fisheries, 2012:9). However, the world demand for food and energy consumption is still growing (Zeller & Häring, 2007:157). For more background on the South African maize market regarding the maize supplied, demanded, surplus, and exported, see Figure 2.8.

Figure 2.8: The South African maize distribution during the 2011 to 2012 season



Source: Department of Agriculture, Forestry and Fisheries (2012:7-9)

Figure 2.8 illustrates that the total estimated supply of maize during 2011 to 2012 was 13,611 million tons of maize (8,157 million tons of white and 5,454 million tons of yellow maize). The commercial demand for domestic usage for maize was estimated at 10,502 million tons (5,946 million tons of white and 4,557 million tons of yellow maize). Therefore, the expected maize to be exported was 2,425 million tons of maize (1,635 million tons of white and 0,790 million tons of yellow maize). South Africa, therefore, will have 1,662 million tons of maize (1,461 million tons white and 0,201 million tons yellow) left for domestic demand in 2012. The two main factors that contributed to the demand of maize were food security and energy production (Chakauya *et al.*, 2009:175; Department of Agriculture, Forestry and Fisheries, 2012:7-9), which will be discussed in the following sections.

2.5.4.1. Growing demand for maize due to population growth and dietary preferences

The South African food security bulletin reports that the demand for yellow maize increased during the 2010/11 to 2011/12 production season (Department of Agriculture, Forestry and Fisheries, 2012:9).

Table 2.3: Demand for yellow maize during 2010/11 and 2011/12 (in thousands of tons)

Demand for yellow maize	2010/11	2011/12
Consumption	3924	4388
Human	356	400
Animal (feed)	2613	3200
Retentions by producers	395	360
Gristing	17	15
Seed for planting purposes	14	14
Other (released to end-con & withdrawn by producers)	530	400
Non-commercial	184	168

Source: Department of Agriculture, Forestry and Fisheries (2012:9)

Table 2.3 illustrates that the demand for yellow maize for consumption increased with 464 thousand tons, which includes the increase of maize demand for human consumption and animal feed by 44 thousand tons and 587 thousand tons, respectively. Overall, the demand for maize increased from the 2010/2011 to 2011/2012 season. Retentions by producers decreased with 35 thousand tons for the same period. The demand for yellow maize does not consist only of population growth and dietary preferences (section 2.4.4.1 and 2.4.4.2), but also of a highly changing world, which increases the demand for bio-energy sources (Chakauya *et al.*, 2009:175) Therefore, the increased demand for bio-fuel production in South Africa will be discussed in the following section.

2.5.4.2 Bio-fuel production

The South African population growth rate is currently growing more rapidly than the energy supply, with more than half of the African population relying on solid biomass like firewood, coal, and animal waste to satisfy their basic energy needs (Chakauya *et al.,* 2009:175). Chakauya *et al.* (2009:175) argue that this leaves South Africa in a very vulnerable position economically, due to the climate change response measures that were presently implemented by developed countries. Therefore, bio-fuels could be a possible solution in solving the energy supply shortage, but evidently would increase the demand for maize.

In South Africa, the first proposal was made in 2007 to produce bio-fuel from maize (Chakauyaa *et al.*, 2009:177), which was refused during 2008 when world maize stocks were low and food security fears arose (Radebe, 2010:2). Due to the over-supply of maize during 2010, maize prices decreased and caused approximately 10 800 small farmers to go bankrupt. Therefore, the proposal to use maize for the production of bio-fuel was made (Radebe, 2010:2). The advantage of bio-fuel is that it provides 20 to 50 percent of renewable energy. In other words, the market penetration of bio-fuels will be up to 40 million litres per annum by 2013. However, the ethanol production in South Africa is under 1 percent in terms of world production (Table 2.4), which causes the demand to stimulate ethanol production (Chakauyaa *et al.*, 2009:177).

Table 2.4 illustrates that the USA (39.1%) is the leading producer of bio-ethanol, followed by Brazil (33.3%). Both of these countries accounted for over 70 percent of the world production, while China (7.5%) and India (3.7%) occupied the third and fourth positions, respectively. During the same year, South Africa (0.8%) produced two thirds of the whole African continent's production. The total world production was estimated at 51 billion litres in 2006 (Chakauya *et al.*, 2009:176). Table 2.4 accentuates the fact that South Africa is producing insufficient quantities of bio-fuels in comparison with the rest of the world.

Table 2.4: Percentage of world production in bio-fuels in 2006

Country	Percentage of world production
USA	39.1
Brazil	33.3
China	7.5
India	3.7
France	1.9
Germany	1.5
Russia	1.3
Spain	0.9
South Africa	0.8
Africa (excl. South Africa)	1.2
Others	8.8

Source: Chakauya et al. (2009:176)

In addition, the studies by Alexander (2005:1) and Grain SA (Radebe, 2010:2) stated that there are five reasons for South Africa to produce more bio-fuels:

- Three million tons of maize can produce 1,26 billion litres of diesel; and this accounts for 12 percent of the local consumption.
- Renewable fuels such as ethanol will stabilise the grain industry and ultimately benefit new farmers as well as stimulate rural development.
- Bio-fuel would add nine percent to the volume of oil produced in South Africa.
- It will create an extra 39 percent of protein feed for animal use.
- 105 000 jobs could be created by the bio-fuel industry.

Therefore, the production of bio-fuels will aid in the demand for bio-energy in Africa, which is growing due to the increase in population, where Africa has shown a population growth of about three percent for the past five years. (Chakauyaa *et al.*, 2009:174). According to the study by Chakauyaa *et al*. (2009:174), another reason for the increasing demand for bio-fuels is because the price of crude oil increased from $27 to over $100 per barrel from 1997 to 2008.

To summarise, although the demand for South African maize is much smaller than the supply, South Africa still lacks the initiative to use the surplus maize in the development and production of bio-fuels that can be used as a cheaper substitute for electricity in the near future.

Furthermore, with the continuous population growth, substantial shortages in terms of electricity and maize can become a problem for future generations.

2.6 SUMMARY AND CONCLUSION

The goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This chapter commenced by providing the basic background required to understand the two markets (sections 2.3 and 2.4). Each market was considered to be unique, because the USA and South African production seasons differ (section 2.5.2). However, some of the supply and demand factors that influenced the maize price in South Africa were identified to also have an influential effect on the USA maize prices. These factors include a limit in the supply of water, high input costs, limited farmland, politics, and farmer knowledge on the supply side and population growth, dietary preferences, and bio-fuel production on the demand side (section 2.4.3 and 2.4.4).

From this chapter, it can be concluded that SAFEX and CBOT do share an integrated relationship, which will be further investigated in the following chapter. The following chapter will continue with this investigation by providing the methodology required to conduct a more in-depth analysis regarding the measurement of the existing integrated relationship between SAFEX and CBOT. The different measures (proxies) that will be explored include the direction of causality (section 3.3), the Johansen (1991) cointegration analysis (section 3.4), and the co-movement effect by means of the covariance and Pearson correlation coefficient (section 3.5), between the SAFEX and CBOT yellow maize prices. Examining these different proxies may provide useful information for South African farmers and agricultural traders in future decision-making processes, making this study a suitable contribution for agricultural dynamics.

CHAPTER 3

The volatility spill-overs between two international markets

"Complexity without order produces confusion and order without complexity produces boredom"

Rudolf Arnheim (1966:124)

3.1 INTRODUCTION

The main goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This goal can be achieved by defining two objectives. The first objective is discussed in Chapter 2, where the fundamental demand and supply factors are examined, indicating how the yellow maize prices in the South African and USA markets are determined. The second objective is to determine the volatility spill-over effect between the two markets in different seasons. Chapter 3 will elaborate on the second objective by investigating how the price volatility in one market, caused by these fundamental factors, will spill over to the other market. The goal of Chapter 3 is, therefore, to examine the different techniques to measure the volatility spill-over effect[31] between CBOT and SAFEX. This chapter will only provide the methodology that will be applied in this study, whereas the results will be reported in Chapter 4.

The chapter will investigate the volatility spill-over effect in two distinct parts. The first part will indicate the intensity of the price volatility in each market. The Markov Switching Vector Autoregressive (MS-VAR) model will be used to emphasise the intensity of the price volatility in the two markets (section 3.2). Due to the high volatility, it is impossible to indicate the planting and harvesting season regimes.[32] A visual inspection of the price volatility and MS-VAR graphs will indicate possible confluence between SAFEX and CBOT yellow maize prices, which will be

[31] Volatility spill-over effect refers to an event that causes volatility in one region, resulting in an interdependent reaction of volatility in another region (Gallo, 2007:2).

[32] The price volatility is too high to identify the planting and harvesting season regimes. The study, therefore, was adjusted according to literature, which indicated the South African planting (September to March) and harvesting (April to September) seasons (Department of Agriculture and Land Reform, 2008:6).

reported in Chapter 4. Thereafter, it is necessary to divide the data into new datasets as follows: the South Africa planting season and USA harvesting season (October to March) will be referred to as period 1. In addition, period 2 will represent the harvesting season of South African and planting season of the USA (April to September) (Department of Agriculture and Land Reform, 2008:6). It is important to acquire the two different periods in order to examine the volatility spill-over effect in different seasons more elaborately, which will be measured in the second part of the second objective.

The second part will study the volatility spill-over effect of each period and will be compared by making use of different measuring criteria. Firstly, the direction of causality flow will be determined between the two markets in each individual period. By assessing the Granger (section 3.3.2) and Sims (section 3.3.3) causality tests, the direction of the causality flow can be determined in each period. Secondly, the co-movement between these two markets in each individual period will be identified by examining the covariance (section 3.4.4) and the Pearson correlation (section 3.4.3). By investigating the co-movement between SAFEX and CBOT yellow maize prices, this study will be able to elaborate on the influential intensity of one market on the other in different seasons. The final criterion that will be used in examining the volatility spill-over effect, includes the test for cointegration and the estimation of a Vector Error Correction (VEC) model (section 3.5), which will establish whether there is a long-run relationship between the SAFEX and CBOT yellow maize prices and the speed of adjustment coefficient.

3.2 MARKOV REGIME SWITCHING MODEL

3.2.1 Introduction

The Markov regime switching models were first introduced by Hamilton (1988, 1989)[33], which are used to model non-linearities in time-series data (Pape, 2005:31). The Markov regime switching model is popular in financial time-series analysis, especially for the modelling of exchange rates, stock returns and interest rates (Chen & Hang, 2010:445). However, in this

[33] The study of Hamilton (1989:357) applied the model to a Gross National Product (GNP) autoregressive model, where the parameters of the model switched between two regimes.

study, it will be used to illustrate the intensity of price volatility between the SAFEX and CBOT yellow maize prices, which will form the first part of the second objective. The Markov regime switching model will help in investigating the volatility spill-over effect from the market onto the other market. This result will enable this study to go forth to the second part, which will investigate the additional information of the volatility spill-over effects by incorporating different measuring criteria.

3.2.2 The Markov regime switching methodology

Moolman (2004:76) describes the Markov regime switching model as a mechanism that indicates the switch from one regime to another. This regime is assumed to be conditional on an unobserved state variable known as s_t at any given time (Styger *et al.,* 2005:2-3). The unobserved state variable is the core identity of the Markov regime switching model, because it classifies the relevant regime for the time series at a specific period (Styger *et al.,* 2005:2). The Markov regime switching model will now be explained in terms of the regime generating process (section 3.2.2.1), followed by the data generating process (section 3.2.2.1) (Lacerda, 2008:36).

3.2.2.1 The regime generating process

Under the regime generating process, the regimes are reconstructed based on a first-order Markov process, also known as the Markov chain (Morris, 2010:98). A Markov chain governs the behaviour of the unobserved state variable, which estimates the transition probability of switching from one regime to another. The transition probabilities characterise the evolution of $s_t \epsilon \{1 \ldots m\}$, where m indicates the number of regimes included in the Markov regime switching model (Morris, 2010:98). The general version of the transition probabilities can be illustrated as follows (Hamilton, 2005a:2):

$$p_{ij} = \Pr(S_{t+1} = j | s_t = i) \ , \qquad (3.1)$$

where:

$\sum_{j=1}^{m} p_{ij} = 1, \ \forall i, j \in (1, \ldots, m).$

Equation 3.1 illustrates the transition probability, p_{ij}, where the transition occurs from regime i during time t to regime j during time $t+1$. The regime switches are dependent on the lag component of time (Morris, 2010:98). However, because there is more than one regime in the Markov regime switching model, the transition probabilities can be illustrated in a transition probability matrix as follows (Wang, 2003:83):

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix}, \tag{3.2}$$

Every element of the transition probability matrix is computed by Equation 3.1. The transition probability matrix also has two characteristics (Morris, 2010:98): none of the transition probabilities are equal to a negative value; and the rows amount to unity, $P_1 = 1$.

Furthermore, the Markov chain also has the following two assumptions (Lacerda, 2008:37):

1. s_t is assumed to be irreducible. In other words, if there are two state regimes known as i and j, then state i leads to state j if state j can be reached from state i in infinite time. These two states, i and j, also communicate, which can be represented as $i \leftrightarrow j$ and implies that if state i leads to state j then state j leads to state i. Therefore, if $i \leftrightarrow j$, for all different regimes, it is said that die Markov chain is irreducible (Lacerda, 2008:37); and
2. The Markov chain is assumed to be ergodic, which implies that the states of the Markov chain are positive recurrent (irrecurrent) and aperiodic (non-periodic) (Lacerda, 2008:37).

The Markov regime switching model can assume two regimes, where s_t can take one of two values (Engel & Hamilton, 1989:4). For instance, the value 0 can be given to an observation that is regime one and the value 1 can be given to an observation in regime two. The process from regime one to two (or from two to one) can be defined by the transition probabilities, which is conditional on the available information at time t (Morris 2010:99). The general version of the transition probabilities (Equation 3.1) can be alternated for two regimes, which can be illustrated as follows (Engel & Hamilton, 1989:4):

$$
\begin{gathered}
P(s_t = 0|s_{t-1} = 0) = p_{11} \\
P(s_t = 1|s_{t-1} = 0) = 1 - p_{11} \\
P(s_t = 0|s_{t-1} = 1) = 1 - p_{22} \\
P(s_t = 1|s_{t-1} = 1) = p_{22}
\end{gathered}, \tag{3.3}
$$

Based on Equation 3.3, there are four different possible outcomes (Styger *et al.,* 2008:30):

1. p_{11} indicates the probability of the time series being in regime 0 at time t, given that at time $t-1$ the time series was also in regime 0;
2. $1-p_{11}$ indicates the probability of the time series being in regime 1 at time t, given that at time $t-1$ the time series was also in regime 0. Therefore, the second conditional probability indicates the transitional probability from regime 0 to regime 1 in the subsequent period;
3. $1-p_{22}$ indicates the transition probability from regime 1 at time t; and
4. p_{22} indicates the probability of the given time series to be in regime 1 at time t, given that the time series was in regime 1 at time $t-1$.

In this study, the Markov regime switching model will be used to establish two regimes, therefore $m = 2$. The following section will discuss the data generating process, which will explain the dynamics for a two-regime Markov regime switching model.

3.2.2.2 The data generating process

The first step in the data generating process is to define the likelihood function for the observed time series as follows (Styger *et al*., 2005:3):

$$
L \equiv p(y_1, \dots, y_T; \underline{\theta}) \ , \tag{3.4}
$$

where:

- $\underline{\theta} = (u_1, u_2, \sigma_1, \sigma_2, p_{11}, p_{22})$;
- u_1 and u_2 are the first and second regime, respectively;
- σ_1 and σ_2 are the variance of the first and second regime, respectively;
- p_{11} is the probability of being in regime one at time t and $t-1$;
- p_{22} is the probability of being in regime two at time t and $t-1$; and
- $y_1, \dots, y_T$ is the sample size (T) for a real-value process y_T.

According to the study of Engel and Hamilton (1989:6), in the data generating process, estimators must be derived for all the above-mentioned parameters in Equation 3.4. This can be achieved by estimating an Expected Maximization (EM) algorithm[34], which Styger *et al.* (2005:4) estimated for the following probabilities:

- The observed series;
- The smooth series known as $p(s_{t-1} = i|y_1, \dots, y_T; \underline{\theta})$ and $p(s_t = j, s_{t-1} = i|y_1, \dots, y_T; \underline{\theta})$;
- The filter probabilities known as $p(s_t = j|y_1, \dots, y_T; \underline{\theta})$; and
- The conditional likelihoods known as $p(y_t|y_1, \dots, y_T; \underline{\theta})$.

According to these above-mentioned probabilities, the vector $\underline{\theta}$ can be derived as follows (Engel & Hamilton, 1989:6):

$$\hat{u}_t = \frac{\sum_{t=1}^{T} y_t . p(s_t = j|y_1, \dots, y_T; \hat{\theta})}{\sum_{t=1}^{T} p(s_t = j|y_1, \dots, y_T; \hat{\theta})}, \qquad j = 1,2 \tag{3.5}$$

$$\hat{\sigma}_j^2 = \frac{\sum_{t=1}^{T} (y_t - u_t)^2 . p(s_t = j|y_1, \dots, y_T; \hat{\theta})}{\sum_{t=1}^{T} p(s_t = j|y_1, \dots, y_T; \hat{\theta})}, \tag{3.6}$$

$$\hat{p}_{11} = \frac{\sum_{t=2}^{T} p(s_t = 1, s_{t-1} = 1|y_1, \dots, y_T; \hat{\theta})}{\sum_{t=2}^{T} p(s_{t-1} = 1|y_1, \dots, y_T; \hat{\theta}) + \hat{p} - p(s_t = 1, |y_1, \dots, y_T; \hat{\theta})}, \tag{3.7}$$

$$\hat{p}_{22} = \frac{\sum_{t=2}^{T} p(s_t = 2, s_{t-1} = 2|y_1, \dots, y_T; \hat{\theta})}{\sum_{t=2}^{T} p(s_{t-1} = 2|y_1, \dots, y_T; \hat{\theta}) + \hat{p} - p(s_t = 2, |y_1, \dots, y_T; \hat{\theta})}, \tag{3.8}$$

where:

- $\hat{\theta}$ is the parameter to be estimated; and
- $\hat{p} = \frac{(1-\hat{p}_{22})}{(1-\hat{p}_{11})+(1-\hat{p}_{22})}$.

According to the study of Engel and Hamilton (1989:7), singularity[35] may occur in Equations 3.5 and 3.6, which will cause Equation 3.4 (the likelihood function) to be infinite. A Bayesian approach was, therefore, proposed by Hamilton (1989), which eliminates the predicament of

[34] The EM algorithm is a two-step estimate procedure, namely the expectation step and the maximisation step. See Lacerda (2008:127) for a more detailed description.

[35] Singularity implies that there is no unique solution for Equations 3.6 and 3.7 (Morris, 2010:104).

singularity. The Bayesian approach derives estimates for $\hat{u}_t$ and $\hat{\sigma}_j^2$ and can be illustrated as follows (Styger *et al.*, 2005:5):

$$\hat{u}_t = \frac{\sum_{t=1}^{T} y_t . p\left(s_t = j | y_1, \dots, y_T; \hat{\theta}\right)}{v + \sum_{t=1}^{T} p\left(s_t = j | y_1, \dots, y_T; \hat{\theta}\right)}, \tag{3.9}$$

$$\hat{\sigma}_j^2 = \frac{\beta + \frac{1}{2}\sum_{t=1}^{T} (y_t - u_t)^2 . p\left(s_t = j | y_1, \dots, y_T; \hat{\theta}\right) + \frac{v.\left(\hat{u}_j\right)^2}{2}}{\alpha + \frac{1}{2}\sum_{t=1}^{T} p\left(s_t = j | y_1, \dots, y_T; \hat{\theta}\right)}, \tag{3.10}$$

where:

α, β and v are constants from the normal-gamma Bayesian prior.

Equation 3.4 can, therefore, be transformed into a generalised objective function, that can be illustrated as follows (Engel & Hamilton, 1989:8):

$$z(\underline{\theta}) = \log p\left(y_1, \dots, y_T; \hat{\theta}\right) - \left(\frac{v.u_1^2}{2\sigma_1^2}\right) - \left(\frac{v.u_2^2}{2\sigma_2^2}\right) - \alpha \log \sigma_1^2 - \alpha \log \sigma_2^2 - \left(\frac{\beta}{\sigma_1^2}\right) - \left(\frac{\beta}{\sigma_2^2}\right), \tag{3.11}$$

By maximising Equation 3.11, the estimated values of the parameters summarised in vector $\underline{\theta}$ can be obtained (Engle & Hamilton, 1989:8). By deriving the estimated parameter values of Equation 3.11, the underlining regime classification can be computed.

However, the Markov regime switching model, as developed by Hamilton (1989), has a number of shortcomings (Morris, 2010:105). The following section will continue to discuss these limitations, followed by a discussion of the Markov Switching Vector Autoregressive (MS-VAR) model as a solution to these limitations (section 3.2.5).

3.2.3 Limitations of the Markov regime switching model

The study of Bolding (1996:35) was the first to identify some of the limitations of the Markov regime switching model, as developed by Hamilton (1989). Bolding (1996:35) found that when relaxing the cross-section restriction on the model specification, there are more local maximums (turning points), illustrating some insufficiency within the model. Another study by Krolzig

(1997:2) also stated that the Markov regime switching model could only be applied to univariate analysis, implying the inability to model the interactions between more than one time series. However, Krolzig (1997:2) recommended a Markov Switching Vector Autoregressive (MS-VAR) model to overcome these limitations. The MS-VAR model can serve as a solution for univariate analysis, because it formulates a combination of the Markov regime switching model and the Vector Autoregressive (VAR) model. The following section will continue with a discussion of the dynamics of a VAR model, which will form the basis for an understanding of the MS-VAR model (section 3.2.5).

3.2.4 Vector Autoregressive (VAR) models

The bivariate[36] first-order VAR model is the simplest form of a VAR model, which implies that the dependant lag variables must be used as regressors (Lacerda, 2008:14). The bivariate first-order VAR model can be illustrated as follows (Wang, 2003:140):

$$y_t = v + \pi_1 y_{t-1} + \varepsilon_t \; , \tag{3.12}$$

where:

- y_t is the vector in the stochastic process;
- $v = (v_1, v_2)$, which contains drifts;
- $\pi_1 = \begin{bmatrix} \pi_{11.1} & \pi_{12.1} \\ \pi_{21.1} & \pi_{22.1} \end{bmatrix}$, which is the coefficient matrix;
- $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})$, which is $i.i.d.$[37] random vector of innovations at time t relative to $y_{t-1} = (y_{1t-1}, y_{2t-1})$; and
- $\varepsilon_t \sim N(0, \Omega)$.

According to Morris (2010:107), it is possible to model the two time variables, y_{1t-1} and y_{2t-1}, independently as univariate autoregressions. However, this is not ideal because the interactions between the two time variables are not taken into account. The VAR model can serve as a solution, by modelling variables with their own lags and other variables' lags in the response

[36] Bivariate refers to two stochastic processes that are included in the analysis (Lacerda, 2008:14).
[37] $i.i.d.$ means independent and identically distributed (Clarida *et al.*, 2003:70).

vector y_t (Gujarati, 2003:837). Equation 3.13, therefore, represents a *p-th* order VAR model with k variables, which can be illustrated as follows (Lacerda, 2008:14):

$$y_t = v + \pi_1 y_{t-1} + \pi_2 y_{t-2} + \cdots + \pi_p y_{t-p} + \varepsilon_t \,, \tag{3.13}$$

The parameters of Equations 3.12 and 3.13 depend on time and are not regime varying. However, the MS-VAR model can be used to estimate some of the parameters of Equation 3.13 that are conditional to s_t (Morris, 2010:107). This leads to the following section that will discuss the MS-VAR model.

3.2.5 The Markov Switching Vector Autoregressive (MS-VAR) model methodology

According to Morris (2010:108), the MS-VAR model can be illustrated in a two-step procedure. In the first step, the Markov chain is used to generate the underlining regimes; while in the second step, the VAR model is used as the conditional data generating process. In order to elaborate on these two procedures, the MS-VAR model must be explained by the regime generating process (section 3.2.5.1) and the data generating process (section 3.2.5.2).

3.2.5.1 The regime generating process

Under the regime generating process, the MS-VAR indicates the conditional probability density of vector y_t, which can be illustrated as follows (Krolzig, 1998:3):

$$p(y_t|y_{t-1}, s_t) = \begin{cases} f(y_t|Y_{t-1}, \theta_1) & if \;\; s_t = 1 \\ \vdots & \\ f(y_t|Y_{t-1}, \theta_m) & if \;\; s_t = m \end{cases}, \tag{3.14}$$

where:

- $s_t = 1 \dots m \in \{1, \dots, m\}$;
- m is the number of regimes;
- θ_m is the VAR parameter vector;
- y_t is the vector of the time series; and
- $Y_t = \{y_{t-j}\}_{j=1}^{\infty}$.

Equation 3.14 illustrates the conditional probability density of the vector of time series y_t, being in a specific regime at the exact period. These probabilities are based on the information known at time t, as well as the state of the regime at time $t-1$ (Moolman, 2004:68). Lacerda (2008:36) also argued that the Markov chain governs the regime generating process. Therefore, the $VAR(p)$ process generates data of the underling time series, given that the time series are in any of the underling m regimes at time t, where $s_t = 1, \dots, m$. The $VAR(p)$ process can be illustrated as follows (Krolzig, 1998:3):

$$E[y_t | y_{t-1}, s_t] = v(s_t) + \sum_{j=1}^{p} A_j\,(s_t) y_{t-j}\,, \tag{3.15}$$

where:

- $u_t = y_t - E[y_t | y_{t-1}, s_t]$;
- $u_t \sim NID(0, \sum s_t)$; and
- $\sum s_t$ is the variance co-variance matrix.

The modelling of the VAR model parameters (see section 3.2.4), conditional to the unobserved regime s_t, forms part of the data generating process. The data generating process of the MS-VAR model also consists of the assumptions, which state that the Markov chain is ergodic and irreducible (see section 3.2.2). The following section will continue the discussion of the data generating process of the MS-VAR model.

3.2.5.2 The data generating process

Under the data generating process, the MS-VAR model can be illustrated as follows (Lacerda, 2008:126):

$$y_t = v(s_t) + \pi_1(s_t) y_{t-1} + \pi_2(s_t) y_{t-2} + \cdots + \pi_p(s_t) y_{t-p} + \varepsilon_t\,, \tag{3.16}$$

where:

- $v(s_t)$ is the regime varying intercept vector;
- $\pi_1, \dots, \pi_p$ is the vector of the autoregressive parameters;
- $y_{t-1}, \dots, y_{t-p}$ is the vector of the lag values;
- ε_t is the vector of the innovation terms; and

- $\varepsilon_t|s_t \sim N(0, \Omega(s_t))$.

Equation 3.16 can be described as an MS-VAR model of p-order and with m regimes, which can be denoted as MS(m)-VAR(p) (Morris, 2010:109). According to Lacerda (2008:78), $\pi_1, \ldots, \pi_p$, v, and Ω depend on the unobserved underlying regime. It is also necessary to remember that Equation 3.16 can be referred to as the "intercept form of the linear VAR", because the intercept term, $v(s_t)$, is dependent on the unobserved regimes (Krolzig:1997:5). Therefore, the adjustment from one regime to another can be referred to as a smooth transition, due to the intercept $v(s_t)$. However, in contrast to the smooth transition from one regime to another, the MS-VAR model can be formulated in terms of the mean $u_t(s_t)$, which will cause the transition to be instant. The MS-VAR model with a "mean adjusted form of the linear VAR model: can be illustrated as follows (Krolzig, 1997:13):

$$y_t - u_t(s_t) = \pi_1(s_t)[y_{t-1} - u_t(s_{t-1})] + \cdots + \pi_p(s_t)[y_{t-p} - u_t(s_{t-p})] + \varepsilon_t \, , \qquad (3.17)$$

where:

- $u_t(s_t)$ is the regime varying mean term.

In addition, there are different forms of the MS-VAR model, which can be distinguished by different acronyms (Krolzig, 1998:7). To identify the different MS-VAR models, the first letter of the parameters that are regime varying can be used for specification. Examples are listed as follows (Krolzig 1998:7):

- The letter *M* can be used to specify whether the mean is the regime that is varying;
- *I* can be used to specify whether the intercept is the regime that is varying;
- The letter *H* is used to indicate whether the variance (heteroskedasticity) is regime varying; and
- *A* indicates that the autoregressive coefficients are dependent on the underlining regime.

For example, a model where both the intercept (I) and the error variance structure (H) are regime varying and where there are four regimes ($m = 4$) in the model with two orders ($p = 2$)

can be illustrated as MSIH(4)-VAR(2). The study of Krolzig (1998:6) indicates that there are a few different MS-VAR specifications, which can be summarised in Table 3.1 below:

Table 3.1: The different forms of the MS-VAR model

		MSM specification		MSI Specification	
		u **Varying**	u **In-varying**	v **Varying**	v **In-varying**
π_j In-varying	**Ω In-varying**	MSM-VAR	Linear MVAR	MSI-VAR	Linear VAR
	Ω Varying	MSMH-VAR	MSH-VAR	MSIH-VAR	MSH-VAR
π_j Varying	**Ω In-varying**	MSMA-VAR	MSA-MVAR	MASI-VAR	MSA-VAR
	Ω Varying	MSMAH-VAR	MSAH-MVAR	MSIAH-VAR	MSAH-VAR

Source: Krolzig (1998:6)

Krolzig (1998:25) showed that there are nine different model specifications that can be tested, although only five specifications will be used in this study because of the RATS 7 software programme (RATS 2007:454) capabilities. Only five different MS-VAR model specifications will be estimated, which can be illustrated as follows (RATS, 2007:454):

- MS(2)-VAR(1);
- MSMH(2)-VAR(1);
- MSI(2)-VAR(1);
- MSM(2)-VAR(4); and
- MSMH(2)-VAR(4).

The Akaike Information Criterion (AIC), Schwarz criterion (SIC) and Hannan-Quinn criterion (HQC) tests will be used to determine which specification should be used. The preferred model will have the lowest AIC, SIC and HQC test values, which will be calculated with the RATS 7 software programme (RATS 2007:454).

3.2.6 Summary

The MS-VAR model is considered to be the best regime switching model to use, because it can analyse a model that consists of univariate variables and comprises two models, which include the Markov regime switching model and the VAR model. However, in this study, the MS-VAR model will be used to assist in identifying the intensity of price volatility in the two markets. After identifying the magnitude of price volatility, it is necessary to divide the datasets to represent periods 1 and 2. The second part in the investigation of the volatility spill-over effect can then begin by subjecting these two periods to a few measuring criteria. The first step in investigating the volatility spill-over effect is to identify the direction of causality flow between the two markets (in each period). The direction of causality flow will be established by applying the Sims (1972) and Granger (1969) causality tests, which will be discussed in the following section.

3.3 TESTING THE DIRECTION OF CAUSALITY BETWEEN SAFEX AND CBOT

3.3.1 Introduction

The direction of causality can provide four different possible outcomes (Asteriou & Hall, 2007:310):

1. X_t causes Y_t; or
2. Y_t causes X_t; or
3. A unidirectional feedback, better known as causality among variables; or
4. The two variables are independent and are useless in forecasting each other.

There are two popular causality tests known as the Granger (1969) and Sims (1972) causality tests. The Granger (1969) causality test can only test for a one-way direction of causality, whereas the Sims (1972) causality test has the ability to test for unidirectional feedback[38]. Asteriou and Hall (2007:283) also stated that one method should not be preferred above the other and recommended that both tests should be estimated. The main difference between the two tests is that the Granger (1969) test makes use of lag values in the estimation of the model, whereas the Sims (1972) test uses lag and lead values (Asteriou & Hall, 2007:283). The following section will discuss the Granger causality test (section 3.4.2) and the Sims causality test (section 3.4.3).

[38] Unidirectional causality refers to causality running in both directions (Sims, 1972:545).

3.3.2 The Granger (1969) causality tests

According to the study by Granger (1969:424), if causality flows from Y_t to X_t, variable X_t can be predicted with more precision by using lagged Y_t values. If this is the case, it is said that X_t granger causes Y_t, which can be illustrated by the following equation (Wooldridge, 2006:659):

$$E(Y_t \mathrm{I} I_{t-1}) \neq E(Y_t \mathrm{I} J_{t-1}) \, , \tag{3.18}$$

where:

- I_{t-1} contains past information on Y_t and X_t; and
- J_{t-1} contains past information on Y_t.

If Equation 3.18 holds, the lagged values of Y_t and X_t are useful for predicting Y_t and only then is it correct to say X_t granger causes Y_t (Wooldridge, 2006:660). The following step is to decide how many lags of the independent variable should be inserted into the model. To illustrate the Granger (1969) causality test statistically, consider the following VAR model with any number of lags (Asteriou & Hall, 2007:282):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \varepsilon_t \, , \tag{3.19}$$

where:

- Y_t is the dependant variable;
- X_t is the independent variable;
- X_{t-i} is the lag value of X_t;
- Y_{t-j} is the lag value of Y_t;
- α_1 is the intercept coefficient;
- β_i is the slope coefficient;
- θ_i is the slope coefficient; and
- ε_t is the stochastic error term.

According to the null hypothesis that X_t does not Granger cause Y_t, any lags of X_t that are added to the equation should have zero population coefficients. Furthermore, if X_{t-1} is added to Equation 3.19, a t test would be sufficient. In addition, an F test should be done to test the joint significance if two lag variables of X_t were to be added to Equation 3.19. Therefore, if the computed F value exceeds the F-critical value, reject the null hypothesis (Asteriou & Hall, 2007:283). The following section will examine the Sims causality test as an alternative to the Granger causality test.

3.3.3 The Sims (1972) causality tests

This Sims causality test can be performed by executing the following steps (Van der Westhuizen, 1991:151). Firstly, estimate an unrestricted model, which will be conducted by regressing the dependent variable on the current five leading and five lagging values of the independent variable. The unrestricted Sims (1972) causality test model can be illustrated as follows (Sims, 1972:545; Asteriou & Hall, 2007:283):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \sum_{p=1}^{k} \zeta_p X_{t+p} + \varepsilon_t \,, \tag{3.20}$$

where:

- Y_t is the dependant variable;
- X_{t-i} is the lag value of X_t;
- Y_{t-j} is the lag value of Y_t;
- X_{t+p} is the lead value of X_t;
- α_1 is the intercept coefficient;
- β_i, γ_j and ζ_p are the slope coefficients; and
- ε_t is the stochastic error term.

and

$$X_t = \alpha_2 + \sum_{i=1}^{n} \theta_i Y_{t-i} + \sum_{j=1}^{m} \delta_j X_{t-j} + \sum_{p=1}^{k} \xi_p Y_{t+p} + \epsilon_t \,, \tag{3.21}$$

where:

- X_t is the dependant variable;
- X_{t-j} is the lag value of X_t;
- Y_{t-i} is the lag value of Y_t;
- Y_{t+p} is the lead value of Y_t;
- α_1 is the intercept coefficient;
- θ_i, δ_j and ξ_p are the slope coefficients; and
- ϵ_t is the stochastic error term.

In the second step, estimate a restricted model using only the statistically significant variables from the unrestricted model in the first step. Thirdly, by summing together the t-statistics of the coefficients of the lag values, the t-statistic as a group can be established. Fourthly, determine whether the leading values of the independent variable as a group are statistically different from zero. If so, the direction of causality will flow from the independent- to the dependent variable. The dependent variable is, therefore, found to be dependent on the future values of the independent variable (Sims, 1972:541). In other words, if the t-statistic of the leading values as a group is greater than the t-critical value, the causality flows from the independent- to the dependant variable (Koutsoyiannis, 1977:660; Table 2). Lastly, repeat steps 3 and 4 in order to determine the t-statistic as a group for all the lagged values.

3.3.4 Summary

It is important to determine the direction of causality flow between SAFEX and CBOT yellow maize prices (for each period), as it forms a crucial step to investigate the price influence that CBOT has on the South African yellow maize market or *vice versa* (volatility spill-over effect). The Granger (1969) causality test was estimated firstly, followed by the Sims (1972) causality test to verify the findings of the former. The following step is the co-movement analysis. By exploring the covariance and Pearson correlation between SAFEX and CBOT in each period, the co-movement can be established.

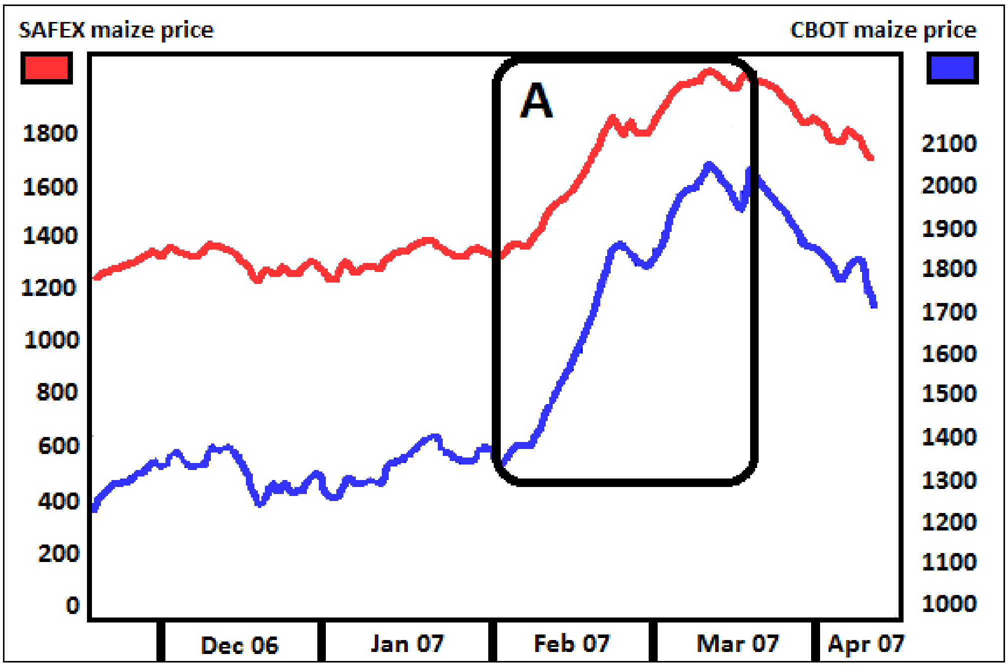
3.4 CO-MOVEMENT BETWEEN SAFEX AND CBOT

3.4.1 Introduction

This section will examine the relationship between SAFEX and CBOT in terms of co-movement, which will be estimated by the covariance and the Pearson correlation coefficients. These estimates will help to understand the influence that one market has on the other, which will be applied to period 1 (October to March) and period 2 (April to September). Other studies also investigated the co-movement of maize prices between SAFEX and CBOT. For instance, the study by Geyser and Cutts (2007a:30) found that the CBOT maize price and the monthly average SAFEX maize price have a Pearson correlation of 0.911, because the USA is the largest grain producer. Zant (2005:14) further assessed the basis risk between SAFEX and CBOT, which calculated the correlation coefficient for three, six, and nine months' returns as 0.494, 0.618, and 0.666, respectively. Evidence was also found that the CBOT yellow maize prices indirectly influence the South African white maize supply and demand, as well as the import and export parity price (Rossouw, 2007:33). These effects can be illustrated by Figure 3.1.

According to Figure 3.1, the CBOT maize prices spiked in 2007, which caused the SAFEX maize futures price to follow. This figure illustrates that there is a distinct relationship (co-movement) between the SAFEX and CBOT maize prices. In addition to these findings, this study will make use of covariance (section 3.3.2) and the Pearson correlation (section 3.3.3) to investigate the co-movement of yellow maize prices between SAFEX and CBOT with daily data, which will be discussed in the following section.

Figure 3.1 Correlation between SAFEX white maize and CBOT corn prices



Source: Rossouw (2007:34)

3.4.2 Covariance

Covariance is known as the absolute measure of the extent to which two variables move together over a period of time (Reilly & Brown, 2003:102). The covariance between variables i and j can be illustrated as follows (Reilly & Brown, 2003:102):

$$COV_{ij} = \frac{\sum(i-\bar{\imath})(j-\bar{\jmath})}{n}, \tag{3.22}$$

where:

- COV_{ij} is the covariance between i and j;
- $\bar{\imath}$ is the mean of variable i;
- $\bar{\jmath}$ is the mean of variable j; and
- n is the number of observations.

If both variables, i and j, are continually above or below their individual means at the same time, it will result in positive covariance values. However, if one of the figures is below the mean and the other figure above, the covariance will have a negative value. The covariance can range from $+\infty$ to $-\infty$, which is noted as the 'absolute measure' between to variables (Reilly &

Brown, 2003:102). The absolute measure implies that if i and j are not closely related, then the covariance will be small, and if i and j are similar, then the covariance will be large. To further investigate the co-movement, a relative measure of the given relationship between two variables is calculated by the Pearson correlation coefficient, which will be discussed in the following section.

3.4.3 The Pearson correlation coefficient

Correlation can be used as a descriptive tool for the co-movement between two variables and it is known that two variables are correlated when they have something in common (Rodgers & Nicewander, 1988:59). According to Rodgers and Nicewander (1988:59), the "coefficient" of correlation is used to express the intensity of the correlation, which is usually known as the Pearson coefficient of correlation. The Pearson correlation coefficient was first introduced by Galton (1886) and was later formalised by Karl Pearson (1896). The Pearson correlation coefficient is used in this study, because of its sensitivity to the linear relationship between two variables, which may exist even if one is a nonlinear function of the other (Croxton *et al.*, 1967:625). The Pearson correlation coefficient can be illustrated as follows (Reilly & Brown, 2003:103):

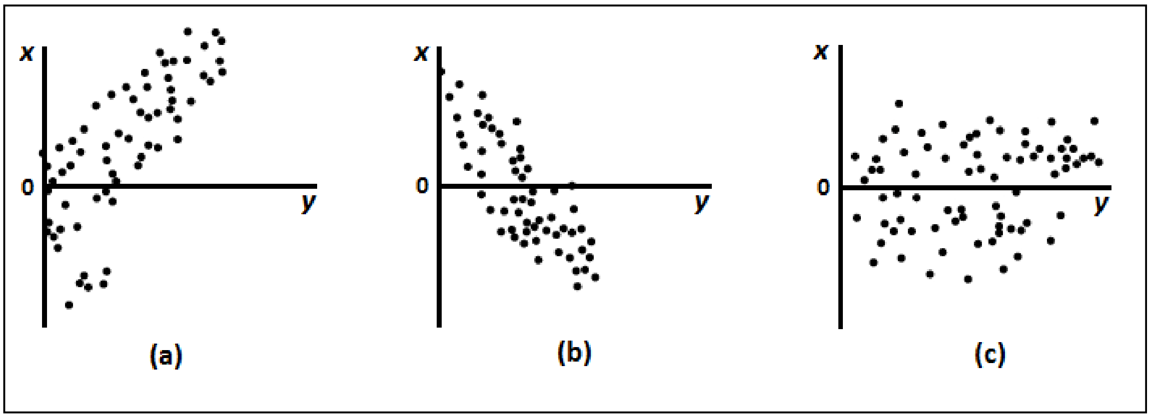
$$r_{ij} = \frac{COV_{ij}}{\sigma_i \sigma_j}, \tag{3.23}$$

where:

- r_{ij} is the correlation coefficient between variable i and j;
- COV_{ij} is the covariance between i and j;
- σ_i is the standard deviation of variable i; and
- σ_j is the standard deviation of variable j.

The Pearson correlation coefficient can range from any value between -1 and $+1$ (Abdi *et al.*, 2009:16). The value of $+1$ indicates a positive relationship between two variables, whereas the value of -1 illustrates a negative relationship between the two variables. Furthermore, the value of 0 indicates that the two variables have nothing in common (Abdi *et al.*, 2009:16). These different values of coefficient correlations can be illustrated in Figure 3.2. The two variables in (a) are positively correlated, (b) illustrates two variables that are negatively correlated, and (c) illustrates two variables that are not correlated at all.

Figure 3.2 illustrates different correlations



Source: Abdi et al. (2009:29)

3.4.4 Summary

The co-movement relationship will be measured by the covariance and the Pearson correlation coefficients in each of the two periods. The co-movement results of the two periods will be compared with each other, which will indicate the difference in price volatility between different seasons. The final step in investigating the volatility spill-over effect includes the estimation of the Johansen (1991) cointegration test, which requires that the direction of causality is pre-determined. The Johansen (1991) cointegration test provides an indication of which variable should be used as the dependent variable in the cointegration analysis. The Johansen (1991) cointegration test (section 3.4) will provide information regarding the presence of a long-run relationship between the SAFEX and CBOT yellow maize prices. Only when the datasets are cointegrated can the Vector Error Correction (VEC) model be estimated; this will indicate the speed of adjustment necessary to return to equilibrium when a shock occurs in one of the markets.

3.5 TESTING FOR COINTEGRATION

3.5.1 Introduction

The purpose of this section is to establish an estimate that has the capability to incorporate the interaction between the SAFEX and CBOT more clearly. This approach will determine if there is a long-run relationship between SAFEX and CBOT and will estimate a speed of adjustment series from a VEC model. The concept of cointegration was first developed by Granger (1981) and was elaborated upon by Engle and Granger (1987:251). In order to achieve significant results from the cointegration model, it is necessary to establish the level of stationarity, because an Ordinary Least Squares (OLS) model requires stationary variables. Regressing a non-stationary (unit root) time series on another non-stationary time series will cause a spurious[39] estimation (Asteriou & Hall, 2007:231). However, it is possible that two non-stationary variables in a linear combination may cancel out stochastic trends if the error term is stationary and thus *I(1).* This condition is also referred to as two variables that are cointegrated (Gujarati, 2003:822). Cointegration states that there exists a long-run relationship between the variables that will not drift too far apart over time (Engle & Granger, 1987:253). Furthermore, for an equation to be meaningful, it should be consistent with the explanatory right-hand side of the equation generating the key properties of the explained variables (Granger, 1981:121).

The first step in testing for cointegration is to test whether there is a unit root (non-stationary) present in both series, which can be determined by the Augmented Dickey Fuller (ADF) test (section 3.5.2). A cointegration approach can only be followed if a unit root is present or the two price series are at the same level of stationarity (Granger, 1986:216). The following section will discuss the Augmented Dickey Fuller (ADF) unit root test, which will be followed by a discussion on the cointegration process (section 3.5.3) and the interpretation of a VEC model (section 3.5.4).

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39 Spurious refers to a regression model that is associated with a high R^2 and t-ratio, a low Durbin Watson statistic, and highly significant coefficients. Spurious variables have no meaningful interrelationship (Gujarati 2003:806; Asteriou & Hall, 2007:291).

3.5.2 Augmented Dickey Fuller unit root test

Assume an autoregressive process of order one, AR(1), which can be illustrated as follows (QMS, 2007:92):

$$Y_t = \rho Y_{t-1} + x_t'\delta + \varepsilon_t \, , \qquad (3.24)$$

where:

- x_t is the optional exogenous repressor that can consist of a constant and a trend, or only a constant;
- ρ and δ are parameters to be estimated; and
- ε_t is assumed to be white noise.

Y_t is a non-stationary series if $|\rho| \geq 1$, which implies that the variance of Y_t increases with time and approaches infinity. If $|\rho| < 1$, then Y_t is a stationary series also known as a trend series. The hypothesis of stationarity can, therefore, be determined by testing whether the absolute value of ρ is strictly less than one. The null and alternative hypothesis can be illustrated as $H_0\!: \rho = 1$ and $H_1\!: \rho < 1$, respectively (QMS 2009:348). If the absolute value of ρ is smaller than 0.05, there is no unit root present, because the null hypothesis is rejected. However, if the absolute value of ρ is greater than 0.05, the null hypotheses is not rejected, which indicates that there is a unit root present.

To determine whether ρ is statistically equal to 1, Y_t can be regressed on its lagged value, Y_{t-1}. Therefore, if ρ is equal to 1, then Y_t will be non-stationary (Gujarati, 2003:814). By subtracting Y_{t-1} on both sides of Equation 3.24, the following equation can be estimated (QMS, 2009:384):

$$\Delta Y_t = \alpha Y_{t-1} + x_t'\delta + \varepsilon_t \, , \qquad (3.25)$$

where:

α is equal to $\rho - 1$.

The null and alternative hypothesis for the unit root test can, therefore, be illustrated as $H_0: \alpha = 0$ and $H_1: \alpha < 0$, respectively (QMS 2009:348). If α is equal to zero it will imply that $\rho = 1$, thus the time series will be non-stationary (Gujarati, 2003:814). The appropriate test to use to determine whether the estimated coefficient in Equation 3.25, Y_{t-1}, is zero or not is to use the Dickey-Fuller test (Gujarati, 2003:814-815).

The Dickey-Fuller test makes the assumption that ε_t is a white noise; however, if ε_t is correlated, an Augmented Dickey-Fuller (ADF) test can be used. The ADF can be formulated by means of a parametric correction for higher-order correlation by assuming that the Y series follows an AR(p) process and by adding p lagged difference terms of the dependant variable Y to the right-hand side of the equation, which can be illustrated as follows (QMS 2009:348):

$$\Delta Y_t = \alpha Y_{t-1} + x_t'\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + v_t \, , \tag{3.26}$$

The ADF specification tests Equation 3.25 by using the t-ratio from Equation 3.27. Note that the asymptotic distribution of the t-ratio for α is independent of the number of lagged first differences that are included in the ADF regression. This augmented specification is then used to test null and alternative hypotheses and is illustrated as follows:

$$t_\alpha = \frac{\hat{\alpha}}{se(\hat{\alpha})}, \tag{3.27}$$

where:

- $\hat{\alpha}$ is the estimate of α; and
- $se(\hat{\alpha})$ is the coefficient standard error.

The results of the ADF unit root test will be reported in Chapter 4, which will be performed with the Eviews 7 program (QMS, 2009). **In this study, each ADF unit root test will include an intercept in the equation.** Note that if the two variables have a unit root or are at the same level of stationarity, one variable can be regressed on the other variable in order to perform a unit root test on the residuals. Two variables will only be cointegrated if the residuals contain no unit roots (Maddala & Kim, 2000:40). The following section will discuss cointegration, which forms the first measure in the investigation of volatility spill over effect between SAFEX and CBOT.

3.5.3 Cointegration

Two non-stationary time series can be stationary in a linear equation, which is also called a cointegration equation (Engle & Granger, 1987:253). This cointegrating equation can be interpreted as a long-run equilibrium relationship between the variables. This approach, as introduced by Engle and Granger (1987), is not always preferred, which consists of the Durbin Watson test for stationary residuals and the ADF test for the existence of a unit root (Heymans, 2008:134). This approach has been highly criticised and should be avoided due to its low estimation power and size distortions (Maddala & Kim, 2000:45; Maddala, 2002:549). However, another approach that is preferred to test cointegration is called the Johansen's (1991) cointegration test. This approach is a Vector Autoregression (VAR)-based cointegration test and will be performed in the Eviews 7 program (QMS, 2009). A VAR is used to analyse the dynamic impact of a random disturbance on variables, where there is no need for structural modelling by treating endogenous variables as a function of the lagged values of all the endogenous variables (QMS, 2009:685). The VAR-based Johansen (1991) cointegration test will be discussed in the following section.

3.5.3.1 The Johansen (1991) cointegration test

The first step in the cointegration process is the estimation of a standard VAR model with a lag of 1-2 specification, which is illustrated in the Eviews 7 program (QMS, 2009). The second step is to determine whether the correct dependent variable had been chosen, which can be established by performing a Granger causality and Block exogeneity test. However, the direction of causality has already been determined, as discussed in section 3.4. The VAR model must also be stable, which can be established by the AR root table and graph. The final step before executing the Johansen (1991) cointegration test is to determine an appropriate lag structure. By using the lag criteria in Eviews 7 (QMS, 2009), which determine the amount of lags necessary, statistically significant results can be assured when estimating a Johansen (1991) cointegration test and a VEC model. However, only with the presence of a cointegrating relationship can a VEC model be estimated.

When executing the Johansen (1991) cointegration test in Eviews 7 (QMS, 2009), the null hypothesis to be tested is that there is no cointegration present (QMS, 2009:686). The Vector Error Correction (VEC) model can be used to illustrate a process where X_t is considered to be integrated to the order of one. This process can be defined as an unrestricted VAR system of an order $(n \times 1)$ (QMS, 2009:685). The VEC model is a restricted VAR that is used for non-stationary series that are identified as cointegrated (Bautista, 2008:36). The VEC model of the process X_t can be illustrated as follows (Johansen, 1988:232):

$$\Delta X_t \ = \ \Pi_1 \, X_{t-1} + \ \Pi_2 \, X_{t-2} + \cdots + \ \Pi_p \, X_{t-k} + \ u_t \ , \tag{3.28}$$

where:

- $X_t = (n \times 1)$ is the vector of *I(1)* variables;
- $\Pi_i = (n \times n) \; i = 1{,}2, \ldots, k$ is the matrix of unknown parameters to be estimated;
- X_{t-k} is the lagged value of the dependant variable X_t for k periods; t =1,2,...,m observations; and
- $u_t \; is$ the dependent and identically distributed $(n \times 1)$ vecto$r$ error term.

The VEC model can also be rewritten to demonstrate short-run and long-run effects in a model. This can be illustrated as follows (Asteriou & Hall, 2007:312):

$$\Delta Y_t = \gamma_0 \Delta X_t - (1-\alpha)\left[Y_{t-1} - \frac{\alpha_0}{1-\alpha_1} - \frac{\gamma_0 + \gamma_1}{1-\alpha_1} X_{t-1}\right] \tag{3.29}$$

where:

- γ_0 is the short-run effect of Y_t after a change in X_t;
- $\frac{\gamma_0+\gamma_1}{1-\alpha_1}$ is the long-run elasticity between variables Y_t and X_t; and
- $(1-\alpha)$ or π is the speed of adjustment needed in the case of disequilibrium. The speed of adjustment can also be referred to as the feedback effect or the adjustment effect.

It is assumed that $a_1 < 1$ is in order for the short-run model to convert to a long-run solution. By incorporating $\Delta = (1 - L)$, where L is the lags operator, Equation 3.28 can be rewritten, which can be illustrated as follows (Hjalmarsson & Österholm, 2007:3):

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \, \Delta X_{t-i} + \Pi X_{t-k} + \, u_t \, , \tag{3.30}$$

where:

- ΔX_t is an *I(0)* vector;
- $\Pi = \sum_{j=1}^{k} \Pi_j - I$;
- $\Gamma_i = \sum_{i=1}^{k-1} \Pi_i - I \qquad i = 1,2, \dots, k-1$;
- I is an *I(0)* vector; and
- u_t is a (n x n) identity matrix.

Johansen (1988:233) incorporated an independent error, which can be used to derive the maximum likelihood estimators of the cointegrating vectors for the autoregressive process. The $(n \times n)$ matrix Π can be illustrated as the product of two matrices, α and β, each with rank r, in order for $\Pi = \alpha\beta'$. If the matrix Π reduced rank $r < k$, then there exist $k \times r$ matrices α and β, each with rank r. The α is also known as the adjustment parameter in the VEC model (QMS, 2007:364). The number of cointegrating relations can be symbolised by r and each column of β is the cointegrating vector (Johansen & Juselius, 1990:169). Equation 3.30 can therefore be rewritten as follows (Johansen & Juselius, 1990:170-171):

$$\Delta X_t = \sum_{i=1}^{k-1} \Gamma_i \, \Delta X_{t-i} + (\alpha\beta')X_{t-k} + \, u_t \, , \tag{3.31}$$

The hypothesis of r cointegration relationship between the elements of X_t can be tested as follows (Johansen & Juselius, 1990:170):

$$H_0 \colon \Pi = \alpha\beta', \tag{3.32}$$

The null hypothesis of no cointegrating relationships is where $r = 0$, which implies that $\Pi = 0$. When estimating the Johansen (1991) cointegrating test in Eviews 7 (QMS, 2009), the Π

metrics from the unrestricted VAR are estimated to determine whether the restrictions from the reduced rank of Π can be rejected or not (QMS, 2009:686). For instance, the number of cointegration vectors (or the rank r of the Π matrix) can be determined by examining whether the Eigenvalues of Π are significantly different from zero. The rank of the Π matrix can be evaluated by means of the Trace statistic and the maximum Eigenvalue statistic (Johansen & Juselius, 1990:181). The Trace statistic can be illustrated as follows (Johansen, 1991:1555):

$$-2lnQ = -T \sum_{i=r=1}^{p=2} (1 - \hat{\lambda}_i)\,, \tag{3.33}$$

where:

$\hat{\lambda}_{r+1}, \dots, \hat{\lambda}_p$ are the estimated $p - r$ smallest Eigenvalues.

According to the null hypothesis of the Trace statistic test, there are at most r cointegrating vectors. Therefore, the rejection of the first null hypothesis, which states that $r \leq s - 1$, will result in $r \geq 1$. The following null hypothesis will, therefore, be $r \leq s$ and will then be reduced to $r = s$. This process will continue until the null hypothesis is not rejected (Burke & Hunter, 2005:102-103). The maximum Eigenvalue test can be illustrated as follows (Burke & Hunter, 2005:100):

$$-2lnQ = -T \sum_{i=r=1}^{p=2} \left(1 - \hat{\lambda}_{r+1}\right), \tag{3.34}$$

The null hypothesis of the maximum Eigenvalue statistic test of the r cointegrating vectors $r = 0$, is tested against the alternative $r + 1$ cointegrating vectors $r = 1$. The original $r + 1$ cointegrating vector ($r = 1$) is then tested against the alternative $r + 1$ cointegrating vectors ($r = 2$), and so on (Burke & Hunter, 2005:100).

When executing the Johansen (1991) cointegrating test, there are a number of deterministic trend options when testing for a cointegrating interaction between two variables with Johansen's (1991) test for cointegration (Heymans, 2008:134). These deterministic trend specifications will be briefly discussed in the following section.

3.5.3.2 The deterministic trend specification

The Eviews 7 program (QMS, 2009) consists of five deterministic trend options that are available when testing for cointegration (Johansen 1995:80; QMS, 2009:687). The first option excludes a deterministic trend from the level data, y_t, and the cointegration equations do not include intercepts. This option should be used when all the series are known to have zero means (QMS, 2009:687):

$$H_2(r): \Pi y_{t-1} + Bx_t = \alpha\beta' y_{t-1}, \tag{3.35}$$

The second option also excludes a deterministic trend from the level data, y_t, but includes intercepts in the cointegration equation. This option should be used when none of the series have a trend (QMS, 2009:687):

$$H_1^*(r): \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0)\,, \tag{3.36}$$

The third option includes a deterministic trend in the level data, y_t, but excludes intercepts in the cointegration equations. This option should be used when none of the series have a trend (QMS, 2009:687):

$$H_1(r): \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0) + \alpha_\perp \gamma_0\,, \tag{3.37}$$

The fourth option includes linear trends in the level data, y_t, and in the cointegration equations. This option should be used when the trends of the series appear to be stationary (QMS, 2009:687):

$$H^*(r): \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp \gamma_0\,, \tag{3.38}$$

The fifth option includes quadratic trends in the level data, y_t, and linear trends in the cointegration equations. This option can be used to produce a good in-sample fit, but it may produce implausible estimates in the case of out-sample forecasts (QMS, 2009:687):

$$H(r): \Pi y_{\mathrm{t}-1} + Bx_{\mathrm{t}} = \alpha(\beta' y_{t-1} + \rho_0 + \rho_1 t) + \alpha_\perp(\gamma_0 + \gamma_1 t)\,, \tag{3.39}$$

The terms $\alpha_{\perp}$ are the deterministic terms outside the cointegration relations. According to Johansen (1995:167), $\alpha_{\perp}$ is the null space of α such that $\alpha'\alpha_{\perp} = 0$. EViews 7 (QMS, 2009) identifies the part inside the error correction term by regressing the cointegration relationships $\beta' y_t$ on a constant and on a linear trend (QMS, 2009:688).

According to the study of Mitchell-Innes (2006:63), the Johansen (1991) cointegration test will estimate two test results known as the Trace test and the maximum Eigenvalue test, at a given lag length. The Trace and maximum Eigenvalue tests are a sequential testing procedure, where the rank/number of cointegration equations (r) tested depends on the number of variables (p) in the cointegration model, and can continue as long as $r \leq p$. As long as the Trace and maximum Eigenvalue statistics are smaller than the critical value, the hypothesis will be rejected, with a maximum number of hypotheses of p. For example, if the null hypothesis $(r = 0)$ is rejected, then the sequential testing procedure will continue to the next hypothesis ($r \leq 1$), and to the alternative $r + 1$ cointegration equations. This process will continue for a maximum of p cointegration equations until the hypothesis is not rejected, which means that the Trace and maximum Eigenvalue statistics will be greater than the critical value (Mitchell-Innes. 2006:63). After establishing the cointegration relationship between the two markets, the VEC model will be estimated. The following section will provide a brief discussion on how to interpret the output as generated by the VEC model.

3.5.4 The interpretation of the VEC model output

A VEC model estimates the speed of adjustment to equilibrium from two non-stationary variables that are cointegrated. The equilibrium is the cointegrated relationship (mean) between the two non-stationary variables. Therefore, the VEC model establishes the adjustment needed for a non-stationary variable to return to equilibrium (mean) for each period. For instance, if the yellow maize prices experience a shock, the VEC model will determine the time it will take for the price to return to equilibrium in both the SAFEX and CBOT markets. The speed of adjustment estimate, π, is also known as the error correction coefficient or the adjustment coefficient, which can be illustrated as follows (Asteriou & Hall, 2007:314):

$$\pi = Y_{t-1} - \frac{\alpha_0}{1-\alpha_0} - \frac{\gamma_0 + \gamma_1}{1-\alpha_1} X_{t-1} \,, \tag{3.40}$$

The adjustment coefficient π estimates can take any value between zero and one. An adjustment coefficient of zero will indicate that no adjustment will occur, whereas the value one indicates that a 100% adjustment will occur (Asteriou & Hall, 2007:312-314). Note that all the terms in a VEC model are also stationary, which implies that a standard OLS approach will be valid (Asteriou & Hall, 2007:312-314).

3.5.5 Summary

When estimating non-stationary time series, the first step is to establish the presence of a unit root. The cointegrating process can only be implemented if the two variables consist of the same level of stationarity. Before the final cointegration model can be estimated, a stable VAR model with an appropriate lag length should be established. The VAR-based Johansen (1991) cointegration model will indicate whether there is a long-run relationship between the South African and USA maize markets. After establishing the presence of the cointegrating relationship (where the Trace and maximum Eigenvalue statistics exceed the critical values) the VEC model can be estimated. The result acquired by the VEC model will indicate the speed of adjustment required for the non-stationary variables to return to equilibrium.

3.6 CONCLUSION

The main goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This chapter examined the different techniques used to measure the volatility spill-over effect between CBOT and SAFEX. The MS-VAR model was discussed in the first part of this chapter (section 3.2.5). This model will assist in indicating the intensity of the price volatility in each market. The second part of this study will commence by acquiring two seasonal time periods in order to establish the two datasets, for both SAFEX and CBOT, which must be examined for the volatility spill-over effect. This will be followed by the application of different measuring criteria to examine the volatility spill-over effect, which consists of the following process.

The co-movement between the two markets will be investigated, which will form the first step in examining the volatility spill-over effect. The co-movement will be indicated by estimating the covariance and Pearson correlation coefficients between the two markets of each period. For instance, the covariance and Pearson correlation coefficients in period 1 and period 2 will be compared to establish which season is more likely to have co-movement. Thereafter, it is necessary to determine the direction of causality flow between these two markets in each individual period. The Granger (section 3.3.2) and Sims (section 3.3.3) causality tests will be used to achieve this. The final measuring criteria used are the Johansen (1991) cointegration test and the VEC model (section 3.5), which will establish whether there is a long-run relationship between the SAFEX and CBOT yellow maize prices and the speed of adjustment coefficients.

This chapter only provided the methodology behind the empirical approach of this study. The following chapter will report the results found and will provide the evidence necessary to justify whether there is an interactive relationship present between SAFEX and CBOT.

CHAPTER 4

Empirical results

"However beautiful the strategy you should occasionally look at the results"

Winston Churchill (1954)

4.1 INTRODUCTION

Traders in the South African maize markets use fundamental and technical analysis to guide them in their trading decision-making process (Heymans, 2008:6). These analyses are mostly influenced by the USA maize import and export parity prices and the ZAR/US$ exchange rate.[40] Evidence from previous studies[41] also suggests that the SAFEX yellow maize prices may be influenced by a volatility spill-over effect between the CBOT and SAFEX maize markets. Since the volatility spill-over effects may vary in the planting and harvesting seasons, respectively, it is important to determine the volatility spill-over effect in each season in order to aid maize traders in South Africa during their decision-making process.

This chapter will be divided into two sections, which entail examining the price volatility of yellow maize prices in SAFEX and CBOT (sections 4.2 and 4.3) and the volatility spill-over effect between SAFEX and CBOT (sections 4.4 to 4.7). The section on price volatility will consist of a graphical evaluation and the use of the MS-VAR model, which will examine the price volatility intensity in the markets (section 4.2.4.1).[42] Thereafter, the data will be divided into two representative seasons for each market, which include the planting and harvesting seasons (section 4.3.1). The planting season for South Africa and the USA harvesting season range from October to March, which will be referred to as period 1. The planting season for the USA and the South African harvesting season range from April to September, which will be referred

[40] See section 2.3.
[41] See section 2.5.2.
[42] The study was adjusted due to the high intensity price volatility. The price volatility made it impossible to identify the planting and harvesting season regimes by using the MS-VAR model. The South African planting (September to March) and harvesting (April to September) seasons were, therefore, identified according to literature (Department of Agriculture and Land Reform, 2008:6).

to as period 2. A graphical evaluation of each market in representative seasons will be examined, which will conclude the section on price volatility (section 4.3.2).

After the data are successfully divided into the two representative seasons, the next section will commence by investigating a volatility spill-over effect between the SAFEX and CBOT markets. This section will firstly examine the presence of co-movement between the two markets. This will entail the determination of the direction of causality (section 4.5), and examining the co-variance and the Pearson correlation (section 4.6) for each market and period. This section will then continue by examining the extent of the volatility spill-over effect between SAFEX and CBOT by estimating a Johansen (1991) cointegration test (section 4.7.2), a VEC model (section 4.7.3), and a variance decomposition model (section 4.7.4) for each period. The Johansen (1991) cointegration test, VEC model and variance decomposition model will provide insight into the long-run co-integration relationship between the two markets and the influential capabilities of the markets.

4.2 DATA SCREENING PROCESS

4.2.1 Introduction

In the following section, the data will be examined by means of descriptive figures and statistics estimated in Eviews 7 (QMS, 2009). The data-screening process will provide the necessary background for the application of regression analysis and the interpretations of results. Furthermore, the data-screening process will also be used to emphasise the high volatility in the two maize markets by graphically illustrating first differenced data (Figure 4.2). The advantages of a data-screening process can be summarised as follows (Agung, 2009:10; Asteriou & Hall, 2007:12):

- By estimating the minimum and maximum values it can be established whether each variable of the data is within the expected range; and
- The information can be understood a lot more easily when the summary statistics are in table or graph format.

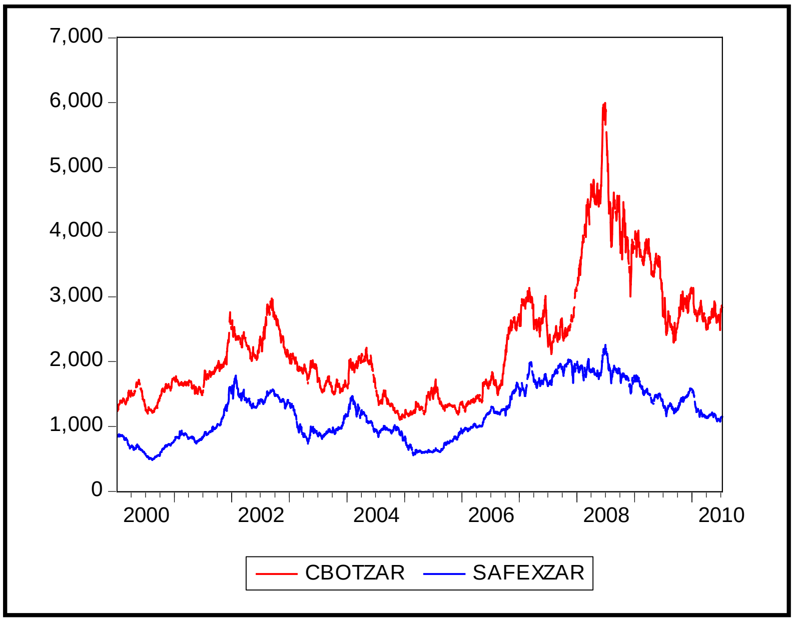
4.2.2 The data

The data consist of daily spot closing prices, which range from 4 January 2000 to 12 July 2010 (due to the availability of the data) and were collected from a number of databases. The South African yellow maize prices were obtained from SAFEX's website (SAFEX, 2011), whereas the USA yellow maize prices were obtained from the Bloomberg Database (Bloomberg, 2010). The ZAR/US$ exchange rate data, which will be used to convert the USA yellow maize prices in ZAR terms, were obtained from the South African Reserve Bank's (SARB) website (SARB, 2011). The use of daily spot closing prices was applied for the entire empirical study, except for the MS-VAR model, where average monthly prices were used.[43] Each variable that will be used in this study will consist of a total of 2 566 observations over the estimated period.

4.2.3 The descriptive statistics and figures

Eviews 7 (QMS, 2009) is used to obtain the graphs, histogram, and descriptive statistics required to evaluate the properties of the empirical data. The graphical analysis helps in the examination of the data for outliers (Asteriou & Hall 2007:12). Figure 4.1 illustrates the line graph of the daily SAFEX price in ZAR terms, and the daily CBOT price in ZAR terms.

Figure 4.1: Descriptive line graph – SAFEX and CBOT



Source: Compiled by author.

[43] See section 4.3.2 for more detail.

Figure 4.1 illustrates that the CBOT yellow maize price started to increase around the end of 2007 and spiked in mid-2008. Therefore, the food price crisis of 2007 and 2008 that was caused by manipulative speculation may be a reason for the maize price fluctuation (Bobenrieth & Wright, 2009:1). Furthermore, the low harvest yields and unexpected shocks related to biofuel demand during this period may also have caused a magnified volatility effect of the maize price (Bobenrieth & Wright, 2009:11). In addition to the graphical analysis, Table 4.1 reports the descriptive statistics.

Table 4.1: Descriptive statistics

Variables	CBOT in USD	CBOT in ZAR	SAFEX in ZAR
Mean	291.24	2246.66	1205.64
Maximum	754.75	5994.00	2256
Minimum	174.75	1105.47	483
Std. Dev.	107.17	921.17	411.98
Skewness	1.52	1.23	0.27
Kurtosis	5.28	4.32	2.03
Jarque-Bera	1543.59*	834.23*	130.31*
Observations	2566	2566	2566

Source: Compiled by author

**Rejected H_0: the data are not normally distributed.*

As reported in Table 4.1, the difference in maximum and minimum values is substantial, which could be an indication of volatile price movements. Table 4.1 also reports on the skewness estimate, which is a measure of asymmetry of the distribution of the series around its mean. Positive skewness indicates a long right tail and negative skewness indicates that the distribution has a long left tail (QMS, 2009:317). All the variables have positive values, indicating that all the variables have long tails to the right. The kurtosis value of the SAFEX yellow maize prices is less than 3, which implies that the distribution is relatively flat, compared to the CBOT yellow maize prices, which illustrates a relatively peaked distribution. Further evidence from Table 4.1 reports that the null hypothesis for normal distribution was rejected for all the variables at the 95% level of statistical significance. This illustrates that the maize prices are not normally distributed, which is an expected outcome when working with prices and return values (Mangani, 2005:2).

The next step of the data-screening process was to test for stationarity, by estimating the ADF unit root test (section 3.5.2). The ADF equation can be illustrated as follows (QMS 2009:348):

$$\Delta Y_t = \alpha Y_{t-1} + x_t^{'}\delta + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \cdots + \beta_p \Delta Y_{t-p} + v_t , \qquad (4.1)$$

where:

- x_t is the optional exogenous repressor that can consist of a constant and a trend, or only a constant;
- ρ and δ are parameters to be estimated; and
- ε_t is assumed to be white noise.

Table 4.2 reports that all the variables have a unit root, which implies that all the variables are non-stationary at a 95% level of statistical significance. The results from Table 4.3 emphasise that all the variables are all integrated to the order of one, *I*(1). These results, therefore, imply that the variables must be first differenced in order eliminate the unit root present in the data.

Table 4.2: Unit root test output (level format)

Variables		t-statistic	t-probability
CBOT	ADF test statistic	-1.721869	0.4200
	1% level	-3.433059	
	5% level	-2.862623	
	10% level	-2.567392	
SAFEX	ADF test statistic	-2.081457	0.2524
	1% level	-3.432873	
	5% level	-2.862541	
	10% level	-2.567348	

Model assumption: Intercept was included in the ADF equation.
Source: Compiled by author

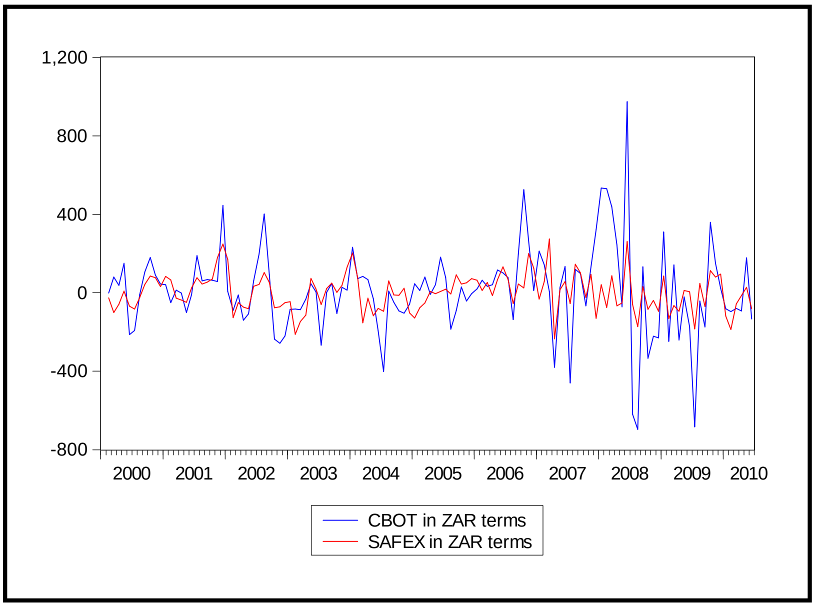
Table 4.3: Unit root test output (first differenced format)

Variables		t-statistic	t-probability
CBOT	ADF test statistic	-48.58284	0.0000*
	1% level	-3.433059	
	5% level	-2.862623	
	10% level	-2.567392	
SAFEX	ADF test statistic	-44.80944	0.0001*
	1% level	-3.433059	
	5% level	-2.862623	
	10% level	-2.567392	

Model assumption: Intercept was included in the ADF equation.
** Reject the null hypothesis for the presence of a unit root.*
Source: Compiled by author

The first differenced data are graphically illustrated in Figure 4.2, which illustrates high price volatility in the SAFEX and CBOT yellow maize markets. Figure 4.2 indicates high volatility in the SAFEX and CBOT yellow maize prices during the period from November 2006 to December 2009.

Figure 4.2: The price volatility of SAFEX and CBOT yellow maize



Source: Compiled by author

To summarise, the data-screening process reported that the SAFEX and CBOT yellow maize prices are not normally distributed and are positively skewed. The SAFEX and CBOT yellow maize prices also demonstrate high volatility behaviour, which is illustrated by the huge difference in the minimum and maximum values (Table 4.1) and the first differenced data graph (Figure 4.2). These results emphasise the fact that the maize price is suitable to be investigated further to establish the price volatility. Therefore, the following section will estimate the MS-VAR model to further examine the high price volatility identified by the data-screening process. Thereafter, the data will be divided into two representative seasons for each market, which will be graphically examined for price volatility.

4.2.4 The MS-VAR model

The MS-VAR model results will be generated for the SAFEX and CBOT yellow maize prices, which will confirm high price volatility by indicating a regime shift from a bearish (bullish) to a bullish (bearish) market. In order to estimate the MS-VAR model, the data must first be transformed to a monthly format, because only monthly data can be used in the MS-VAR model (Morris, 2010:153). The study by Wang (2003:94) emphasised the use of monthly data, by stating that the Markov regime switching models are data and lag-length sensitive. In order to transform the data into a monthly format, the following equation will be used (Heymans, 2008:68):

$$P_t = \frac{1}{n}\sum_{t=1}^{n} Price_t \,, \tag{4.2}$$

where:

- P_t is the monthly average price;
- n is the number of observations in the month; and
- $Price_t$ is the daily closing price on day t.

Only after deriving the average monthly prices and differencing the data to achieve stationarity (section 4.2.3) can the MS-VAR model be estimated. The following section will report the results found for the MS-VAR model.

4.2.4.1 The MS-VAR model results

The study by Krolzig (1998:6) suggested a variety of MS-VAR specifications with different regime varying terms (as discussed in section 3.2.5.2). In order to identify which MS-VAR specifications suit the data the best, the AIC, SIC and HQC criterion values were used, which indicated that MSI(2)-VAR(1) model specification should be used. The MSI(2)-VAR(1) specification model includes one lag variable, a varying intercept, and two regimes. These two regimes are used to describe the maize price behaviour, which is referred to as the bearish[44]

[44] The bearish market indicates that prices depreciate over an extended time period (Maheu & McCurdy, 2000:106).

and bullish[45] markets. Whenever high price volatility in a market is evident, a regime shift will occur. Therefore, the magnitude of the regime shift will provide an indication of the intensity of the price volatility. The MSI(2)-VAR(1) model can also be illustrated as follows (Lacerda, 2008:126):

$$y_t = v(s_t) + \pi_1(s_t)y_{t-1} + \varepsilon_t \,, \qquad (4.3)$$

where:

- $v(s_t)$ is the regime varying intercept;
- $\pi_1(s_t)$ is the vector of the autoregressive parameters;
- y_{t-1} is the lag vector of the y_t;
- $\varepsilon_t | s_t \sim NID(0, \Omega(s_t))$;
- ε_t is the error term; and
- $\Omega(s_t)$ is the error variance.

By estimating the MSI(2)-VAR(1) specification model in RATS 7 (RATS, 2007), the transition probability matrix is derived. The SAFEX and CBOT transition probability matrix results are reported in Tables 4.4 and 4.5. These transition matrix results for SAFEX and CBOT yellow maize prices are accurate because the transition probability matrices amount to zero, which indicates that the Markov chains are irreducible (Lacerda, 2008:119). This means that maize prices can move from the first regime (Bearish regime) to the second regime (Bullish regime) and *vice versa*. Furthermore, the Markov chains are also ergodic, because the transition probability matrices are positive and irreducible (Lacerda, 2008:120).[46]

Table 4.4: SAFEX transition probability matrix

Transition matrix	1st Regime – bearish at t	2nd Regime – bullish at t
1st Regime – bearish at $t-1$	0.96	0.06
2nd Regime – bullish at $t-1$	0.04	0.94

Source: Compiled by author

[45] The bullish market indicates a market that is dominated by a strong trader sentiment with a persistent increase in the price (Maheu & McCurdy, 2000:101).

[46] See section 3.2.5.2 for more detail regarding irreducible and ergodic Markov chains.

The results from Table 4.4 can be interpreted as follows:

- The probability of being in the first regime at time $t-1$ and at time t is 96%;
- The probability of being in the first regime at time $t-1$ or in the second regime at time t is 6%;
- The probability of being in the second regime at time $t-1$ and at time t is 94%; and
- The probability of being in the second regime at time $t-1$ or in the first regime at time t is 4%.

As reported by Table 4.4, the probability of the SAFEX yellow maize prices staying in the residing regime at time $t-1$ is very high and the probability of experiencing a regime shift at time t is very low. The transition probability matrix results indicated by Table 4.4 can be better understood together with the regime duration results in Table 4.6, which indicate the period (measured in months) that the SAFEX yellow maize prices will stay in one of the regimes. Before continuing to the regime duration results, the transition probability matrix results of period 2 are reported in Table 4.5.

Table 4.5: CBOT transition probability matrix

Transition matrix	1^{st} Regime – bearish at t	2^{nd} Regime – bullish at t
1^{st} Regime – bearish at $t-1$	0.89	0.43
2^{nd} Regime – bullish at $t-1$	0.11	0.57

Source: Compiled by author.

Table 4.5 reports the CBOT transition probability matrix, which can be interpreted as follows:

- The probability of being in the first regime at time $t-1$ and at time t is 89%;
- The probability of being in the first regime at time $t-1$ or in the second regime at time t is 43%;
- The probability of being in the second regime at time $t-1$ and at time t is 57%; and
- The probability of being in the second regime at time $t-1$ or in the first regime at time t is 11%.

The results reported by Table 4.5 indicate that the probability of the CBOT yellow maize prices staying in the residing regime at time $t-1$ is also higher than the probability of experiencing a regime shift at time t. The transition probability matrix results reported in Table 4.5 can be better explained together with the regime duration results in Table 4.7, which indicate the period (measured in months) that the CBOT yellow maize prices will stay in one of the regimes. The SAFEX and CBOT regime duration estimates are also derived in RATS 7 (RATS, 2007), which are reported in Tables 4.6 and 4.7, respectively.

Table 4.6: Regime duration for SAFEX yellow maize prices

Regime	Duration*
Expected duration of 1st Regime	23.59
Expected duration of 2nd Regime	17.84

Source: Compiled by author
**Duration is measured in monthly units.*

Table 4.7: Regime duration for CBOT yellow maize prices

Regime	Duration*
Expected duration of 1st Regime	9.31
Expected duration of 2nd Regime	2.32

Source: Compiled by author
**Duration is measured in monthly units.*

The results from Table 4.6 reports that the SAFEX yellow maize prices remain in a bearish regime for 23.59 months and in a bullish regime for 17.84 months. The results from Table 4.7 also reported that the CBOT yellow maize prices remain in a bearish regime for 9.31 months and in a bullish regime for 2.32 months. From regime duration estimate results (Tables 4.6 & 4.7), it is evident that both markets reside mostly in the first regime or bearish market over the estimated period of ten years. Furthermore, it is evident from transition probability matrix results (Tables 4.4 & 4.5) that both markets are likely to stay in the regime that prevails at that given period in time, although a regime shift occurs due to increased price volatility. By estimating the MS-VAR model in RATS 7 (RATS, 2007), the smoothed and filtered probability estimates can be derived in order to establish when a regime shift occurred in each of the two yellow maize markets. The smoothed and filtered probability estimates will also provide a better understanding and visual illustration of regime duration results, which will be discussed next.

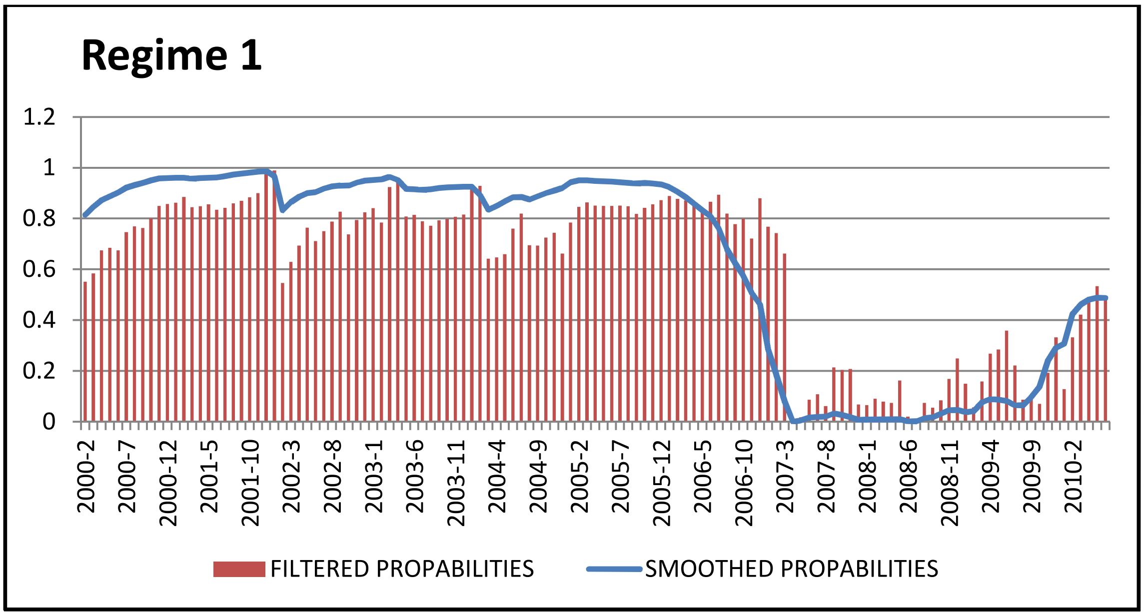
The smoothed probabilities also indicate the exact regime classification[47] of the SAFEX and CBOT yellow maize prices, which specifies the exact periods that a market is residing in a particular regime. In order to identify the exact regime classification, all the estimated smoothed probability values approximately equal to one (100%)[48] will be used to accurately predict the regime that prevails at that given period in time. The SAFEX estimates are reported in Table 4.8. Furthermore, Figures 4.3 and 4.4 graphically illustrate the SAFEX smoothed and filtered regime probabilities, which is followed by the exact regime classification estimates of CBOT.

Table 4.8: The regime classifications for the SAFEX yellow maize prices[49]

Regime 1 (Bearish market)	Regime 2 (Bullish market)
2000:6 – 2002:1	2007:3 – 2009:9
2002:5 – 2004:1	
2004:10 – 2006:2	

Source: Compiled by author

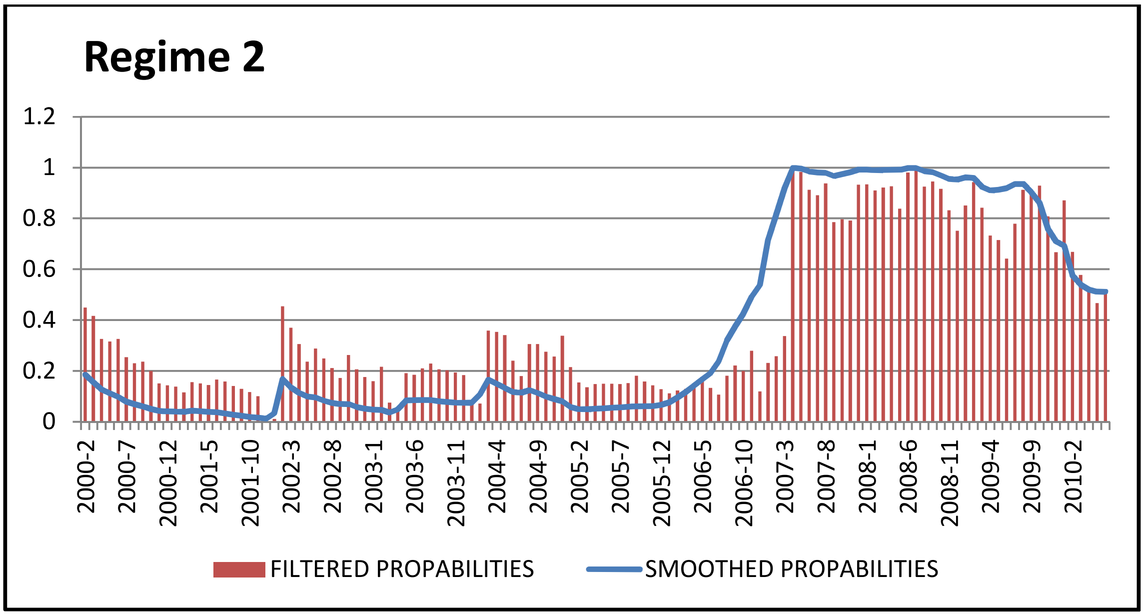
Figure 4.3: Bearish regime probabilities for SAFEX: MSI(2)-VAR(1)



Source: Compiled by author

[47] Classification refers to the exact date of being in a specified regime (Morris, 2010:166).
[48] All the smoothed probabilities that were 90% and higher were regarded as close to 100% (Morris, 2010:116).
[49] See Figures 4.4 and 4.5 for graphical illustrations of the SAFEX bearish and bullish regimes, respectively.

Figure 4.4: Bullish regime probabilities for SAFEX: MSI(2)-VAR(1)



Source: Compiled by author

The results from Table 4.8 report that the SAFEX yellow maize prices remained mainly in the first (bearish) regime and shifted to the second (bullish) regime in March 2007, which is also illustrated by Figures 4.4 and 4.5. This regime shift occurred shortly after the volatility increase that occurred in November 2006, which is illustrated in Figure 4.2. The CBOT exact regime classification estimates are reported in Table 4.9 and the smoothed and filtered regime probabilities are illustrated in Figures 4.5 and 4.6.

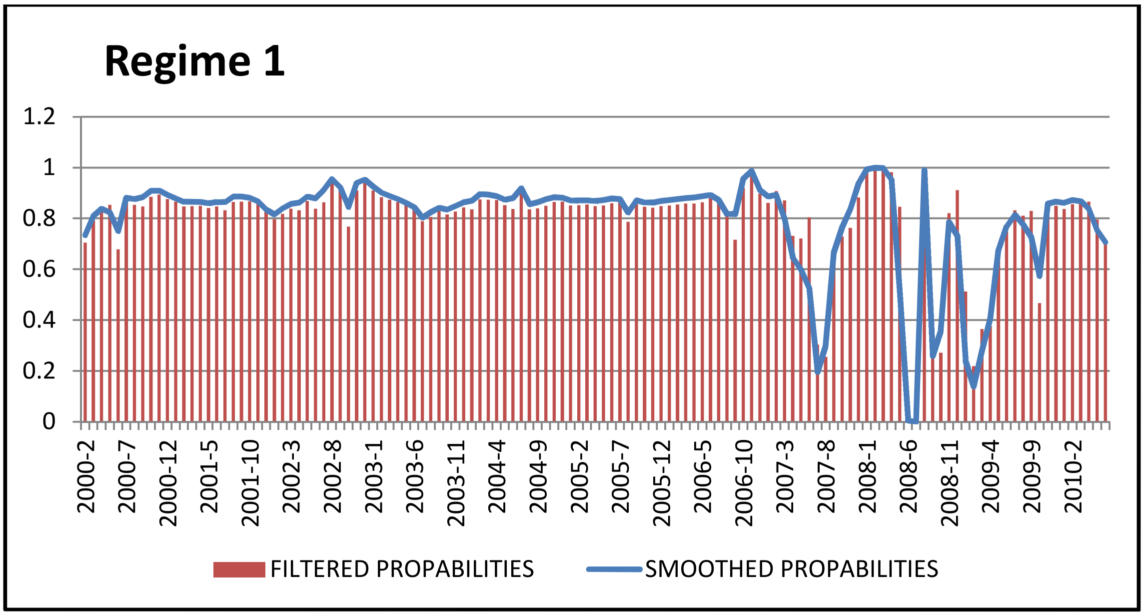
Table 4.9: The regime classifications for CBOT50

Regime 1 (Bearish market)	Regime 2 (Bullish market)
2000:10 – 2000:11	2008:6 – 2008:8
2002:7 – 2002:9	
2002:11 – 2003:2	
2004:7	
2006:10 – 2006:12	
2007:12 – 2008:4	
2008:8	

Source: Compiled by author

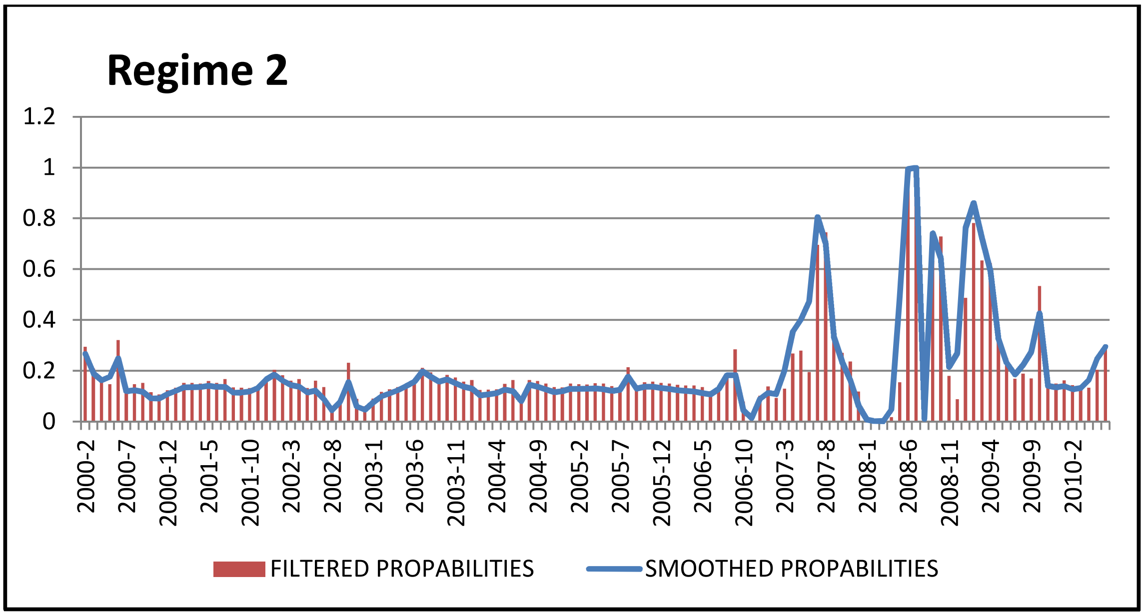
[50] See Figures 4.6 and 4.7 for graphical illustrations of the CBOT bearish and bullish regimes, respectively.

Figure 4.5: Bearish regime probabilities for CBOT: MSI(2)-VAR(1)



Source: Compiled by author

Figure 4.6: Bullish regime probabilities for CBOT: MSI(2)-VAR(1)



Source: Compiled by author

The results from Table 4.9 report that the CBOT yellow maize prices remained in the first (bearish) regime until June 2008, where the regime shifted to the second (Bullish) regime, which is also visually illustrated in Figures 4.5 and 4.6. There was nearly a regime shift in July of 2007, which occurred shortly after the volatility increase from November 2006 (illustrated in Figure 4.2), but a full regime shift occurred in May of 2008. In contrast with these results, Figure 4.2 also illustrates high price volatility in the same time frame ranging from 2007 to 2009.

4.2.5 Summary

The section on the price volatility started by examining the summary statistics, which reported a large difference between the minimum and maximum data values (Table 4.1). This led the investigation to examine the first differenced data in a graphical format (Figure 4.2) to establish the existence of price volatility in each market. The first differenced graph (Figure 4.2) indicated an increase in volatility that started at the end 2006 up until the end of 2009, in both markets. The following step, therefore, was to verify the increased volatility illustrated by Figure 4.2 by estimating the MS-VAR model. The MS-VAR model results indicated that the SAFEX yellow maize prices experienced a regime shift from a bearish- to a bullish market in March 2007 and CBOT yellow maize prices also experienced the same regime shift in May 2008, which was caused by the increased price volatility that started in November 2006. The increased price volatility and regime shift in each market could have been caused by the increase in food and bio-fuel demand. The final step in the section on price volatility is to establish the price volatility of SAFEX and CBOT in each season (periods 1 and 2). The data will be divided into the planting and harvesting seasons of each market, which will be discussed in the following section.

4.3 DIVIDING MARKETS INTO TWO SEASONAL REGIMES

4.3.1 Introduction

In this section, the SAFEX and CBOT yellow maize price data will be divided into seasonal regimes in order to (a) inspect the price volatility of the SAFEX and CBOT yellow maize process in each season and (b) to measure the volatility spill-over effect between the two markets in each season (sections 4.4 to 4.7). The price volatility and volatility spill-over effect during each season may differ due to seasonal effects, for example during the planting season, South African maize consumption is greater than the maize stock levels, and during the harvesting season, the opposite outcome occurs (Department of Agriculture and Land Reform, 2008:6). This seasonal cycle continues throughout each season: from October to March (South African planting season), and from April to September (the South African harvesting season). In the case of the USA, the seasonal cycle is form March to October (the USA planting season), which is known for high maize price volatility, and from November to February (the USA harvesting season), where the opposite effect occurs (Seeley, 2009:11). The South African and USA the seasonal cycles can be illustrated as in Figure 4.7 below.

During the seasonal cycles mentioned above, there are phases where the CBOT and SAFEX maize prices have the same volatility movements and periods where they differ (Geyser & Cutts, 2007a:30). The phases where the CBOT and SAFEX price volatility movements differ could be due to fundamental factors that are regarded as a superior price indicator on SAFEX in the South African planting season (see sections 2.4 and 2.5). In addition, during the periods where the CBOT and SAFEX price volatility movements are more correlated, the USA yellow maize prices are regarded as a superior price indicator on SAFEX in the South African harvesting season (Geyser & Gutts, 2007a:295). The USA is the leading producer of grain, therefore the price fluctuations on CBOT can result in similar price fluctuations on SAFEX (Geyser & Gutts, 2007a:295). A maize trader on SAFEX would then determine the superior price indicator with regard to the current season.

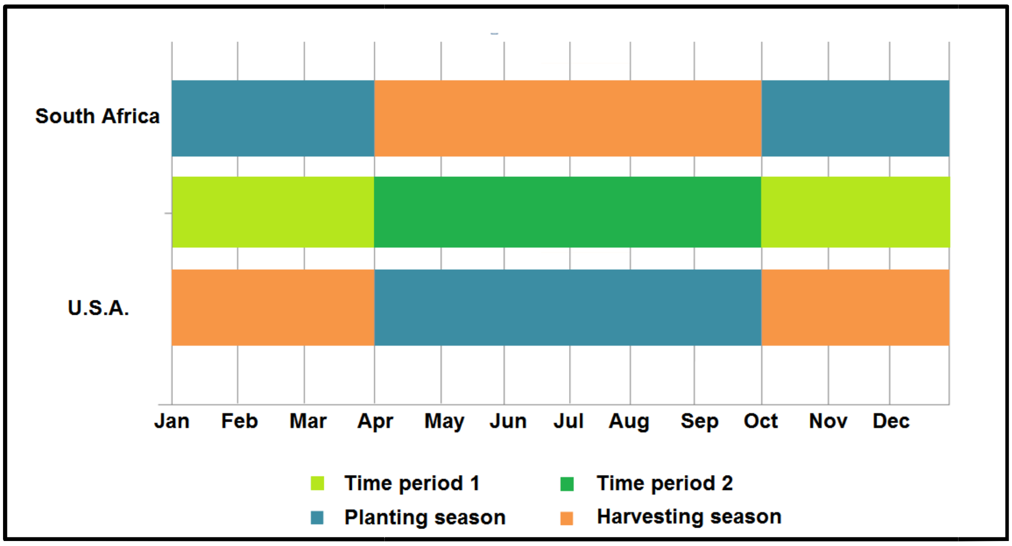
The SAFEX and CBOT price data will be divided as follows (Department of Agriculture and Land Reform, 2008:6):[51]

- The planting season for South Africa and the USA harvesting season range from October to March, and is referred to as period 1; and
- The planting season for the USA and the South African harvesting season range from April to September, and is referred to as period 2.

Periods 1 and 2 can be illustrated as in Figure 4.7 below. In the following section, periods 1 and 2 will be subjected to the Bollinger band analysis for each market, which will be estimated to inspect the intensity of the price volatility (section 4.3.2).

[51] The South African and USA seasonal cycles are not perfect opposites; however, the datasets are divided from South Africa's perspective.

Figure 4.7: Illustration of Time period 1 and 2 (South Africa and USA)



Source: Compiled by author

4.3.2 Seasonal volatility in SAFEX and CBOT

In this section, the Bollinger band will be estimated in order to inspect the price volatility during periods 1 and 2. The Bollinger band analysis will identify time phases where the yellow maize prices for each market experienced high and low volatility (Leung & Chong, 2003:340). The Bollinger band depends on the fluctuation of the prices around the mean and, when the price volatility increases, the upper and lower Bollinger bands will expand. In addition, when the price volatility decreases, the upper and lower Bollinger bands will contract (Leung & Chong, 2003:340). The upper and lower Bollinger bands can be calculated by using the standard deviation of the yellow maize prices, which can be illustrated as in Equation 4.4 (Bollinger: 1992:48):

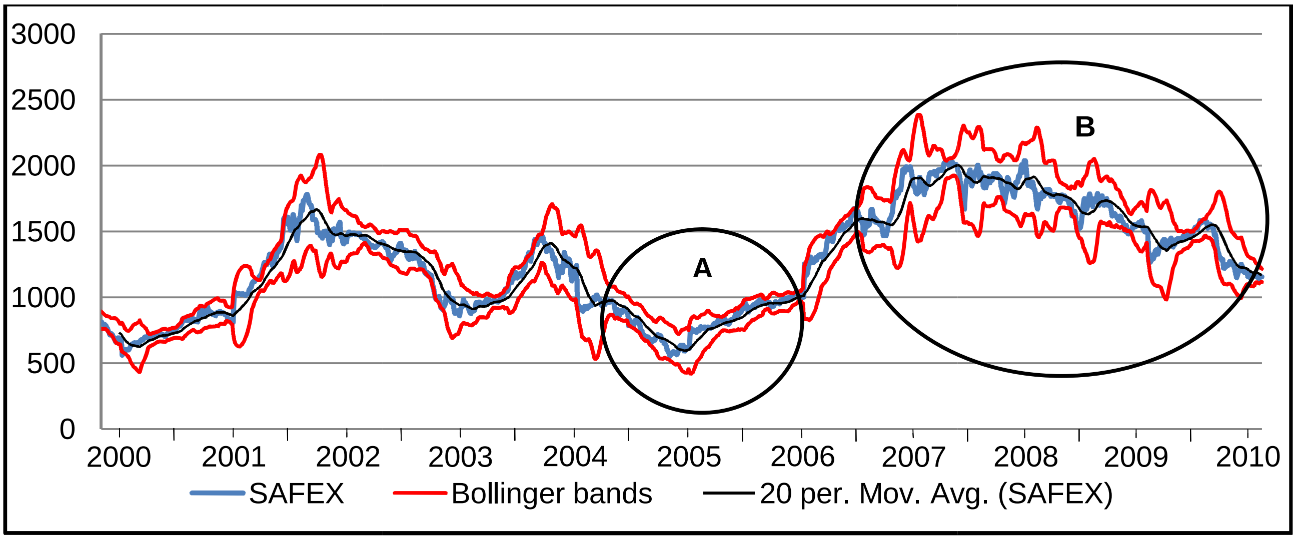
$$\begin{aligned} UB &= \bar{X} + 2\sigma\,, \\ LB &= \bar{X} - 2\sigma\,, \end{aligned} \tag{4.4}$$

where:

- UB is the upper band;
- LB is the lower band;
- $\sigma = \sqrt{\frac{\sum_{j=1}^{N}(X_j - \bar{X})^2}{N}}$, which is known as is the standard deviation;
- X_j is the yellow maize price at time j;
- $\bar{X}$ is the moving average; and
- N is the chosen intermediate-term trend.

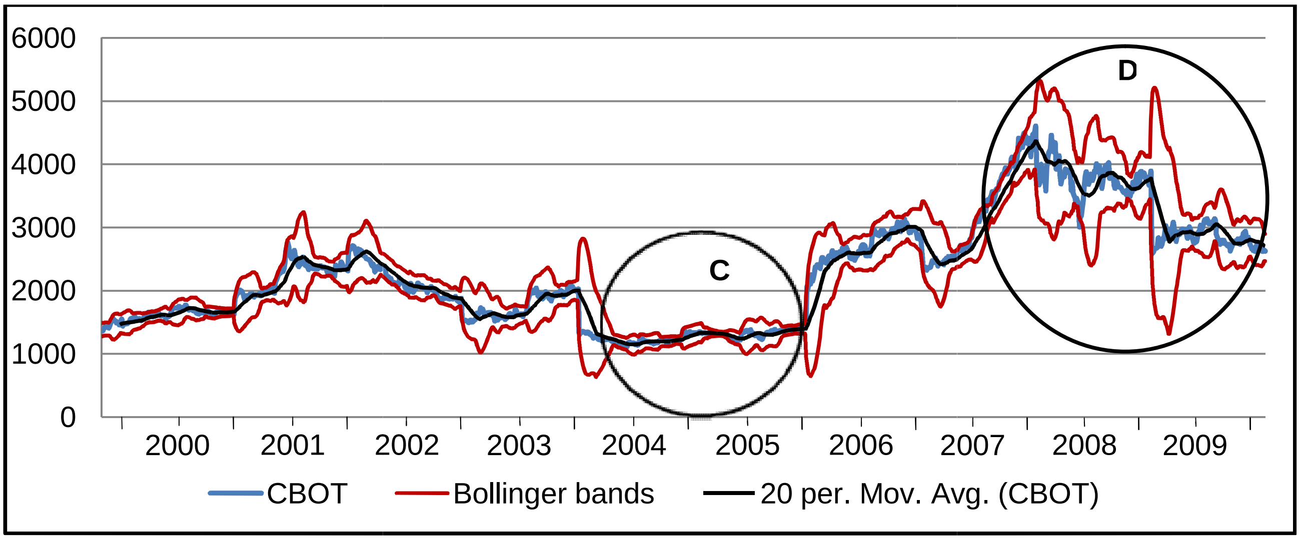
It is necessary to indicate the intermediate-term trend, N, which is suggested by the Bollinger (1992:47) to be chosen as 21 periods in order to include the maximum observed volatility within the price data. Figures 4.8 and 4.9 illustrate the SAFEX and CBOT yellow maize prices and Bollinger bands, respectively, during period 1.

Figure 4.8: The South African planting season – period 1



Source: Compiled by author

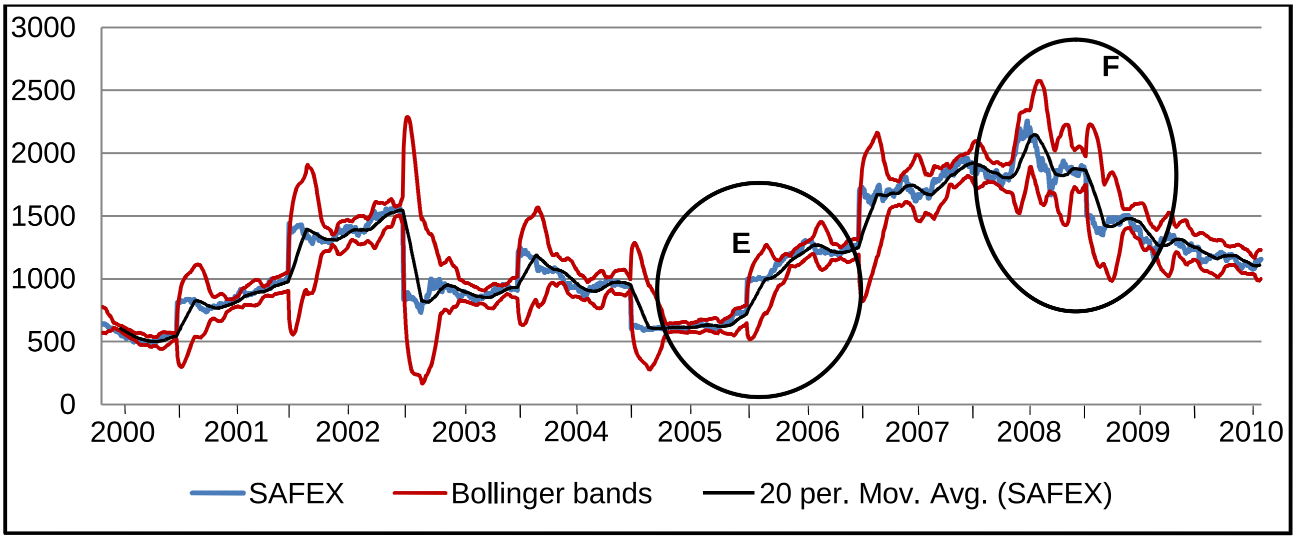
Figure 4.9: The USA harvesting season – period 1



Source: Compiled by author

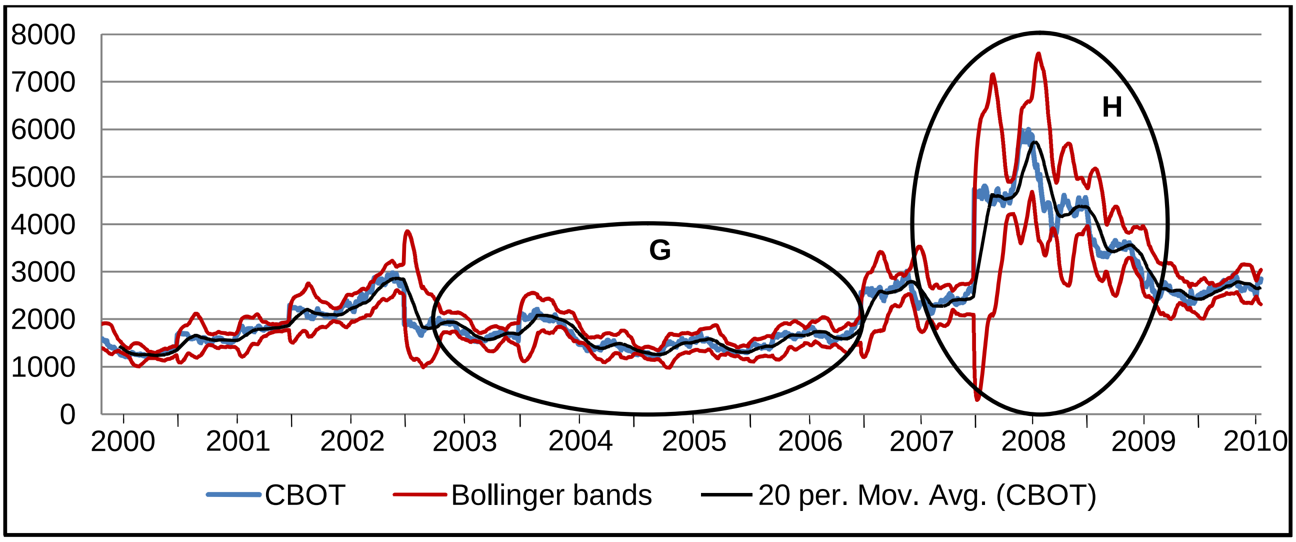
Circle A in Figure 4.8 indicates a time phase where SAFEX experienced low price volatility because the Bollinger bands are contracted, whereas circle B indicates a time phase where SAFEX experienced high price volatility due to the expanded Bollinger bands. The similar occurrence is illustrated by the CBOT yellow maize prices in Figure 4.9, where circle C indicates low price volatility and circle D indicates high price volatility. These findings indicate that both markets experienced low volatility during 2004 to 2005. Thereafter, both markets experienced an increase of yellow maize prices during 2006 to 2007 and an increase in price volatility during mid-2007 to 2010. These results, therefore, indicate that SAFEX and CBOT yellow maize prices had similar price volatility movements during period 1. Before continuing to the section on measuring the volatility spill-over effect, the SAFEX and CBOT yellow maize prices and Bollinger bands during period 2 will be inspected, which are illustrated in Figures 4.10 and 4.11, respectively.

Figure 4.10: The South African harvesting season – period 2



Source: Compiled by author

Figure 4.11: The USA planting season – period 2



Source: Compiled by author

As illustrated by Figures 4.10 and 4.11, the SAFEX and CBOT markets experienced low price volatility time phases (during period 2), as indicated by the contracted Bollinger bands in circles E and G. The SAFEX and CBOT markets also experienced high price volatility time phases (during period 2), which is indicated by the expanded Bollinger bands in circles F and H. These findings indicate that both markets experienced low volatility: SAFEX during 2005 to mid-2006 and CBOT during 2003 to mid-2006. Thereafter, both markets experienced an increase in yellow maize prices during mid-2006 to the end of 2007, followed by an increase in price volatility during the end of 2007 to 2010. These results, therefore, also indicate that SAFEX and CBOT yellow maize prices had similar price volatility movements during period 2.

4.3.3 Summary

The SAFEX and CBOT yellow maize price data were divided according to seasonal regimes in order to inspect whether there exists high price volatility in each season in the SAFEX and CBOT markets and, thereafter, whether there are time phases where SAFEX and CBOT yellow maize prices had the same volatility movements (sections 4.4 to 4.7). In each of the SAFEX and CBOT seasonal regimes, the Bollinger band analysis was used to visually illustrate the price volatility, which indicated that the SAFEX and CBOT yellow maize prices experienced similar price volatility movements during each period. The Bollinger band analysis formed the final step in determining the price volatility between SAFEX and CBOT yellow maize.

To conclude the section on price volatility, the summary statistics indicated a large difference between the minimum and maximum data values (Table 4.1), which led to the visual inspection of the differenced data (Figure 4.2). The differenced data graph (Figure 4.2) illustrated the increase in price volatility movements from November 2006 to December 2009 in both markets. The estimated MS-VAR model indicated that the SAFEX yellow maize prices experienced a regime shift from a bearish- to a bullish market in March 2007, and the CBOT yellow maize prices in May 2008, due to increased price volatility that occurred in November 2006 (section 4.2.4.1). Finally, the Bollinger band analysis illustrated that the SAFEX and CBOT markets experienced similar increased price volatility movements during each period. The findings of this section on price volatility clearly indicate that there is some form of price volatility interaction between SAFEX and CBOT, which leads this study to the point where the intensity of the volatility spill-over effect should be measured.

The following section will continue to investigate the volatility spill-over effect between SAFEX and CBOT yellow maize prices. This section will commence by estimating the optimal lag length structure (section 4.4), which is necessary to estimate the Granger (1969) causality test and the Johansen cointegration test. Thereafter, the presence of co-movement between the two markets will be examined. This will entail the determination of the direction of causality (section 4.5), and examining the co-variance and the Pearson correlation (section 4.6) for each market and period. The section will then continue by examining the extent of the volatility spill-over effect between SAFEX and CBOT yellow maize prices by estimating the Johansen (1991) cointegration test (section 4.7.2), the VEC model (section 4.7.3) and the variance decomposition model (section 4.7.4) for each period.

4.4 OPTIMAL LAG LENGTH

It is necessary to determine the optimal lag interval in order to perform the Granger (1969) causality test in section 4.5, which is lag length sensitive (Shan & Tian, 1998:202; Davidson & Mackinnon, 1993:83). Likewise, the appropriate lag interval will also be used to estimate the Johansen (1991) cointegration test in section 4.7.2 (Agung, 2009:30). In the following section, the lag interval criteria structure results will be reported.

The lag interval criteria structure was estimated in Eviews 7 (QMS, 2009), which computes various information criteria to indicate the optimal lag interval. Tables 4.10 and 4.11 report the lag interval for periods 1 and 2, respectively.

Table 4.10: The optimal lag length structure (period 1)

Lag	LOGL	LR	FPE	AIC	SC	HQ
0	-19015.99	NA	3.17e+10	29.85555	29.86363	29.85859
1	-13434.55	11136.58	4995321.	21.09977	21.12402	21.10888
2	-13415.57	37.80838*	4879230.*	21.07625*	21.11668*	21.09143*
3	-13412.42	6.268685	4885733.	21.07758	21.13418	21.09884

** Indicates the optimal lag length.*
Source: Compiled by author

Table 4.11: The optimal lag length structure (period 2)

Lag	LOGL	LR	FPE	AIC	SC	HQ
0	-19377.04	NA	5.33e+10	30.37467	30.38275	30.37770
1	-13889.78	10948.72	9864620.	21.78022	21.80444	21.78932
2	-13868.68	42.03646*	9603722.*	21.75342*	21.79379*	21.76858*
3	-13865.90	5.526435	9622128.	21.75533	21.81185	21.77656

** Indicates the optimal lag length.*
Source: Compiled by author

From the results in Tables 4.10 and 4.11, the Final Prediction Error (FPE), Schwartz criterion (SC), Akaike information criterion (AIC) and Hannan-Quinn criterion indicate that the optimal lag length for both periods are equal to two lags. Due to the different lag structure suggestions, the Granger (1969) causality test and Johansen cointegration test will be estimated using two lags.

In order to effectively estimate the Granger (1969) causality test (section 4.5) and the Johansen (1991) cointegration (section 4.7.2) test, a lag interval of two will be used, which will be discussed in more detail in each corresponding section. In the following section, the co-movement analysis will commence by estimating the Granger (1969) and Sims (1972) causality tests in order to establish the direction of causality flow between the two markets, for each period. It is necessary to establish the direction of causality flow in order to determine which market should be regarded as the dependant or independent variable. After the direction of causality has been established, the co-movement analysis will continue by determining the co-variance, and the Pearson correlation (section 4.6) will be examined for each market and period. The volatility spill-over effect between SAFEX and CBOT yellow maize prices will then be examined by estimating the Johansen (1991) cointegration test (section 4.7.2), the VEC model (section 4.7.3) and the variance decomposition model (section 4.7.4) for each period.

4.5 CAUSALITY TESTS

4.5.1 Introduction

In the following section, the co-movement analysis will start by estimating the Granger (1969) and Sims (1972) causality tests and will form the first step in testing the volatility spill-over effect between the two markets. The purpose of executing the causality tests is to determine from which market the volatility spill-over originates and to identify which market is influenced by the other in each of the two seasons. The results of each period will be examined in order to identify whether there are seasonal differences in the influence from one market to the other. The Granger (1969) causality test can be illustrated as follows (Asteriou & Hall, 2007:282):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \varepsilon_t \, , \tag{4.5}$$

where:

- Y_t is the dependant variable;
- X_t is the independent variable;
- X_{t-i} is the lag value of X_t;
- Y_{t-j} is the lag value of Y_t;
- α_1 is the intercept coefficient;
- β_i is the slope coefficient;
- θ_i is the slope coefficient; and
- ε_t is the stochastic error term.

The null hypothesis of the Granger (1969) causality test states that X_t does not Granger cause Y_t. If the computed F statistic value exceeds the F-critical value, the null hypothesis is rejected (Asteriou & Hall, 2007:282). In order to execute the Granger causality (1969) test, the appropriate lag length should be used because it is lag length sensitive (Shan & Tian, 1998:202; Davidson & Mackinnon, 1993:83). After the Granger causality (1969) test has established the direction of causality flow and identified which market is dependent on the other, the Sims (1972) causality test will be executed to verify the results. This Sims causality test can be performed by executing the following steps (Van der Westhuizen, 1991:151):

1. Estimate an unrestricted model by regressing the dependent variable on a large number of leading and lagging values of the independent variable, which can be illustrated as follows (Sims, 1972:545; Asteriou & Hall, 2007:283):

$$Y_t = \alpha_1 + \sum_{i=1}^{n} \beta_i X_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \sum_{p=1}^{k} \zeta_p X_{t+p} + \varepsilon_t , \qquad \textbf{(4.6)}$$

where**:**

- Y_t is the dependant variable;
- X_{t-i} is the lag value of X_t;
- Y_{t-j} is the lag value of Y_t;
- X_{t+p} is the lead value of X_t;
- α_1 is the intercept coefficient;
- β_i, γ_j and ζ_p are the slope coefficients; and
- ε_t is the stochastic error term.

and

$$X_t = \alpha_2 + \sum_{i=1}^{n} \theta_i Y_{t-i} + \sum_{j=1}^{m} \delta_j X_{t-j} + \sum_{p=1}^{k} \xi_p Y_{t+p} + \epsilon_t , \qquad (4.7)$$

where:

- X_t is the dependant variable;
- X_{t-j} is the lag value of X_t;
- Y_{t-i} is the lag value of Y_t;
- Y_{t+p} is the lead value of Y_t;
- α_1 is the intercept coefficient;
- θ_i, δ_j and ξ_p are the slope coefficients; and
- ϵ_t is the stochastic error term.

2. Estimate a restricted model by using only the statistically significant variables (leading and lagging variables) from the unrestricted model.
3. Determine the t-statistic of the lagged coefficient values as a group, by calculating the sum of all the t-statistics of all the lagged coefficient values.
4. If the t-statistic of the lagged coefficient values as a group is greater than the t-critical value[52], the direction of causality flows from the lagged values of the independent variable to the dependant variable.
5. Repeat step 3 for the leading values and determine the t-statistic of the coefficients of the leading values as a group.
6. Repeat step 4 for the leading values. If the t-statistic of all the leading coefficient values as a group is greater than the t-critical value, the direction of causality flows from the leading values of the independent variable to the dependant variable (Sims, 1972:541).

The causality test results for periods 1 and 2 will be reported in sections 4.5.2 and 4.5.3, respectively.

4.5.2 Direction of causality flow between SAFEX and CBOT for period for period 1

When the Granger (1969) causality test is estimated in Eviews 7 (QMS, 2009), it is necessary to specify the number of lags that should be included in the regression. The appropriate lag length was estimated in section 4.4.2 (Table 4.10), which indicates that the optimal lag interval is 2. After specifying the lag length, the Granger (1969) causality test for period 1 was estimated and the results are reported in Table 4.12.

Table 4.12: Granger (1969) causality test results (Time period 1)

Null Hypothesis	Lags	F-statistic	Probability	Decision
SAFEX does not Granger cause CBOT CBOT does not Granger cause SAFEX	2	1.26369 4.47363	0.2830 0.0116	No rejection Rejection*

**The rejection/non-regression is for at 95% level of statistical significance.*
Source: Compiled by author

52 The t-critical value can be viewed in Koutsoyiannis (1977:660).

As reported in Table 4.12, the null hypothesis, which states that CBOT does not Granger cause SAFEX, is rejected at the 95% level of statistical significance for period 1. In addition, the null hypothesis, which states that SAFEX does not Granger cause CBOT, is not rejected at the 95% level of statistical significance. Therefore, the volatility spill-over during period 1 originates in CBOT and flows in the direction of SAFEX. This result implies that the SAFEX maize prices are dependent on the CBOT maize prices. During this period, South Africa is in planting season and maize consumption is more than the maize stock levels (Geyser & Gutts, 2007a:295).[53] Therefore, SAFEX traders will rather use fundamental factors as indicators for price movements (see section 2.5.3). The next step is to estimate the Sims (1972) causality test to verify the Granger test results.

The Sims (1972) causality test for period 1 is estimated where SAFEX is regarded as the dependent variable because the Granger (1969) causality test results indicated that SAFEX yellow maize prices are dependent on the CBOT yellow maize prices. By applying the first step, as mentioned above (see section 4.5.1), the unrestricted model was estimated and identified the independent CBOT lagged (one period) yellow maize price variable as statistically significant.[54] The second step was to estimate the restricted model using only the statistically significant variables from the unrestricted model. The results of the restricted model are reported in Table 4.13.

Table 4.13: Sims (1972) causality test results – Dependent variable: SAFEX (period 1)

Variable	Coefficient	Std. Error	t-Statistic	Probability
CBOT	0.150775	0.010316	14.61620	0.0000*
CBOT_LAG1	0.053031	0.010313	5.142341	0.0000*
C	0.017383	0. 809756	0.021466	0.9829
AR(-1)	0.016676	0.028027	0.594978	0.5520

** Statistically significant at the 99% level.*
Source: Compiled by author

In the third step, the t-statistic of the lagged values as a group for period 1 was calculated and equal to 5.14, which is greater than the t-critical value of 2.326. According to the fourth step, the

[53] See section 1.1 for more detail.
[54] The unrestricted model for period 1 is reported in Tables A.1 in Appendix A. Note, there was no leading yellow maize price variable statistically significant in the unrestricted model for period 1.

independent CBOT lagged (one period) yellow maize price variable is statistically significant at a 99% level. The fifth and sixth steps can be ignored because there were no leading values that were statistically significant. This implies that the current yellow maize price values of SAFEX for period 1 are influenced by lagging yellow maize price values of CBOT, which are similar to the results found by the Granger (1969) causality test result for period 1.

4.5.3 Direction of causality flow between SAFEX and CBOT for period for period 2

The Granger (1969) causality test for period 2 was also estimated using the specified lag length equal to 2, which was estimated in section 4.4.2 (Table 4.11). The Granger (1969) causality test results for period 2 are reported in Table 4.14.

Table 4.14: Granger (1969) causality test results (period 2)

Null Hypothesis	Lags	F-statistic	Probability	Decision
SAFEX does not granger cause CBOT	2	1.23353	0.2916	No rejection
CBOT does not granger cause SAFEX		19.5719	4.E-09	Rejection*

**The rejection/non-regression is for at 95% level of statistical significance.*
Source: Compiled by author

As reported in Table 4.14, the null hypothesis, which states that CBOT does not Granger cause SAFEX, is rejected at the 95% level of statistical significance for period 2. However, the null hypothesis, which states that SAFEX does not Granger cause CBOT, is not rejected at the 95% level of statistical significance. Therefore, the volatility spill-over during period 2 originates in CBOT and flows in the direction of SAFEX. This result implies that the SAFEX yellow maize prices are dependent on the CBOT yellow maize prices. This result is similar to the Granger (1969) causality test for period 1; however, the results for period 2 are expected, because during period 2, the maize stock levels in South Africa are more than consumption. Furthermore, traders on SAFEX will mainly rather use CBOT maize prices as indicators for price movement during this period, because CBOT is a larger market than SAFEX is (Geyser & Gutts, 2007a:295).[55] In order to verify the Granger (1969) causality test results for period 2, the Sims (1972) causality test will be estimated.

[55] See section 1.1 for more detail.

The Sims (1972) causality test for period 2 will be conducted in the same manner as explained for period 1. The first step was to estimate the unrestricted model, which identifies the independent CBOT lagged (one period) yellow maize price variable as statistically significant.[56] The second step was to estimate the restricted model using only the statistically significant variables from the unrestricted model. The results of the restricted model are reported in Table 4.15.

Table 4.15: Sims (1972) causality test results – Dependent variable: SAFEX (period 2)

Variable	Coefficient	Std. Error	t-Statistic	Probability
CBOT	0.141328	0.010492	13.46973	0.0000*
CBOT_LAG1	0.062251	0.010486	5.936790	0.0000*
C	0.140121	0.876666	0.159834	0.8730
AR(-1)	-0.084488	0.027899	-3.028364	0.0025*

** Statistically significant at the 99% level.*
Source: Compiled by author

The third step was to calculate the t-statistic of the lagged values as a group for period 2, which is equal to 5.94 and greater than the t-critical value of 2.326. According to the fourth step, the independent CBOT lagged (one period) yellow maize price variable is statistically significant at a 99% level. The fifth and sixth steps can be ignored, because there were no leading values that were statistically significant. Therefore, the current yellow maize price values of SAFEX for period 2 are influenced by lagging yellow maize price values of CBOT, which indicates similar results as the Granger (1969) causality test results for period 2.

4.5.4 Summary

The Granger (1969) and Sims (1972) causality tests, as the initial measures of co-movement, formed the first step in testing the volatility spill-over effect between the two markets during each season. In both seasons, the Granger (1969) causality test indicated that the volatility spill-over originates in CBOT and flows in the direction of SAFEX, which implies that the SAFEX yellow maize price movements are dependent on the CBOT yellow maize price movements. The Sims (1972) causality test was also estimated for both periods in order to verify the results

[56] The unrestricted model for period 2 is reported in A.2 in Appendix A. Note, there were no leading variables that were statistically significant.

found by the Granger (1969) causality test. The Sims (1972) causality test results for both periods indicated that the lagged yellow maize price values of CBOT cause the current yellow maize price values of SAFEX. The Granger (1969) and Sims (1972) causality test results for period 1 are unexpected, because during this period, the consumption in South Africa is more than the maize stock levels. During this period, South Africa is in its planting season and SAFEX traders will rather consider fundamental factors as indicators for price movements (see section 2.5.3). Therefore, these results are contradicting to literature; however, the Granger (1969) and Sims (1972) causality test results for period 2 were to be expected, because during period 2, South Africa is in its harvesting season and the maize stock levels are higher than the consumption. Therefore, SAFEX traders will rather make use of the CBOT yellow maize prices as indicators for price movements (see section 2.5.3). The results of this section therefore imply that price volatility that originates in the CBOT maize market will spill over to the SAFEX maize market during each season.

In the following section, the co-movement will be further investigated by estimating the covariance and the Pearson correlation coefficients for each period. Thereafter, study will continue by estimating a Johansen (1991) cointegration test (section 4.7.2), a VEC model (section 4.7.3) and a variance decomposition model (section 4.7.4). The Johansen (1991) cointegration test, VEC model and variance decomposition model will supply more insight into the long-run co-integration relationship between the two markets and the influential capabilities of the markets.

4.6 CO-MOVEMENT BETWEEN SAFEX AND CBOT YELLOW MAIZE PRICES

4.6.1 Introduction

In this section, the co-movement analysis will continue by examining the confluence between the SAFEX and CBOT yellow maize prices. The confluence relationship between the SAFEX and CBOT yellow maize prices will be examined by estimating the covariance and the Pearson correlation coefficients for each period. Covariance is known as the absolute measure of the extent to which two variables move together over a period of time (Reilly & Brown, 2003:102).

The covariance between variable i (SAFEX) and j (CBOT) can be illustrated as follows (Reilly & Brown, 2003:102):

$$COV_{ij} = \frac{\sum(i - \bar{\imath})(j - \bar{\jmath})}{n}, \tag{4.8}$$

where:

- COV_{ij} is the covariance between i and j;
- $\bar{\imath}$ is the mean of variable i;
- $\bar{\jmath}$ is the mean of variable j; and
- n is the number of observations.

After the covariance between the two markets has been estimated, the Pearson correlation coefficient will be estimated. The Pearson correlation coefficient between variable i (SAFEX) and j (CBOT) can be illustrated as follows (Reilly & Brown, 2003:103):

$$r_{ij} = \frac{COV_{ij}}{\sigma_i \sigma_j}, \tag{4.9}$$

where:

- r_{ij} is the correlation coefficient between variable i and j;
- COV_{ij} is the covariance between i and j;
- σ_i is the standard deviation of variable i; and
- σ_j is the standard deviation of variable j.

The covariance and the Pearson correlation coefficients for time period 1 and 2 will indicate the confluence between the SAFEX and CBOT yellow maize prizes, which is a necessary measurement to illustrate the volatility spill-over effect between the two markets. The covariance and Pearson correlation coefficient results for time period 1 will be discussed in section 4.6.2, followed by the results for time period 2 in section 4.6.3.

4.6.2 The co-movement results for period 1

The covariance and Pearson correlation coefficient results between SAFEX and CBOT yellow maize prices for period 1 are reported in Tables 4.16 and 4.17, respectively. As reported in Table 4.16, the covariance between SAFEX and CBOT yellow maize prices for period 1 (October to March) is 283693.8. The positive covariance estimate indicates that both variables are continually above or below their means at the same time.

Table 4.16: The covariance coefficient for period 1

	CBOT	SAFEX
CBOT	723205.7	283693.8
SAFEX	283693.8	156304.0

Source: Compiled by author

Table 4.17: The Pearson correlation for period 1

	CBOT	SAFEX
CBOT	1.000000	0.843789
SAFEX	0.843789	1.000000

Source: Compiled by author

As reported in Table 4.17, the Pearson correlation coefficient between SAFEX and CBOT yellow maize prices for period 1 (October to March) is 0.843789. An 84.4% correlation between SAFEX and CBOT yellow maize prices is very high and indicates that there is a distinct confluence between the two market maize prices. During this period, South Africa is in its planting season and traders mostly consider the fundamental factors as a good price indicator; however, the co-movement between SAFEX and CBOT yellow maize prices is still highly correlated (Geyser & Gutts, 2007a:295). These results, therefore, imply that there is a distinct confluence and co-movement between the two markets disregarding the fact that it is during period 1. The covariance and Pearson correlation coefficient results for period 2 are reported in the following section.

4.6.3 The co-movement results for period 2

The covariance and Pearson correlation coefficient results between SAFEX and CBOT yellow maize prices for period 2 are reported in Tables 4.18 and 4.19, respectively. As reported in

Table 4.18, the covariance between the two markets is 344554.4 for period 2 (April to September). The covariance estimate for period 2 is positive, which indicates that both variables are repeatedly above or below their means at the same time.

Table 4.18: The covariance coefficient for period 2

	CBOT	SAFEX
CBOT	974944.6	344554.4
SAFEX	344554.4	178137.5

Source: Compiled by author

Table 4.19: The Pearson correlation for period 2

	CBOT	SAFEX
CBOT	1.000000	0.826780
SAFEX	0.826780	1.000000

Source: Compiled by author

As reported in Table 4.19, the correlation between the SAFEX and CBOT yellow maize prices from October to March (period 2) is 0.826780. The Pearson correlation coefficient of 82.7% is very high and indicates that there exists a distinct confluence between the two markets for period 2. During this period (October to March), South Africa is its in harvesting season and SAFEX traders will rather use the CBOT maize prices as price indicator (Geyser & Gutts, 2007a:295). By examining the results found for period 2, the confluence between SAFEX and CBOT yellow maize prices is highly correlated. The results, therefore, imply that there is also a distinct confluence between the two markets during period 2, which is similar to the co-movement results found for period 1.

4.6.4 Summary

The purpose of this section was to determine whether there is confluence present between the SAFEX and CBOT yellow maize prices in each season. By estimating the covariance and Pearson correlation coefficient for both seasons, the results reported that the SAFEX and CBOT yellow maize prices have a distinctive confluence and are highly correlated.

Evidence from the Sims (1972) and Granger (1969) causality test indicated that the price volatility will originate in the CBOT market and will spill over to the SAFEX market during both periods (section 4.5). The covariance and Pearson correlation coefficients established that SAFEX and CBOT yellow maize prices move highly correlated during each period (section 4.6). In the following section, the co-movement analysis will be extended by estimating the Johansen (1991) cointegration test and a VEC model, which will provide more insight into the long-run cointegration relationship between the two markets.

4.7 THE COINTEGRATION PROCESS

4.7.1 Introduction

The cointegration process forms the final step in the investigation of the volatility spill-over effect and includes the estimation of the Johansen (1991) cointegration test (section 4.7.2), the Vector Error Correction (VEC) model (section 4.7.3) and the variance decomposition model (section 4.7.4). In addition to the Johansen (1991) cointegration test that will provide information regarding the presence of a long-run relationship between the SAFEX and CBOT yellow maize prices, the Vector Error Correction (VEC) model will indicate the speed of adjustment necessary for the maize prices to return equilibrium when a shock occurs in one of the markets. Thereafter, the variance decomposition model results will elaborate on the long-run coefficient from the VEC model.

4.7.2 The Johansen (1991) cointegration approach

The first step in the cointegration process is to determine whether the variables consist of the same order of integration. Only variables that consist of the same level of integration can be used for the Johansen (1991) cointegration test. In section 4.2.3, the ADF unit root test was estimated, which indicates that all the variables in each period are integrated to the order one, $I(1)$. In the second step of the Johansen (1991) cointegration analysis, the VAR model for each period was established as stable.[57] In the third step, the lag interval of the VAR for each period

[57] Figures B.1 and B.2 in the appendix illustrate the stability tests graphically, indicating that the VAR is stable for periods 1 and 2, respectively.

was specified, which was established in section 4.4.2 as two lag lengths for each season (Agung, 2009:30).

After determining the appropriate lag intervals, the Johansen (1991) cointegration test was estimated in Eviews 7 (QMS, 2007). In the Johansen (1991) cointegration test, both the Trace (Tr) and maximum Eigenvalue (L-max) statistics are used to determine the number of cointegrating relationships. If the Tr and L-max statistics are smaller than the critical value, the hypothesis cannot be rejected, which will indicate the presence of a co-integration relationship, indicated by the null and alternative hypothesis (Hawtrey 1997:341). The null and alternative hypothesis can be presented as follows:

$H_0: r = 0$ (no co-integration relationship present), (4.10)

$H_1: r \leq 1$ (one co-integration relationship present), (4.11)

$H_2: r \leq 2$ (two co-integration relationship present), (4.12)

The Tr and the L-max test results for period 1 are reported in Table 4.20 and Table 4.21, respectively. As reported in Table 4.20, the H_0 hypothesis could not be rejected because the Tr statistic is less than the critical value. The Tr statistic justifies that there does not exist cointegration relationship between the SAFEX and CBOT yellow maize prices. However, the results in Table 4.21 indicate that the H_0 hypothesis can be rejected because the L-max test statistic is greater than the critical value. The L-max test statistic at the H_1 hypothesis, however, cannot be rejected, emphasising the existence of a cointegrating relationship between SAFEX and CBOT yellow maize prices (for period 1). Overall, the results confirm that there exists a long-run cointegration relationship between the SAFEX and CBOT yellow maize prices during period 1, which implies that the VEC model can be estimated to elaborate on the long-run relationship found by the Johansen (1991) cointegration analysis.

Table 4.20: The Trace test results for period 1

Hypothesized	Tr Statistic	0.05 Critical Value	Prob.
$\boldsymbol{H_0: r = 0}$	23.79107	25.87211	0.0888
$\boldsymbol{H_1: r \leq 1}$	2.789511	12.51798	0.9005

**Reject hypothesis at the 95% level of statistically significance.*
Trend assumption: linear, intercept and trend; one lag interval.
Source: Compiled by author

Table 4.21: The maximum Eigenvalue test results for period 1

Hypothesized	L-max Statistic	0.05 Critical Value	Prob.
$\boldsymbol{H_0: r = 0}$	21.00156	19.38704	0.0289*
$\boldsymbol{H_1: r \leq 1}$	2.789511	12.51798	0.9005

**Reject hypothesis at the 95% level of statistically significance.*
Trend assumption: linear, intercept and trend; one lag interval.
Source: Compiled by author

The results for period 2, reported in Tables 4.22 and 4.23, indicate that the Tr and the L-max statistics are greater than the critical value at the H_0 hypothesis, implying that the H_0 hypothesis could be rejected in both tests. However, the Tr and the L-max statistics are smaller than the critical value at the H_1 hypothesis, indicating that the H_1 hypothesis could not be rejected. The Tr and the L-max results emphasise the existence of one cointegration relationship between the SAFEX and CBOT yellow maize prices during period 2. Overall, the results confirm that there exists a long-run cointegration relationship between the two markets' yellow maize prices, which implies that the VEC model can be estimated to elaborate on the long-run relationship found by the Johansen (1991) cointegration analysis.

Table 4.22: The Trace test results for period 2

Hypothesized	Tr Statistic	0.05 Critical Value	Prob.
$\boldsymbol{H_0: r = 0}$	27.35338	25.87211	0.0325*
$\boldsymbol{H_1: r \leq 1}$	4.491906	12.51798	0.6702

**Reject hypothesis at the 95% level of statistically significance.*
Trend assumption: linear, intercept and trend; one lag interval.
Source: Compiled by author

Table 4.23: The maximum Eigenvalue test results for period 2

Hypothesized	L-max Statistic	0.05 Critical Value	Prob.**
$\boldsymbol{H_0: r = 0}$	22.86147	19.38704	0.0150*
$\boldsymbol{H_1: r \leq 1}$	4.491906	12.51798	0.6702

**Reject hypothesis at the 95% level of statistically significance.*
Trend assumption: linear, intercept and trend; one lag interval.
Source: Compiled by author

The results of the VEC model will be reported in the following section, which will elaborate on the long-run relationship found by the Johansen (1991) cointegration analysis. The VEC model will provide a speed of adjustment estimate that will indicate how long the markets will take to return to their equilibrium price levels after a shock. Thereafter, the variance decomposition model results will be reported in section 4.7.4, which will elaborate on the long-run coefficient from the VEC model (Maroney *et al*., 2004:141).

4.7.3 Vector Error Correction (VEC) model

The VEC model estimated can be illustrated as follows (Johansen, 1998:232):

$$\Delta Y_t = \gamma_0 \Delta X_t - (1-\alpha)\left[Y_{t-1} - \frac{\alpha_0}{1-\alpha_1} - \frac{\gamma_0 + \gamma_1}{1-\alpha_1} X_{t-1}\right], \tag{4.13}$$

where:

- γ_0 is the short-run effect (impact multiplier) of Y_t after a change in X_t;
- $\frac{\gamma_0+\gamma_1}{1-\alpha_1}$ also referred to as β, is the long-run relationship estimate;
- it is assumed that $\alpha_1 < 1$ in order for the short-run model to convert to a long-run solution; and
- $(1-\alpha)$ also referred to as π, is the speed of adjustment needed when disequilibrium occurs.

The speed of adjustment estimate, π, ranges between 0 and 1, where 1 indicates that a 100% adjustment will occur and 0 indicates that no adjustment will take place. The long-run relationship estimate, β, will indicate whether or not there exists a one-to-one relationship between the two variables (Asteriou & Hall, 2007:312-314). The VEC model results for periods 1 and 2 are reported in Tables 4.24 and 4.25, respectively.

Table 4.24: The VEC model output results for period 1

Lags: 1	β	t-stat of β	π	t-stat of π	Adj. R^2	R^2
SAFEX	1.000000	-	-0.000512	[-0.13459]	0.002362	0.004706
CBOT	-0.514002	[-6.73148]*	-	-	0.031674	0.033948

**Statistically significant on a 99% level.*
Source: Compiled by author

Table 4.25: The VEC model output results for period 2

Lags: 1	β	t-stat of β	π	t-stat of π	Adj. R^2	R^2
SAFEX	1.000000	-	0.002440	[0.58674]	-0.001941	0.000409
CBOT	-0.435749	[-6.70889]*	-	-	0.038189	0.040445

Source: Compiled by author

**Statistically significant on a 99% level.*

As reported in Tables 4.24 and 4.25, the long-run relationship estimate, β, for both periods is statistically significant. The long-run relationship between CBOT to SAFEX yellow maize prices during period 1 is -0.51 to 1, whereas the long-run relationship between the two markets during period 2 is -0.44 to 1. The VEC model results suggest the presence of an inverse relationship between the SAFEX and CBOT yellow maize prices. Tables 4.24 and 4.25 also report the speed of adjustment estimate, π, for periods 1 and 2, respectively. The speed of adjustment necessary for period 1 to return to equilibrium after a shock occurs in one of the markets is 0.05% of the observed period to adjust to equilibrium, which is approximately 0.64 das (15 hours). The speed of adjustment necessary for period 2 is 0.24% of the observed time period to return to equilibrium, which is approximately three days.

Accompanying the VEC model results, are the variance decomposition model results, which have the ability to elaborate on the long-run coefficient from the VEC model (Maroney *et al*., 2004:141). This leads to a discussion on the variance decomposition model results that will continue in the following section.

4.7.4 Variance decomposition analysis

The variance decomposition model results will provide more insight into the meaning of the long-run relationship estimate, β, and will provide a better understanding of the out-of-sample causal relationship between the endogenous variables (Maroney *et al*., 2004:141). The variance decomposition model is able to indicate the amount of volatility that each market contributes to the other, which can be illustrated as follows (Weiss, 2005:385):

$$var(X_t) = E\left(\frac{varX_t}{Y_t}\right) + varE\left(\frac{X_t}{Y_t}\right), \tag{4.14}$$

where:

- $var(X_t)$ is the variance of the variable X_t;
- $E\left(\frac{varX_t}{Y_t}\right)$ is the unexplained component of the variance of X_t; and
- $varE\left(\frac{X_t}{Y_t}\right)$ is the explained component of the variance of X_t.

The variance decomposition results for periods 1 and 2 were estimated in Eviews (2009:470) and are reported in Tables 4.26 and 4.27, respectively. The time horizon is indicated by the first column, whereas the variation between current and future values of the endogenous variable caused by a shock is indicated by the second column (labelled S.E.). A higher S.E. value can be interpreted as a greater attribute to an own shock, implying that SAFEX yellow maize prices deviate further from their mean values due to an own shock and due to a shock in the CBOT yellow maize prices.

Table 4.26: The variance decomposition output result for period 1

SAFEX			
Period	**S.E.**	**SAFEX**	**CBOT**
1	30.86994	100.0000	0.000000
2	45.12303	99.98444	0.015562
3	55.88566	99.98124	0.018762
4	64.87738	99.98036	0.019644
5	72.75495	99.98037	0.019627
6	79.84898	99.98079	0.019208
7	86.35300	99.98141	0.018592
8	92.39189	99.98212	0.017879
9	98.05181	99.98288	0.017121
10	103.3952	99.98365	0.016349

Source: Compiled by author

Table 4.27: The variance decomposition output result for period 2

SAFEX			
Period	**S.E.**	**SAFEX**	**CBOT**
1	36.88124	100.0000	0.000000
2	52.12378	99.99020	0.009800
3	63.82892	99.98467	0.015332
4	73.73021	99.97999	0.020012
5	82.47930	99.97548	0.024520
6	90.41088	99.97094	0.029063
7	97.72388	99.96628	0.033724
8	104.5478	99.96146	0.038537
9	110.9727	99.95648	0.043515
10	117.0640	99.95134	0.048663

Source: Compiled by author

Table 4.26 reports the variance decomposition results for period 1, which indicate that all the variations on the SAFEX yellow maize prices during the first period were caused mainly by an own shock. Table 4.26 also indicates that all the variations on the SAFEX yellow maize prices caused by own shocks decreased until the fifth period, from where on it increased until the last period. This implies that the influential ability of the CBOT price volatility increased until the fifth period and then decreased until the last period. The influential contribution of CBOT price volatility on the SAFEX yellow maize prices (during period 1) was estimated at 1.63%.[58] The low influential ability of CBOT on SAFEX for period 1 is expected, because SAFEX traders mostly consider fundamental factors as a price indicator for price movements during planting season (Geyser & Gutts, 2007a:295).

Table 4.27 reports the variance decomposition results for period 2, which indicate that all the variations on the SAFEX prices during the first period were mainly caused by an own shock. Table 4.27 also indicates that all the variations on the SAFEX yellow maize prices caused by own shocks decreased until the last period. The influential ability of CBOT increased from the second period up until the last period, contributing an average variance of 4.86%. The influential contribution of CBOT on SAFEX of period 2 is greater than that of period 1. This result is expected for period 2, because SAFEX traders will rather consider CBOT prices as a price indicator for price movements during the harvesting season (Geyser & Gutts, 2007a:295).

4.7.5 Summary

The cointegration analysis formed the final step in investigating the volatility spill-over effect. The Johansen (1991) cointegration test results indicated that there exists a long-run cointegration relationship between the two markets during each period (section 4.7.2). Thereafter, the VEC model results emphasised the presence of an inverse relationship between the SAFEX and CBOT yellow maize prices, which indicated that during period 1 it will take approximately 15 hours to eliminate the presence of disequilibrium between these two markets and approximately three days for period 2 (section 4.7.3). The variance decomposition model

[58] The results of the variance decomposition model with the CBOT yellow maize prices as dependant variable are reported in the Appendix C.

results accompanied the VEC model results, which indicated that the influential ability that the CBOT yellow maize price movements have on the SAFEX yellow maize price movements during periods 1 and 2 were 1.96% and 4.86%, respectively.

4.8 CONCLUSION

The main goal of this study is to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This goal was divided into two sub-objectives; firstly, to establish how yellow maize prices in South Africa and the USA are compiled and influenced by fundamental factors, which was already discussed in sections 2.4 and 2.5; Secondly, to establish the presence of a volatility spill-over effect between the SAFEX and CBOT maize markets, which was investigated in this chapter by dividing the chapter into two sections. The first section inspected the price volatility of yellow maize prices in SAFEX and CBOT (sections 4.2 & 4.3). The second section measured the volatility spill-over effect between SAFEX and CBOT yellow maize prices (sections 4.4 to 4.7).

In the first section on price volatility, the summary statistics were estimated, which showed high price volatility movements due to the huge difference identified between the minimum and maximum data values (Table 4.1). This led the investigation to visually inspect the differenced data and examine the price volatility during the entire period under investigation. The differenced data graph (Figure 4.2) illustrated the increase in price volatility movements from November 2006 to December 2009 in both markets. Thereafter, the estimated MS-VAR model was estimated, which indicated that SAFEX yellow maize prices experienced a regime shift from a bearish- to a bullish market in March 2007, and yellow maize prices in May 2008 due to increased price volatility from November 2006 (section 4.2.4.1). Finally, the Bollinger band analysis illustrated that the SAFEX and CBOT yellow maize markets experienced similar increased price volatility movements during each period. The findings of the section on price volatility indicate that there exists some form of price volatility interaction between SAFEX and CBOT, which leads this study to the point where the intensity of the volatility spill-over effect should be measured.

In the second section on the volatility spill-over effect evidence from the Sims (1972) and Granger (1969) causality tests confirmed that the volatility spill-over effect will originate in the CBOT market and will spill over to the SAFEX market during both periods (section 4.5). The covariance and Pearson correlation coefficient estimates indicated that SAFEX and CBOT yellow maize prices are highly correlated during each period (section 4.6). The study continued by estimating the Johansen (1991) cointegration test, which indicated that there also exists a long-run cointegration relationship between the two markets during both periods (section 4.7.2). The long-run relationship between the two markets during each period was further elaborated by estimating a VEC model, emphasising the presence of an inverse relationship between the SAFEX and CBOT yellow maize prices. The VEC model results also indicated that it will take approximately 15 hours during period 1 and approximately three days for period 2 to eliminate the presence of disequilibrium between these two markets (section 4.7.3). These results, therefore, confirm the existence of long-run co-movement between the SAFEX and CBOT yellow maize prices during October to March and during April to September each year. Finally, the variance decomposition model was estimated as the final measure to elaborate on the amount of volatility that each market contributes to the other and to provide additional information regarding the influential ability that the two markets have on each other (section 4.7.4). The variance decomposition model results indicated that the influential ability that CBOT yellow maize prices have on SAFEX yellow maize prices during periods 1 and 2 was 1.96% and 4.86%, respectively.

The findings in this chapter indicate that, although there is a volatility spill-over effect from CBOT to SAFEX and a confluence of yellow maize prices, the difference in the volatility spill-over effect from CBOT to SAFEX in each period is significantly small. The following chapter will conclude this study and review some recommendations for future research.

CHAPTER 5

Summary, Conclusion and Recommendations

"It always seems impossible until it's done."

Nelson Mandela

5.1 INTRODUCTION

The question that was posed for this study is as follows: Are there certain periods where the CBOT yellow maize prices influence the SAFEX yellow maize prices more than in other periods? Furthermore, can fundamental factors be used as a price indicator in the periods where CBOT does not have a significant effect on the SAFEX prices? In order to answer this question, the following main goal and objectives were set: The main goal was to investigate the influential effect that fundamental factors and CBOT maize prices have on SAFEX maize prices. This goal was divided into two sub-objectives; firstly, to provide a broad discussion on the fundamental factors that influence the South African and USA yellow maize markets (Chapter 2); secondly, to determine and measure the intensity of the volatility spill-over effect between the two markets in the planting and harvesting seasons, respectively (Chapter 4).

This chapter will briefly summarise how these research objectives were achieved by providing a broad review of the literature and the results from the empirical study (section 5.2). The literature review will focus on the main agricultural supply and demand factors that influence the South African and USA yellow maize prices as well as the different seasonal periods of the two markets. The empirical review will focus on how the price volatility of yellow maize prices in SAFEX and CBOT was established and how the co-movement and volatility spill-over effect from CBOT on SAFEX in each season were measured. This chapter will conclude with recommendations for future studies.

5.2 REVIEW OF THE LITERATURE[59] AND EMPIRICAL RESULTS[60]

Traders in the South African maize markets continuously look at various forces that influence the SAFEX maize prices throughout the year; which include fundamental supply and demand factors, the CBOT yellow maize prices, and the ZAR/US$ exchange. Some of the supply factors include the weather and diseases, low water supply, high input costs, the shortage of farmland, and the farmer's knowledge of farming. Additionally, several of the demand factors include the population growth, increased bio-fuel production, dietary preferences, and animal feed.[61] The CBOT yellow maize prices are considered due to the effect of the import and export parity prices.[62] Before a trader on SAFEX can attain comfort over a trading decision, the seasonal differences between the South African and USA maize markets should be considered.[63] A seasonal cycle in South Africa continues throughout each year from October to March (consumption is more than the maize stock levels) and from April to September (the opposite effect occurs). In the case of the USA, the growing season is from March to October, which indicates that the volatility of maize prices is at a high and from November to February the opposite effect occurs.

The influence of CBOT on SAFEX is also expressed by the fact that the USA is the world's largest yellow maize producer and will, therefore, affect the supply and demand in the rest of the smaller yellow maize producing countries like South Africa. The SAFEX price volatility will, therefore, have the same price volatility patterns as on CBOT, which implies that CBOT produces a volatility spill-over effect on SAFEX. The intensity of the volatility spill-over effect, however, is influenced by the seasonal cycles and fundamental factors that are mentioned above. Consequently, the price volatility patterns between CBOT and SAFEX may be less correlated in certain periods and more correlated in other periods.[64]

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[59] See Chapter 2 for a detailed discussion on the literature findings.
[60] See Chapter 4 for a detailed discussion on the empirical findings.
[61] See sections 2.4 and 2.5 for a detailed discussion on the different supply and demand factors.
[62] See section 1.1 for a detailed discussion on import and export parity prices.
[63] See section 2.5.2 for a detailed discussion on the different seasonal periods between South Africa and the USA.
[64] See section 2.5.2 for a detailed discussion on the findings of previous studies.

In order to determine the intensity of the volatility spill-over effect in each season, various measuring criteria were used; firstly, by examining the price volatility of yellow maize prices in SAFEX and CBOT[65] and; secondly, by determining the co-movement and measuring the volatility spill-over effect between SAFEX and CBOT.[66] The section on price volatility initially was to use the MS-VAR model in order to identify seasonal regimes of each market, which would have helped in determining regime switches from one season to another; however, the method did not succeed because the price volatility of the SAFEX and CBOT yellow maize is too high. The inadequate identification of the seasonal regimes by the MS-VAR model proved that the price volatility is high and therefore the seasonal regimes were determined by means of the findings of previous studies.[67] The planting season for South Africa and the USA harvesting season were indicated to range from October to March, which was referred to as period 1. The planting season for the USA and the South African harvesting season were indicated to range from April to September, which was referred to as period 2. After establishing the two seasonal periods for CBOT and SAFEX, the Bollinger band analysis was used to help in determining the extent of the price volatility. The Bollinger band analysis illustrated that the SAFEX and CBOT yellow maize markets experienced similar increased price volatility movements during each period. The conclusion of the MS-VAR model and Bollinger band analysis results indicated that there exists some form of price volatility interaction between the two yellow maize markets, which led this study to the point where the presence of co-movement and the intensity of the volatility spill-over effect was measured.

The section on co-movement and the volatility spill-over effect between SAFEX and CBOT determined the presence of co-movement between the two markets and measured the seasonal price volatility that spills over from CBOT to SAFEX. Firstly, the presence of co-movement between the two markets was determined by estimating the direction of causality,[68] and the co-variance and the Pearson correlation[69] for each market and period. Thereafter, the

[65] See sections 4.2 and 4.3.
[66] See sections 4.4 to 4.7.
[67] See section 4.3.1 for a detailed discussion on how the seasonal regimes were determined.
[68] See section 4.5.
[69] See section 4.6.

extent of the co-movement and volatility spill-over effect between SAFEX and CBOT was estimated using a Johansen (1991) cointegration test[70], a VEC model[71] and a variance decomposition model[72] for each period. The Johansen (1991) cointegration test, VEC model and variance decomposition model provided insight into the long-run co-integration relationship between the two markets and the influential capabilities of the markets.

As the first measure of co-movement, the direction of causality was determined by estimating the Granger (1969) and Sims (1972) causality tests. In both seasons, the Granger (1969) causality test indicated that the volatility spill-over originates in CBOT and flows in the direction of SAFEX, which implies that the SAFEX yellow maize price movements are dependent on the CBOT yellow maize prices movements. The Sims causality test results in both seasons indicated that the previous day's yellow maize price of CBOT influences the current yellow maize price values of SAFEX. The Granger (1969) and Sims (1972) causality test results for period 1 are unexpected, because, during this period, the consumption in South Africa is more than the maize stock levels. During this period, South Africa is in its planting season and SAFEX traders will rather consider local fundamental factors as indicators for price movements (see section 2.5.3). The Granger (1969) and Sims (1972) causality test results for period 2 were to be expected, because, during period 2, South Africa is in its harvesting season and the maize stock levels are higher than the consumption. Consequently, SAFEX traders will rather make use of the CBOT yellow maize prices as indicators for price movements (see section 2.5.3). The results of this section therefore imply that price volatility that originates in the CBOT maize market will spill over to the SAFEX maize market during each season.

After the direction of causality flow was established, the second measure of co-movement measured the presence of confluence between the SAFEX and CBOT yellow maize prices in each season. The confluence was determined by estimating the co-variance and the Pearson correlation coefficient between SAFEX and CBOT (in each season). The covariance and

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[70] See section 4.7.2.
[71] See section 4.7.3.
[72] See section 4.7.4.

Pearson correlation coefficient results established that SAFEX and CBOT yellow maize prices move highly correlated during each period. This implies that the SAFEX price movements are very similar to the price movements on CBOT throughout the year. Traders on SAFEX can therefore use the CBOT prices movements as a price indicator to determine the SAFEX yellow maize prices, disregarding the season that resides at that period in time.

As the final measure of the co-movement between the SAFEX and CBOT yellow maize prices, the extent of the volatility spill-over effect from CBOT on to SAFEX was determined by estimating the Johansen (1991) cointegration test, which indicated that there exists a long-run cointegration relationship between the SAFEX and CBOT during each of the periods. The long-run cointegration relationship between the SAFEX and CBOT implies that the there exists a strong co-movement between the two markets' yellow maize prices. Additional to the Johansen (1991) cointegration test result, the VEC model results emphasised the presence of an inverse relationship between the SAFEX and CBOT yellow maize prices. The results indicated that during period 1 it will take approximately 15 hours to eliminate the presence of disequilibrium between these two markets and approximately three days for period 2. The variance decomposition model results accompanied the VEC model results, which indicated that the influential ability that the CBOT yellow maize price movements have on the SAFEX yellow maize price movements during periods 1 and 2 was 1.96% and 4.86%, respectively. The VEC and variance decomposition model results imply that, in period 1, the influence of CBOT yellow maize prices on SAFEX is less than in period 2.

5.3 CONCLUSION AND RECOMMENDATION

This study provided extensive evidence that within the perspective of South African yellow maize prices, there are certain periods where the CBOT yellow maize prices influence the SAFEX yellow maize prices more than in other periods. Consequently, in the periods where CBOT does have a less significant influence on the SAFEX prices, fundamental factors can be used as an alternative price indicator. Traders on the SAFEX market can therefore use the CBOT yellow maize prices as a reliable price indicator in the South African harvesting season, whereas in the planting season, the CBOT prices in collaboration with fundamental analysis should be used.

In addition to these results, the following recommendations may provide more insight into the volatility spill-over effect between SAFEX and CBOT in different seasonal regimes. In addition to incorporating monthly yellow maize price data, the monthly volume data may produce better results when estimating the MS-VAR model in order to establish the seasonal regimes for each market. Initially, the monthly yellow maize price data were used in an attempt to identify the seasonal regimes. However, the method was unsuccessful due to the high volatility of the price datasets. By using the monthly volume data, the datasets will have, perhaps, less volatility and therefore indicate the seasonal regimes more accurately. By including these improvements, this study can improve in explaining the effects of fundamental factors and CBOT prices on South African yellow maize prices.

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APPENDIX A

Table A.1 and A.1 reports the unrestricted the Sims (1972) causality test results for period 1 and 2, respectively.

Table A.1: The unrestricted Sims (1972) causality test results – Dependent variable: SAFEX (period 1)

Dependent Variable: DSAFEX1
Method: Least Squares
Date: 04/18/12 Time: 20:54
Sample (adjusted): 8 1277
Included observations: 1270 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCBOT1	0.153994	0.010492	14.67799	0.0000
DCBOT1_LAG1	0.053050	0.010463	5.070150	0.0000
DCBOT1_LAG2	0.004284	0.010461	0.409475	0.6823
DCBOT1_LAG3	-0.004314	0.010464	-0.412297	0.6802
DCBOT1_LAG4	0.006527	0.010474	0.623159	0.5333
DCBOT1_LAG5	0.009507	0.010420	0.912449	0.3617
DCBOT1_LEAD1	0.015859	0.010464	1.515685	0.1299
DCBOT1_LEAD2	-0.002593	0.010458	-0.247964	0.8042
DCBOT1_LEAD3	0.015364	0.010461	1.468755	0.1421
DCBOT1_LEAD4	0.002096	0.010469	0.200181	0.8414
DCBOT1_LEAD5	0.009581	0.010409	0.920431	0.3575
C	-0.051366	0.817193	-0.062856	0.9499
AR(1)	0.017114	0.028208	0.606720	0.5441

R-squared	0.157527	Mean dependent var	0.232283
Adjusted R-squared	0.149484	S.D. dependent var	30.99689
S.E. of regression	28.58639	Akaike info criterion	9.553922
Sum squared resid	1027198.	Schwarz criterion	9.606606
Log likelihood	-6053.741	Hannan-Quinn criter.	9.573712
F-statistic	19.58631	Durbin-Watson stat	1.996706
Prob(F-statistic)	0.000000		

Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).

Table A.2: The unrestricted Sims (1972) causality test results – Dependent variable: SAFEX (period 2)

Dependent Variable: DSAFEX2
Method: Least Squares
Date: 09/01/11 Time: 03:15
Sample (adjusted): 8 1279
Included observations: 1272 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DCBOT2	0.139573	0.010588	13.18197	0.0000
DCBOT2_LAG1	0.061392	0.010587	5.798747	0.0000
DCBOT2_LAG2	0.012535	0.010592	1.183356	0.2369
DCBOT2_LAG3	-0.011144	0.010619	-1.049424	0.2942
DCBOT2_LAG4	-0.002197	0.010635	-0.206613	0.8363
DCBOT2_LAG5	0.012404	0.010621	1.167852	0.2431
DCBOT2_LEAD1	0.012530	0.010587	1.183561	0.2368
DCBOT2_LEAD2	0.007337	0.010584	0.693175	0.4883
DCBOT2_LEAD3	0.014068	0.010587	1.328736	0.1842
DCBOT2_LEAD4	-0.000886	0.010602	-0.083590	0.9334
DCBOT2_LEAD5	-0.009474	0.010583	-0.895259	0.3708
C	0.106162	0.882803	0.120256	0.9043
AR(1)	-0.084976	0.028080	-3.026229	0.0025

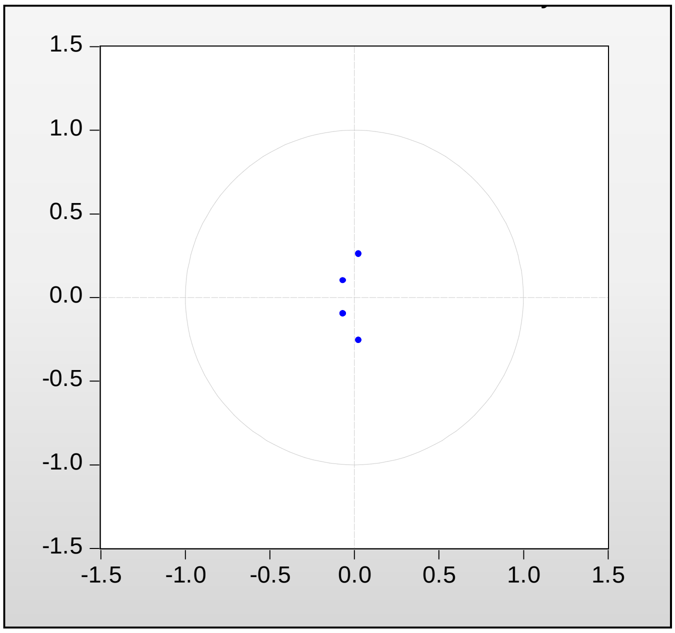
R-squared	0.154581	Mean dependent var	0.352201
Adjusted R-squared	0.146523	S.D. dependent var	36.95663
S.E. of regression	34.14196	Akaike info criterion	9.909099
Sum squared resid	1467582.	Schwarz criterion	9.961715
Log likelihood	-6289.187	Hannan-Quinn criter.	9.928862
F-statistic	19.18346	Durbin-Watson stat	2.004230
Prob(F-statistic)	0.000000		

Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).

APPENDIX B

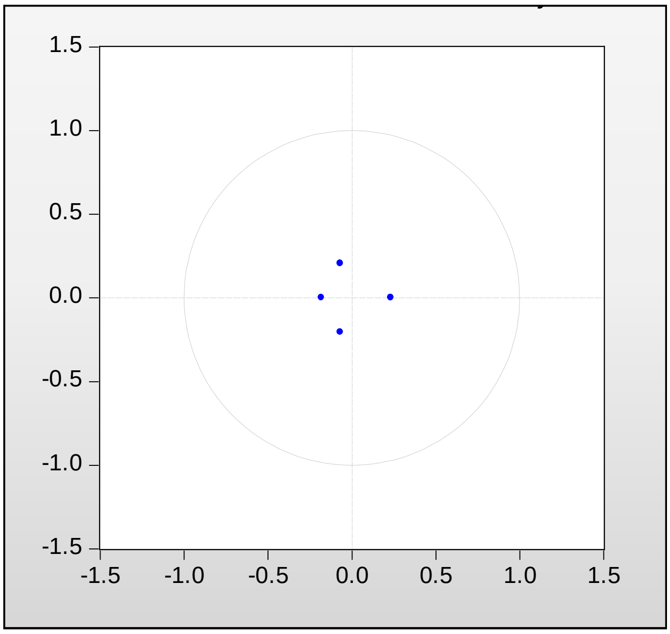
Figure B.1 and B.2 represents the Graphical VAR stability test results obtained from the cointegration approach for period 1 and 2, respectively.

Figure B.1: Graphical VAR stability test for period 1



Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).

Figure B.1: Graphical VAR stability test for period 1



Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).

APPENDIX C

Table C.1 and C.2 report the results of the variance decomposition model with the CBOT yellow maize prices as dependant variable for period 1 and 2, respectively.

Table C.1: The variance decomposition output result for period 1

Period	S.E.	SAFEX_1	CBOT_1
	Variance Decomposition of CBOT_1:		
1	71.27474	0.645743	99.35426
2	100.0534	12.14828	87.85172
3	121.9545	15.55787	84.44213
4	140.2786	17.54639	82.45361
5	156.2827	18.90090	81.09910
6	170.6276	19.94345	80.05655
7	183.7074	20.80762	79.19238
8	195.7807	21.56073	78.43927
9	207.0280	22.24017	77.75983
10	217.5815	22.86833	77.13167

Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).

Table C.2: The variance decomposition output result for period 2

Period	S.E.	SAFEX_2	CBOT_2
	Variance Decomposition of CBOT_2:		
1	84.73095	2.735866	97.26413
2	124.0754	14.62434	85.37566
3	153.6103	17.88102	82.11898
4	178.0695	19.83356	80.16644
5	199.2729	21.16581	78.83419
6	218.1826	22.21091	77.78909
7	235.3596	23.09395	76.90605
8	251.1675	23.87807	76.12193
9	265.8577	24.59748	75.40252
10	279.6130	25.27244	74.72756

Source: Compiled by Author from calculations in Eviews 7 (QMS, 2009).