Timing a Hedge Decision: the Development of a Composite Technical Indicator for White Maize

Susari Geldenhuys, Frans Dreyer and Chris van Heerden

ERSA working paper 423

February 2014

Economic Research Southern Africa (ERSA) is a research programme funded by the National Treasury of South Africa.

Timing a Hedge Decision: The Development of a Composite Technical Indicator for White Maize

Susari Geldenhuys*Frans Dreyer†Chris van Heerden‡§

February 26, 2014

Abstract

South African white maize is considered to be significantly more volatile than any other agricultural product traded on the South African Futures Exchange (SAFEX). This accentuates the need to effectively manage price risk, by means of hedging, to ensure a more profitable and sustainable maize production sector (Geyser, 2013: 39; Jordaan et al., 2007: 320). This paper attempts to address this challenge by making use of technical analysis, focusing on the development of a practical and applicable composite technical indicator with the purpose of improving the timing of price risk management decisions identified by individual technical indicators. This substantiated the compilation of a composite indicator that takes both leading and lagging indicators into account to more accurately identify hedging opportunities. The results validated the applicability of such a composite indicator, as the composite indicator outperformed the individual technical indicators in the white maize market over the period under investigation.

JEL Classifications: G13, G14, G32

Keywords: Agricultural commodity market, efficient market, composite indicator, hedging, technical analysis, trading market, trending market, South Africa, white maize.

1 Introduction

Risk has always been an inherent component in the agricultural market, due to factors such as uncertainty surrounding weather; intricate biological processes; the seasonality of production; price transmission; the domestic and international political economics of food; and globalisation of commodity chains (Geyser, 2013: 35; Stockil & Ortmann, 1997: 139). The agricultural environment has

*Susari Marthina Geldenhuys: Masters student.

†Mr Francois Albertus Dreyer: Supervisor. Lecturer.

‡Dr Petrus Marthinus Stephanus van Heerden: Assistant-Supervisor. Senior lecturer.

§Risk Management, School of Economics, North West University, Potchefstroom, South Africa.

also been very volatile in the past few years, which increased the overall risk associated with the agricultural market; more specifically the risk associated with volatile price movements (Geyser, 2013: 35-40; Goodwin & Schroeder, 1994: 936).

Price risk in the white maize market is significantly higher compared to any other agricultural commodity traded on the South African Futures Exchange (SAFEX) (Geyser, 2013: 39; Jordaan et al., 2007: 320). This is due to the price inelasticity of the white maize market that is caused by the small amount of substitutes available for this commodity (Bown et al., 1999: 277-278; Van Zyl, 1986: 53-54). Another explanation is that the increased price volatility was caused by the deregulation of the agricultural commodities market in the mid-1990s (Groenewald et al., 2003; Monk et al., 2010: 1). Prior to the deregulation of the market mechanism, the Maize Board controlled maize price setting and was the sole buyer and seller of maize in South Africa, which led to a market that was relatively free from price risk (Krugel, 2003: 52; Vink, 2012: 558). Consequently, since no price fluctuations were present market participants had no concern about price risk management and were only interested in minimising the possible consequences of other risks, such as adverse weather conditions (Chabane, 2002: 1; Monk et al., 2010: 447). Since the abolition of the Maize Board, however, agricultural market participants have been responsible for the marketing of maize, as well as managing their own price risk (Bown et al., 1999:276; Chabane, 2002: 1; Krugel, 2003: 52).

Accordingly, SAFEX a division of the Johannesburg Stock Exchange (JSE), created the Agricultural Products Division (APD) which facilitates these price risk management responsibilities by enabling market participants, including producers, buyers and speculators, to come together on one exchange traded platform. The derivatives market, therefore, focus primarily on providing an effective marketing mechanism to market participants, essentially by means of the futures market, due to its efficient role in transparent price determination (JSE, 2013a: 1-2; Krugel, 2003: 4; Monk et al., 2010: 447). Transparent price formulation is however dependant on the presence of an efficient agricultural market (Wiseman et al., 1999: 322), which is still being questioned by maize producers in the South African maize market. This perception remains prevalent, notwithstanding the fact that the majority of previous studies[1] suggested that the white maize market is at least weak-form efficient. Weak-form efficiency implies that all security market information is already incorporated into the current price, including rates of return and historical price trends (Brown & Reilly, 2009: 153, Fama, 1970: 414). It also implies that no correlation between past rates of return and future rates of return exist (Brown & Reilly, 2009: 153).

In spite of the latter, all public information is not always reflected in the current price in a weak form efficient market, where some market participants have monopolistic access to private information (Brown & Reilly, 2009:153; Fama, 1970: 414). This implies that some market participants have the ability of

[1] See studies conducted by McCullough (2010:131), Moholwa (2005:21), Scheepers (2006:61), Viljoen (2003:206), and Wiseman et al. (1999:332-333).

making abnormal profits by means of technical analysis, which rely on three fundamental assumptions. The first assumption states that the market discounts all information, specifically that all underlying factors affecting the price are reflected in the price (Krugel, 2003: 47; Reuters, 1999: 9). The second assumption reasons that prices move in trends or patterns and have a tendency to recur in the future (Geyser, 2013: 20; Reuters, 1999: 9). Lastly, technical analysis assumes that history repeats itself, which implies that human behaviour remains relatively constant over time (Colby, 2003: 6; Reuters, 1999: 9).

Nevertheless, accurate technical analysis still depends on determining whether prices are moving in a trend or if markets are trading (Achelis, 2001: 35-36). Trending markets' prices move either upwards or downwards, whereas trading markets' prices move sideways (Achelis, 2001: 35-36). Specific indicators[2] were developed to help identify the type of market, however, these indicators do not indicate whether a market is primarily trending (trading) or secondarily trading (trending). This concept can be explained further by means of Figure 1, where prices that are primarily in a trending market (line A) may move into a secondarily trading market (box B and box C), before continuing with the initial trend (Marx *et al.*, 2010: 190–192).

It is, therefore, important to firstly distinguish between the different market types, where after applicable individual technical indicators can be applied to determine buy and sell signals. This first step is crucial, since applying the wrong combination of individual technical indicators in a trending or trading market may indicate false buy or sell signals, which in turn may result in losses. Accordingly, to enhance the understanding of applying the correct technical indicators it is important to distinguish between leading- and lagging indicators (Achelis, 2001: 33-35). Leading indicators include – but are not limited to – the Relative Strength Index (RSI) and Stochastic Oscillator, which indicate buy or sell signals (Achelis, 2001: 35, 297, 321). Alternatively, lagging indicators include – but are not limited to – the Moving Average (MA) and Moving Average Convergence Divergence (MACD), which identifies late buy or sell signals (Achelis, 2001: 33, 199, 203). The proposed approach is to use leading indicators in a trading market and lagging indicators in a trending market for effective and accurate technical analysis (Achelis, 2001: 33).

In light of the above, it can become difficult to distinguish between trending and trading markets if the market is very volatile, even with the assistance of specific indicators. This will cause technical analysis to generate false selling signals since the selected indicator can be used in the wrong type of market. Furthermore, besides the fact that the more volatile market generates greater uncertainty, maize producers are also unwilling, hesitant or fearful to adopt price risk management instruments due to a "lack of capacity", "distrust of the market", and "bad experiences" (Jordaan & Grové, 2007: 561). This implies that if the prediction of the trends in daily grain prices can be improved, maize producers may be less hesitant and fearful to adopt derivative instruments as a

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

price risk management tool (Ueckermann et al., 2008: 235).

This leads to the goal of this paper, which will specifically focus on the development of a practical and applicable composite technical indicator with the purpose of improving the timing aspect of price risk management decisions that maize producers struggle with. The development of a composite indicator may improve a maize producer's willingness to adopt derivative price risk management instruments which in turn can result in maize producers hedging more optimally. Additionally, in order to ensure sustainable and profitable maize production, it is necessary for South African maize producers to hedge their expected harvest at the highest possible price. Producers who hedge their produce at lower levels may be subject to substantial variation margin[3] requirements in order to maintain their futures position in the market. Also, potential costly buy-outs of future contracts at higher price levels may occur, in the instance where a producer could not fulfil his contract delivery obligations. In order to achieve this goal this paper will commence by providing a discussion of SAFEX and the efficiency of the South African white maize market in Section 2 and a background of technical analysis in Section 3. The methodology as well as more detailed definitions of the different technical indicators applied in the paper will then be discussed in Section 4, where the empirical results will be reported in Section 5, followed by the concluding remarks and recommendations in Section 6.

2 SAFEX Background and Market Efficiency

The South African agricultural market was a highly government regulated market for decades, with the main objective of minimising the negative effects of volatile prices (Larson et al., 2004:199; Ueckermann et al., 2008: 222). With the main purpose of limiting this price volatility, commodity control boards were established by the Marketing Act of 1937 (Groenewald, 2000: 376). Additionally, a single channel, fixed price marketing system was implemented, where government control boards determined a price for the selected commodity and from the 1980s hedged this fixed price by trading on the Chicago Board of Trade or CBOT (Bown et al., 1999: 276; Cass, 2009: 25). It was however found that regulating markets were unsuccessful, unsustainable and hindering growth. Consequently, due to international and domestic pressure, the South African agricultural market was deregulated in 1996 (Larson, 2004: 199; Chabane, 2002: 1). Since deregulation, prices have been very volatile and producers were now faced with the necessity to hedge against adverse price movements (Chabane, 2002: 1; Krugel, 2003: 52).

Consequently, futures contracts became increasingly popular as a price risk hedging instruments, since their introduction in South Africa in 1996 (Mahalik

[3] Each open futures contract is valued against the days representative price which is called 'marked-to-market'.
The profit or loss from this valuation is payable is calculated and payable on a daily basis (Geyser, 2013:4).

et al., 2009: 1). Also, with guidance provided by SAFEX's Agricultural Markets Division (AMD), producers were able to market their produce on an exchange traded platform (SAFEX), as well as manage their price risk primarily by means of the derivative instruments offered by SAFEX (Geyser, 2013: 3; JSE, 2013c: 1). However, producers do not make use of price risk management instruments on an exchange as often as would be expected, with specific reference to the use of white maize futures contracts. A study by Bown et al. (1999: 275) confirmed an increase from 27 per cent to 49 per cent of white maize producers who apply price risk management tools from 1998 to 1999/2000. However, only 15 per cent of the 49 per cent of producers made use of exchange traded derivative instruments. One might argue that the study is outdated, though Jordaan and Grové (2007: 552) found that this number has stayed relatively constant at 44 per cent of producers who have used some form of forward pricing methods, and with only 4 per cent of producers using white maize futures contracts.

These application rates of futures contracts as risk management tools in South Africa is considerably less than would be expected, despite the fact that price risk seems to be one of the key risks producers face in the agricultural environment (Jordaan & Grové, 2007: 548-549). Maize producers' lack of knowledge and understanding of the white maize derivatives market consequently encourage a producer's lack of self-confidence, bad experiences and distrust of the market's efficiency (Bown et al., 1999:285-286; Monk et al., 2010: 562; Jordaan & Grové, 2007: 561-562; Ueckermann et al., 2008: 234).

Maize producers' distrust of the market function and efficiency can also be ascribed to their belief that the market can be manipulated by other, more influential market participants (Jordaan & Grové, 2007: 561). This implies that the market's efficiency is being questioned, which is of particular importance in the agricultural market, since it provides producers with the ability to determine futures prices more accurately, as well as allowing them to manage price risk more effectively (McCullough, 2010: 5). Although, the efficiency of the South African white maize market have yet to be investigated extensively, with only a few studies focusing solely on agricultural market efficiency. This can be ascribed to the fact that the agricultural market in South Africa is relatively new when compared to international markets. For example, the first maize futures contract listed on CBOT was in 1877, whereas maize was only listed on the JSE in 1996 (CME, 2013:1; JSE, 2013c:1). Since CBOT is considered to be a weak-form efficient market, it can be expected that the South African white maize market is weak-form efficient as well, possibly even inefficient (Armah & Shanmugam, 2013: 73; McKenzie & Holt, 2002: 1530; Yang & Leatham, 1998: 111).

The first study of its kind, after market deregulation in 1996, was done by Wiseman, Darroch and Ortmann (1999: 322) who determined the level of efficiency of the white maize market between 1997 and 1998. The results showed no relationship for the period 1997, but did however indicate a long-run relationship for the period 1998, which suggests a weak-form efficient white maize futures market during this specific time period (Wiseman et al., 1999: 332). This adjustment from an inefficient to a weak-form efficient market was mainly due to better knowledge and understanding of the market by market participants and due to the higher liquidity (Wiseman et al., 1999: 332-333). In 2005, Moholwa (2005: 20) investigated the efficiency of both the white and yellow maize futures markets between 1999 and 2003. Results could not explicitly confirm the presence of weak-form efficiency for both the white and yellow maize futures markets, concluding that the futures prices are only predictable to some extent and thus that market efficiency has not changed over time. Although, when trading costs and the time value of money were incorporated into the future price calculation no evidence existed that past prices could be used to estimate future prices (Moholwa, 2005:21). The most recent study on the efficiency of the white maize futures market was done by McCullough (2010), who illustrated that a long-run relationship was present between the spot- and futures market and that price discovery between these two markets existed (McCullough, 2010: 126). The study of McCullough (2010: 127) also concluded that the South African white maize futures market was weak-form efficient between 1996 and 2009.

Consequently, it is evident from the above mentioned studies that the South African white maize market has generally demonstrated weak-form efficiency. This implies that prices are slow to adjust to new fundamental information entering the market, allowing some market participants to benefit from the price movements using different analytical techniques, such as technical analysis (Brown & Reilly, 2009: 546; Wiseman et al., 1999: 332). However, several international studies[4] found evidence which suggested that technical indicators are unable to outperform the returns that can be generated from buying and holding shares if the cost of conducting transactions is included in the return calculations. In spite of these studies, more recent studies[5] emphasised the usefulness of applying technical analysis to improve profitability in certain markets. Although these studies provide support to the use of technical analysis, it should be noted that the goal of this paper is not to attempt to outperform the market or to determine the level of efficiency. The paper primarily focus on the development of a practical and applicable composite technical indicator with the purpose of improving the timing aspect of price risk management decisions that maize producers find challenging.

3 Background of Technical Analysis

The Dow Theory, developed by Charles Henry Dow in the early 1900s, is considered to be the foundation of modern technical analysis (Achelis, 2001:122; Colby, 2003:224; Reuters, 1999:18). The theory relies on six fundamental assumptions, of which the most relevant may be summarised as follows (Achelis, 2001:123-128; Murphy, 1986:26-32): **(1) The averages discount everything.** All new information regarding the market is rapidly and efficiently discounted in the price and accordingly reflected in the market averages; **(2) The market consists**

[4] See for example Dale and Workman (1980), Jacobs and Levy (1988), and Sweeney (1988).
[5] See for example Lai *et al.* (2002), Lento (2007), and Yu *et al.* (2013).

out of three trends, which entail a primary trend, a secondary trends and minor trends. A primary trend can either be bullish (upward) or bearish (downward) long-term price movements, which is interrupted by secondary changes. These secondary trends are intermediate changes or corrections in the primary trend and tend not to last more than three months. Lastly, secondary trends are made up out of several minor trends, which are short-term, usually daily price movements. However, the Dow Theory considers minor trends as insignificant, since these trends are easily manipulated by market participants to a certain extent; and **(3) Primary trends have three phases**. The first phase, which is better known as the accumulation phase, is characterised by experienced and informed investors that are excessively buying with the expectation of an economic turnaround. When economic conditions then indeed make a turnaround and prices improve quickly, other market participants will start to accumulate shares, which in turn make up the second phase. The third phase is in progress when economic conditions improve further and the general public gains confidence in the trend, which cause trading volumes to increase. The selective few experienced investors, who invested during the first phase, will liquidate their holdings during the third phase, because they anticipate a turnaround in economic conditions.

Extensive research[6] followed the work done by Dow in an attempt to further develop the basic ideas put forward by the Dow Theory, Some of the ideas are only partially applicable in several markets, which necessitated the need for more general ideas that would be applicable in any type of market (Murphy, 1986:33; Reuters, 1999:10). These general ideas became known as the assumptions of technical analysis (as discussed in the background to the paper). Taking into account the assumptions of technical analysis, accurate technical analysis is dependent on whether the market is in a trending or trading phase, since different technical indicators were designed to function better in different market conditions (Achelis, 2001:35-36). Identifying the current type of primary market is simplified by means of indicators specifically developed for this purpose. Several applicable indicators were identified like the Aroon (developed by Chande in 1995), the Chande Momentum Oscillator (CMO) (developed by Chande in 1995) and the Directional Movement Index (DMI) (developed by Wilder in 1978), where the DMI will be used in this paper as discussed in Section 4.2.

In addition, after establishing if the market is trending or trading, individual technical indicators can be applied to generate buy and sell signals. These indicators can be classified into two broad categories, namely leading and lagging indicators. The proposed approach is to use leading indicators in a trading market and lagging indicators in a trending market. Leading indicators generally present an investor with early indications of the future movement of prices,

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

mainly by determining how overbought[7] or oversold[8] the market is. Popular leading indicators (which will be properly defined in section 4.2) include the Relative Strength Index (RSI) (developed by Wilder, 1978), Stochastic Oscillator (developed by Lane, late 1950s) and the Commodity Channel Index (CCI) (developed by Lambert, 1982). In contrast to leading indicators, lagging indicators (which will be properly defined in section 4.2) may also be applied. However, lagging indicators are not used to determine future price movements, but are rather used to follow price movements. Popular lagging indicators include Moving Averages (MA), Bollinger Bands (developed by Bollinger, 1983), and the Moving Average Convergence/Divergence (MACD) (developed by Appel, 2005). With all of these technical indicators available to assist the decision-making process in establishing the correct hedging level, it is crucial to ensure that the correct combination of technical indicator is continuously applied in conjunction with the pre-determined market type, since incorrect technical indicators may generate false buy/sell signals. Also, a more volatile market can make it difficult to establish the current market type, thus making it challenging to determine which individual technical indicator to use and causing uncertainty to escalate for producers who want to hedge their produce. This argument accentuates the importance of developing a composite indicator which can improve a maize producer's willingness to adopt derivative price risk with greater certainty.

4 Method

4.1 Data

The data were collected from the Thomson Reuters database via Metastock 11 software, which was created by Equis International and is a product of Thomson Reuters. This paper will make use of the July white maize futures contract, since it is currently the most liquid futures contract traded on SAFEX, as well as the main delivery and consequent hedging month for white maize (JSE, 2013a: 1). The time period that will be evaluated spans from 1 August 2000 to 20 July 2013. The reason for choosing this time span is that prior to July 2000 market liquidity was low, since the market for derivatives was a fairly recent development for participants (Bown et al., 1999: 285-286).

The contract data consist out of the daily high-, low- and closing prices for every season, since the technical indicators that will be applied in this paper make use of at least one of these aforementioned prices in their respective calculations. Also, given that the exact beginning and expiry dates of each season's contract are inconsistent, fixed dates were chosen so as to ensure comparability between seasons. Consequently, each contract period starts on 1 August of a

[7] An overbought market is associated with the number of sellers being significantly lower than the number of buyers, ultimately leading to a potential price peak as the sellers and buyers reach a new equilibrium (Meyers, 1994:299).

[8] An oversold market is recognised when the number of buyers is significantly lower than the number of sellers, consequently leading to a potential trough as the buyers and sellers reach a new equilibrium (Meyers, 1994:299).

specific planting season and expires on 20 July of the next year, which will be during harvest. Hedging opportunities are only considered from 1 October each season, since the effective planting season in South Africa traditionally starts from the beginning of October causing the liquidity of the futures contract to gradually improve (JSE, 2010: 10). However, to ensure that accurate opportunities can be recognised from 1 October each season, the indicators are applied to the data from 1 August every season, so as to diminish the lag effect of the respective calculations of the technical indicators.

4.2 Method

The first step of the empirical study is to determine the current market trend, as this will enable a more effective choice of applying individual technical indicators that are more applicable to the specified market trend. Consequently, the DMI will be applied in this paper to distinguish between trending and trading market segments. The DMI is an extremely unique indicator in the sense that it diminishes the possibility of attempting to use an indicator in the wrong type of market. The DMI accomplishes this by determining the strength of the trend by more specifically analysing the Average Directional Movement Index (ADX) line (Alexander, 1997: 86; Colby, 2003: 212), which interpreted as follows (Colby, 2003: 213; Murphy, 1986: 468; Wilder, 1978: 47):

1. an ADX value above 25 indicates a possible trending market; and
2. an ADX value below 25 indicates a possible trendless or trading market.

Once the trend of the market has been determined, individual technical indicators can be applied to the data from where meaningful interpretations can be drawn. The indicators chosen to apply, based on their simplicity and application frequency according to the literature study, include the Relative Strength Index (RSI), Stochastic Oscillator, Exponential Moving Average (EMA), and Moving Average Convergence/Divergence (MACD).

4.2.1 *Leading indicator, RSI*

The RSI is considered to be one of the most popular indicators used in modern technical analysis (Geyser, 2013: 29; Murphy, 1986: 296). The RSI is commonly a 14-day price-following oscillator, fluctuating between 0 and 100, which allows for easily detecting buy and sell signals, as well as allowing the indicator to be easily compared to other indicators (Achelis, 2001: 297; Murphy, 1986: 296; Whistler, 2004: 36-38). The name itself, however, can cause some level of confusion to inexperienced investors, since the indicator does not compare the "relative strength" of a security to a benchmark, but compares an instrument to its own historical performance (Achelis, 2001: 297). The RSI can be mathematically formulated as follows (Colby, 2003: 610; Whistler, 2004: 38):

$$RSI = 100 - [{}^{100}/_{(1+RS)}] \quad (1)$$

where:

$$RS = \frac{Average\ of\ n\ days'\ higher\ closing\ prices}{Average\ of\ n\ days\ lower\ closing\ prices} \tag{2}$$

The most frequently applied use is where the RSI tops at 70 and bottoms at 30[9] (Achelis, 2001: 297; Alexander, 1997: 146; Wilder, 1978: 68). When the RSI tops at 70 an overbought market is indicated and this in turn generates a sell signal when the RSI crosses the 70 level from above. When the RSI bottoms at 30 an oversold market is indicated and in turn generates a buy signal when the RSI crosses the 30 level from below.

4.2.2 *Leading indicator, Stochastic Oscillator*

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

In addition, the Stochastic Oscillator calculates two lines, namely the %K-line and the %D-line, of which %D is the more important line as it identifies the major signals (Murphy, 1986:204; Meyers, 1994:165; Whistler, 2004:33). The %K-line can be mathematically expressed as follows (Achelis, 2001:324; Colby, 2003:664; Meyers, 1994:165; Whistler, 2004:34):

$$\%K = 100 \times [{}^{(C-L)}/_{(H-L)}] \tag{3}$$

where:

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

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

The %K and %D-lines are expressed as a value oscillating between 0 and 100 and can be interpreted as crossovers and extreme values (Achelis, 2001: 321; Alexander, 1997: 96). A crossover can be interpreted as a buy signal when the %K-line crossed the %D-line from beneath. Accordingly, a sell signal is generated when the %K-line crossed the %D-line from above (Achelis, 2001:

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

321; Meyers, 1994: 186; Whistler, 2004: 34). Another interpretation of the %K- and %D-lines are when either of the lines moves to extreme values (Achelis, 2001: 321; Alexander, 1997: 96; Colby, 2003: 664; Murphy, 1986: 304). An oversold market is indicated when either lines moves below a specified value, where after a buy signal is generated when the lines cross the specified value from below. Conversely, an overbought market is indicated when either line moves above a specified value, where after a sell signal is generated when the lines cross the specified value from above.

4.2.3 *Lagging indicator, EMA*

Considered one of the oldest, most flexible and commonly used technical indicators, the MA can be easily applied to any price data (Alexander, 1997: 90; Colby, 2003: 644; Murphy, 1986: 234). A MA can be defined as a smoothed rendering of a commodity's price movements for a fixed time span, using only the most recent data available (Achelis, 2001: 27; Murphy, 1986: 234; Whistler, 2004: 30).

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

$$EMA = (C - E_p)K + E_p \tag{4}$$

where:

- E represents the Exponential Moving Average for the current period;
- C represents the closing price for the current period;
- E_p represents the Exponential Moving Average of the previous period; and
- $K = {}^{2}/_{(n+1)}$ represents the exponential smoothing constant

When comparing an EMA with a security's price movements, buy and sell signals are generated and interpreted accordingly with ease. A buy signal is generated when the security's price crosses the EMA from below and a sell signal is generated when the security's price crosses the EMA from above (Achelis, 2001: 203).

4.2.4 *Lagging indicator, MACD*

The MACD is commonly calculated by subtracting a longer EMA, commonly known as the 26-day EMA, from a shorter EMA, commonly known as the 12-day EMA (Achelis, 2001: 199; Alexander, 1997: 88,143; Colby, 2003: 412; Reuters, 1999: 104). This calculated moving average is also better known as the fast MACD-line and measures price velocity (Reuters, 1999: 104). A second line is constructed and plotted on top of the MACD-line so as to determine buy or sell signals (Achelis, 2001: 199; Murphy, 1986: 313). This line is better known as a signal or trigger line, which is constructed by calculating a 9-day EMA of the MACD-line (Alexander, 1997: 88,143; Colby, 2003: 412; Murphy, 1986: 313; Reuters, 1999: 104).

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

However, as the South African maize market is proven to be extremely volatile, it will become more difficult to determine which leading- or lagging technical indicator is more applicable. This implies that the possibility for generating false buy and sell signals is conceivable, thus limiting the ability to manage price risk effectively. This leads to the next section which will discuss the construction of a composite indicator that will overcome this obstacle.

4.2.5 *Composite indicators: The basic idea*

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

The first step of constructing the composite indicator is to calculate the value of each individual indicator, based on the calculations as explained in the previous sections. Combining the individual indicators into one composite indicator is complicated due to the fact that only the RSI and Stochastic Oscillator are bound between 0 and 100, whereas the EMA and MACD consist of no boundaries. To overcome this challenge the EMA and MACD were given boundaries by transforming both indicators into a stochastic version of the indicator (Roffey, 2008: 157-158,162). Consequently, this allows for each individual indicator to fluctuate between 0 and 100. The Stochastic EMA and Stochastic MACD are calculated as follows, assuming a default period of 14 days (Roffey, 2008:

157):

$$StochEMA = 100 \times [^{(EMA_t - EMA_{low})}/_{(EMA_{high} - EMA_{low})}] \quad (5)$$

$$StochMACD = 100 \times [^{(EMA_t - EMA_{low})}/_{(EMA_{high} - EMA_{low})}] \quad (6)$$

where:

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

The second step involves assigning a weight, according to the type of market, to each individual indicator in an attempt to generate more accurate sell signals. More specifically, greater weights are assigned to leading indicators and smaller weights to lagging indicators in a trading market. Similarly, greater weights are assigned to lagging indicators and smaller weights to leading indicators in a trending market.

To further ensure the accuracy of the composite indicator a trending market is divided into three scenarios, based on the value of ADX. These scenarios include an ADX value between 25 and 50, 50 and 75, and between 75 and 100. Several different weight combinations were tested for each of these scenarios by several quantitative simulations, however, it was found that these different weights did not have a significant effect on the results of the composite indicators. Nevertheless, the weights that were applied were determined based on the optimal hedge level that was achieved from assigning different weights to the individual indicators in different market types. The weights assigned to each individual indicator vary as follows:

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

The third step involves multiplying the calculated value of each indicator (from step 1) with the respective weights assigned to the indicator (from step 2). The individual indicators' weighted values are then added together to obtain the total value for the composite indicator, which is interpreted accordingly. Sell signals are generated once the composite value crosses an upper limit. Different upper limits were tested to ensure the highest possible hedge level in accordance with the requirements of at least two sell signals per contract and an average of four sell signals over the entire period.

In addition, three different composite indicators were constructed so as to ensure that the best results were achieved. Composite A and Composite B are based on the same principle calculations as discussed above, except for the calculation of the RSI, where Composite C's calculations of the indicator values differ from the first two composite indicators. Accordingly, Composite A was constructed on the same basis as the basic idea with the specific details and variations as explained in the previous paragraphs. The upper limit value identified for Composite A was 87 per cent. The composite indicator value is interpreted accordingly:

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

2. In a trading market, a sell signal is generated once the composite indicator crosses the upper limit from below.

In order to ensure uniformity of the different individual indicators applied in the construction of a composite indicator, Composite B was constructed. This second proposed composite indicator is similar to Composite A, with the exception of the calculation of the RSI. To ensure that all the indicators' calculations are consistent, a Stochastic RSI value is calculated as follows, assuming a default period of 14 days (Roffey, 2008:157;161):

$$StochRSI = 100 \times [{}^{RSI_t - RSI_{low}}/_{RSI_{high} - RSI_{low}}] \tag{7}$$

where:

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

In addition to modifying the value of the RSI, Composite B required a higher upper limit than Composite A, more specifically 96 per cent, so as to generate sell signals that may ultimately assist in an optimal average hedge level. The remainder of the calculations and interpretations of the composite indicator remain similar to Composite A.

The results (Section 5.1) obtained from Composite Indicators A and B appeared to improve the results of the individual indicators, but in order to ensure the results were not skewed by altering the values of the EMA and MACD a third composite indicator was constructed. Composite C aimed at assigning values to the indicators without altering the statistical characteristics of the indicators. If, for instance, the individual MACD indicator generates a sell signal, a value of 1 or 100% is assigned to the MACD. If the individual RSI indicator also generates a sell signal on the same day, a value of 1 or 100% is also assigned to the RSI. In the same way the individual STOCH indicator and the individual EMA indicator can also generate a sell signal or not, where a value of 1 or 0 will be assigned, respectively. In order to calculate Composite C's value, respective weights are allocated to each individual indicator. Each individual indicator's weights are assigned on the same basis as explained for Composite A and Composite B. Following the allocation of the respective weights, each individual indicator's value is multiplied with its assigned weight to obtain a weighted value. Thereafter, a composite indicator value is computed by adding the individual indicators' weighted values together. Subsequently, this value is interpreted as a sell signal when the composite indicator reaches or crosses the upper limit, applying an upper limit of 40. The upper limit of 40 was used since a lower level, for instance 30, resulted in to many sell signals and a higher level, for instance 50, resulted in certain seasons not having any sell signals at all.

5 Results

5.1 Individual Indicators

The results obtained from applying the individual technical indicators are reported in Table 1, Table 2 and Table 3, respectively. From Table 1 it is evident that the Stochastic Oscillator prevailed by achieving the highest average hedge level for a season the most times. Conversely, the RSI and EMA were only able to realise a few seasons with the highest average hedge level, whereas the MACD failed to produce any season with the highest average hedge level. Nonetheless, the MACD and RSI exhibited more desirable results than the EMA. The results also reported that the EMA produced the most number of seasons with the lowest average hedge level, whereas the MACD and RSI reported only a few seasons with the lowest average hedge level.

These results, however, do not correspond with Table 2's results, indicating that the MACD succeeded in generating an average of 7.231 sell signals per season with a standard deviation of 1.235. Conversely, the EMA generated the highest level of sell signals, with an average of 11.538 sell signals per season along with a standard deviation of 2.727. Generating too many sell signals pose the risk of higher initial margin[10] requirements and potential higher variation margin requirements. Additionally, too many sell signals may also add to the hedgers' uncertainty, since the hedger may only need to hedge two contracts or 200 metric tonnes. On the other hand, generating too few sell signals pose the risk of remaining 'unhedged' for an entire season.

[10] Margins are payable by all market participants once a contract is bought or sold. The initial margin is called a 'deposit of good faith', since the amount is set to cover two consecutive days losses if the variation margin cannot be repaid by either party. The initial margin is interest bearing and repaid once the position or contract is closed out in the market (Geyser, 2013:49).

Lastly, Table 3 reports a summary of the results of the average hedge level per season as a percentage of the highest closing price for the season. The EMA generated inferior results when compared to the other indicators, with the lowest average hedge level to maximum price ratio and the highest standard deviation of this ratio between seasons. On the other hand, the Stochastic Oscillator surpassed the other technical indicators, indicating an average of 81.501 per cent average hedge level to maximum price ratio per season with a standard deviation of 4.690.

The results obtained by the individual indicators and the comparison between the indicators revealed several weaknesses. These weaknesses are that a high number of sell signals are generated, which also varied considerably, as well as a high inconsistency of achieved hedge levels. This may be due to the indicators being applied in the wrong type of market, which in turn may lead to false signals being generated. This challenge was addressed by applying the indicators in conjunction with one another by means of the proposed composite indicators.

5.2 Composite indicators

The results of the Composite Indicators A, B and C are reported in Table 4, Table 5 and Table 6, respectively. These tables report the average hedge level, the amount of sell signals and the hedge level relative to the maximum price. With regards to Composite A, it is evident from Table 4 that the 2005 season achieved the lowest average hedge level, whereas the highest average hedge level was realised in 2013. Also, from Table 6 the highest hedge level relative to the maximum price was achieved during 2010, reaching 95.464 per cent. Conversely, the lowest hedge level as a percentage of the maximum price was achieved during 2005, reaching a hedging level of 69.273 per cent. Overall, an average hedging level of 80.997 per cent was realised by Composite A. Although a significantly high standard deviation of 7.821 was also realised, these results are much more promising compared to the performance reported by some of the individual technical indicators (see Table A, Table B and Table C in the Appendix).

Furthermore, despite the inconsistency in the hedge levels realised, producers are presented with a rather steady number of sell signals (see Table 5) generated when applying Composite A. On average, 7 sell signals per season were generated, with the most number of sell signals (11) being produced in 2006 and the least number of signals (2) being generated in 2009. The number of sell signals generated also remained relatively consistent during the entire period, which is validated by a standard deviation of only 2.769. This may provide producers with greater certainty regarding the number of possible hedging opportunities per season.

It is also evident from Table 4, Table 5 and Table 6 that Composite B could not surpass Composite A's performance. Composite B managed to achieve the third highest average hedge level to the maximum price ratio (80.754 per cent) and a significantly low standard deviation (6.558) of this ratio between seasons. However, it is interesting to note that the results also revealed that both Composite A and Composite B failed to produce any season with the lowest average hedge level when compared to the individual indicators (see Table A, Table B and Table C in the Appendix).

From the above discussed results, it is evident that Composite B failed to improve on Composite A, which can be due to the change in the statistical characteristics of the indicators when applying the Stochastic Oscillator's formula to the indicators' values (Roffey, 2008:158). This lead to the construction of the third composite indicator (Composite C) which is aimed to assign values to the indicators without altering the statistical characteristics of the indicators. From Table 4 it is evident that the 2001 season realised the lowest average hedge level, whereas the highest average hedge level was achieved in 2013. Contrary to the highest average hedge level, the highest hedge level relative to the maximum price was achieved in 2003, reaching 94.444 per cent (see Table 6). The lowest hedge level as a percentage of the maximum price was realised in 2001, reaching a hedge level of only 71.470 per cent. Overall, Composite C managed to average a hedging level of 81.722 per cent of the highest possible hedge level. However, this performance is somewhat overshadowed by the standard deviation of 7.547 (see Table 6). Such a significantly high standard deviation may support market participants' hesitancy to make use of Composite C, as it is an indication of inconsistent hedging levels.

Despite the high spread in the hedging level, Composite C compensates by generating an average of only 3.769 sell signals per season (see Table 5). The applicability of Composite C is further justified by a standard deviation of only 1.739. As mentioned earlier, a low standard deviation regarding the number of sell signals generated may provide producers with more confidence regarding the number of possible future sell signals. When considering only Table 4, it is evident that Composite C prevailed by achieving the highest average hedge level for a season most of the time. Similarly, Table 5 indicated that Composite C surpassed the other indicators by generating the lowest average sell signals (3.769) per season, along with a low standard deviation of 1.739. This is significantly lower than the other indicators, validating the construction of Composite C. Lastly, Table 6 also exhibits the results of the average hedge level per season as a percentage of the highest closing price for the season. Again, Composite C surpassed the other technical indicators, indicating an average of 81.04 per cent average hedge level to maximum price ratio per season, with a standard deviation of 7.81.

Overall, it can be deduced that the EMA is the most inadequate indicator to implement in the South African white maize market, where after the MACD and RSI also demonstrated undesirable results (see Table A, Table B and Table C in the Appendix). Despite the highly advantageous results demonstrated by the Stochastic Oscillator, Composite A and/or Composite C seem to surpass the individual technical indicators. Nonetheless, the indicators (individual indicators and composite indictors) managed to achieve an average hedge level of 75 per cent relative to the maximum price. However, these results are indefinite and allow for subjective interpretation. Thus, a more exact comparison between the indicators is necessary, so as to establish the more superior indicator to implement in the South African white maize market.

5.3 Comparison: Indicator Rankings

In order to determine which indicator is more superior overall, a ranked value was assigned to each indicator, where 1 represents the best and 7 represents the worst, in each respective category which include the following:

1. The average hedge level per season, where the highest value will be the best;
2. The sell signals per season, where the lowest value is deemed the best;
3. The standard deviation of the sell signals over the entire period, where the lowest value is deemed the best;
4. The average hedge level to maximum price ratio per season, where the highest value will be the best; and
5. The standard deviation of the average hedge level to maximum price ratio over the entire period, where the lowest value is deemed the best.

According to these rankings (see Table A, Table B and Table C in the Appendix), Composite C again prevailed superior to the other technical indicators, followed by the MACD as the second best indicator. Although the MACD at first glance in Table 1 to Table 6 seems to achieve inferior results when compared to the individual and composite indicators, the fact that it objectively ranks second is not entirely unexpected. The reason for this argument can be explained by Figure A in the Appendix, which illustrates the DMI results. From Figure A it is clear that the market seems to be trending a lot more since the DMI value is above 25 for a greater part of the time frame under investigation. Since the MACD is a lagging indicator, which is expected to be better suited to a trending market environment, it makes sense that it should in fact perform well.

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

6 Conclusion

As one of the most volatile agricultural products traded on the South African Futures Exchange (SAFEX), the need to effectively and accurately manage price risk in the white maize market is highlighted. This paper attempted to address this challenge by making use of technical analysis as a determinant of accurate hedging opportunities. More specifically, this paper primarily focused on the development of a practical and applicable composite technical indicator, compiled from several individual technical indicators, with the purpose of improving the timing aspect of price risk management decisions, which may ultimately assist producers in realising more advantageous hedging levels.

The accuracy and applicability of the different individual indicators, which are classified as leading and lagging indicators, accentuates the importance of determining the primary tendency of the prices in the market at a specific time. The proposed approach is to apply leading indicators in a trading market and lagging indicators in a trending market. To further ensure the accuracy of these indicators, in assisting a producer in the hedging decision-making process, it is essential that the correct combination of technical indicators is applied in the specified type of market. Applying these indicators in the wrong type of market may lead to false signals generated, which in turn can ultimately result in a significantly low hedging level or even losses. This was confirmed by the results, where the individual indicators generated a significantly high number of selling signals, which also varied considerably, as well as demonstrating inconsistencies in the average hedge levels achieved each season. This may have been due to the implementation of wrong indicators in the market, leading to false selling signals being generated.

Consequently, the construction of Composite Indicators A, B and C attempted to diminish this constraint by including both leading and lagging indicators, which assisted in generating more accurate sell signals and ultimately increase the average hedge level. From the comparison it was evident that Composite C prevailed above the other indicators. Composite C managed to achieve the highest hedge level for the most number of seasons; the lowest average sell signals generated over the entire period; as well as the highest average hedge level as a percentage of the maximum price over the entire period. Furthermore, the MACD, Composite A and Composite B followed Composite C, respectively. These results validates the use of a composite technical indicator in the South African white maize market to identify and realise higher hedging levels more accurately.

Additionally, several recommendations may improve the results obtained from this paper. Firstly, this paper only made use of the default periods used in the calculations of the technical indicators. Other time periods may prove to be more optimal, which may further enhance the accuracy and applicability of the composite indicator. Secondly, the paper showed no significance in the adjustment of the weights assigned to the individual indicators in the construction of the composite indicator. It may be valuable to examine the underlying reason for the weights' insignificant role in the construction of the composite indicator. Furthermore, testing the validity of a composite indicator in agricultural markets other than the white maize market will be an interesting future study. Also, these tests can be expanded to test the validity of a composite indicator in other asset classes, including foreign exchange, equities, shares and assets, among others. Additionally, the composite indicator can be expanded and adjusted to generate buy signals as well. This may improve the applicability of the composite indicator to be implemented by several market participants and not only producers.

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

References

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

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

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

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

[5] Bollinger, J. 1983. Bollinger on Bollinger Bands. New York: McGraw-Hill.

[6] Bown, A.N., Ortmann, G.F. & Darroch, M.A.G. 1999. Use of maize marketing alternatives and price risk management tools by commercial maize farmers in South Africa./Gebruik van mieliebemarkings-alternatiewe en prysrisikobestuursmiddel deur mielieboere in Suid-Afrika. Agricultural economics research, policy and practice in Southern Africa, 38(3): 275-301.

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

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

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

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

[11] Chande, T.S. 1995. The Time Price Oscillator. Technical analysis of stocks and commodities, 13(9): 369-374.

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

[13] Colby, R.W. 2003. The Encyclopedia of Technical Market Indicators. 2nd Ed. New York: McGraw-Hill.

[14] Dale, C. & Workman, R. 1980. The arc sine law and the treasury bill futures market. Financial analysts journal, 36(6): 71-74.

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

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

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

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

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

[20] Jacobs, B.I. & Levy, K.N. 1988. Disentangling equity return regularities: New insights and investment opportunities. Financial analysts journal, 44(3): 18-43.

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

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

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

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

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

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

[27] Lai, M.M., Balachandher, K.G. & Nor, F.M. 2002. An examination of the random walk model and technical trading rules in the Malaysian stock market. Quarterly journal of business and economics, 41(1/2): 81-104.

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

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

[30] Lento, C. 2007. Tests of technical trading rules in the Asian-Pacific equity markets: A bootstrap approach. Academy of financial and accounting studies journal, 11(2): 51-73.

[31] Mahalik, M.K., Acharya, D. & Babu, M.S. 2009. Price Discovery and Volatility Spillovers in Futures and Spot Commodity Markets: Some Empirical Evidence from India. Paper Presented to Fourth Annual International Conference on Public Policy and Management: Quantitative Approaches to Public Policy. August 9-12. http://www.igidr.ac.in/pdf/publication/PP-062-10.pdf Date of access: 26 May 2013.

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

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

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

[35] Meyers, T.A. 1994. The Technical Analysis Course: A Winning Program for Investors and Traders. 2nd Ed. New York: McGraw-Hill

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

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

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

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

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

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

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

[43] Sweeney, R.J. 1988. Some new filter rule tests: Methods and results. Journal of financial and quantitative analysis, 23(3): 285-300.

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

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

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

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

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

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

[50] Wiseman, J.A., Darroch, M.A.G. & Ortmann, G.F. 1999. Testing the efficiency of the South African futures market for white maize/Toetsing van die doeltreffendheid van die Suid-Afrikaanse termynkontrakmark vir witmielies. Agricultural economics research, policy and practice in Southern Africa, 38(3): 321-335.

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

[52] Yu, H., Nartea, G.V., Gan, C. & Yao, L.J. 2013. Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets. International review of economics and finance, 25(January): 356-371.

Figure 1: Primary and secondary trends

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

Table 1: Comparison of average hedge level: Individual indicators

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

Table 2: Comparison of sell signals: Individual indicators

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

Table 3: Comparison of the average hedge level as percentage of maximum price: Individual indicators

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

Table 4: Comparison: Average hedge level

Contract Year	Max Price	Composite A	Composite B	Composite C
2001	959	782.171	793.250	685.400
2002	1893	1540.444	1513.700	1554.000
2003	1989	1415.500	1438.500	1878.500
2004	1578	1268.143	1303.250	1281.500
2005	1100	762.000	725.000	824.300
2006	1419	1147.364	1163.250	1306.250
2007	2049	1511.625	1577.667	1491.500
2008	2200	1789.300	1773.564	1811.400
2009	2078	1738.500	1728.000	1578.500
2010	1680	1603.800	1396.917	1395.667
2011	1866	1622.000	1653.417	1639.000
2012	2728	2020.667	2176.200	2036.571
2013	2459	2290.111	2262.889	2201.500

Source: Compiled by the authors.

Table 5: Comparison: Sell signals

Contract Year	Max Price	Composite A	Composite B	Composite C
2001	959	7	8	3
2002	1893	9	10	5
2003	1989	4	4	2
2004	1578	7	4	2
2005	1100	3	4	2
2006	1419	11	12	4
2007	2049	8	9	2
2008	2200	10	11	5
2009	2078	2	2	2
2010	1680	5	12	6
2011	1866	7	12	5
2012	2728	9	10	7
2013	2459	9	9	4
Average over period		**7.000**	**8.231**	**3.769**
Standard Deviation		**2.769**	**3.539**	**1.739**

Source: Compiled by the authors.

Table 6: Comparison: Hedge level as a percentage of the maximum price

Contract Year	Max Price	Composite A	Composite B	Composite C
2001	959	81.561	82.716	71.470
2002	1893	81.376	79.963	82.092
2003	1989	71.166	72.323	94.444
2004	1578	80.364	82.589	81.210
2005	1100	69.273	65.909	74.936
2006	1419	80.857	81.977	92.054
2007	2049	73.774	76.997	72.792
2008	2200	81.332	80.617	82.336
2009	2078	83.662	83.157	75.962
2010	1680	95.464	83.150	83.075
2011	1866	86.924	88.608	87.835
2012	2728	74.071	79.773	74.654
2013	2459	93.132	92.025	89.528
Average over period		**80.997**	**80.754**	**81.722**
Standard Deviation		**7.821**	**6.558**	**7.547**

Source: Compiled by the authors.

5. APPENDIX

Table A: Comparison: All Indicators: Average hedge level

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

Table B: Comparison: All Indicators: Sell signals

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

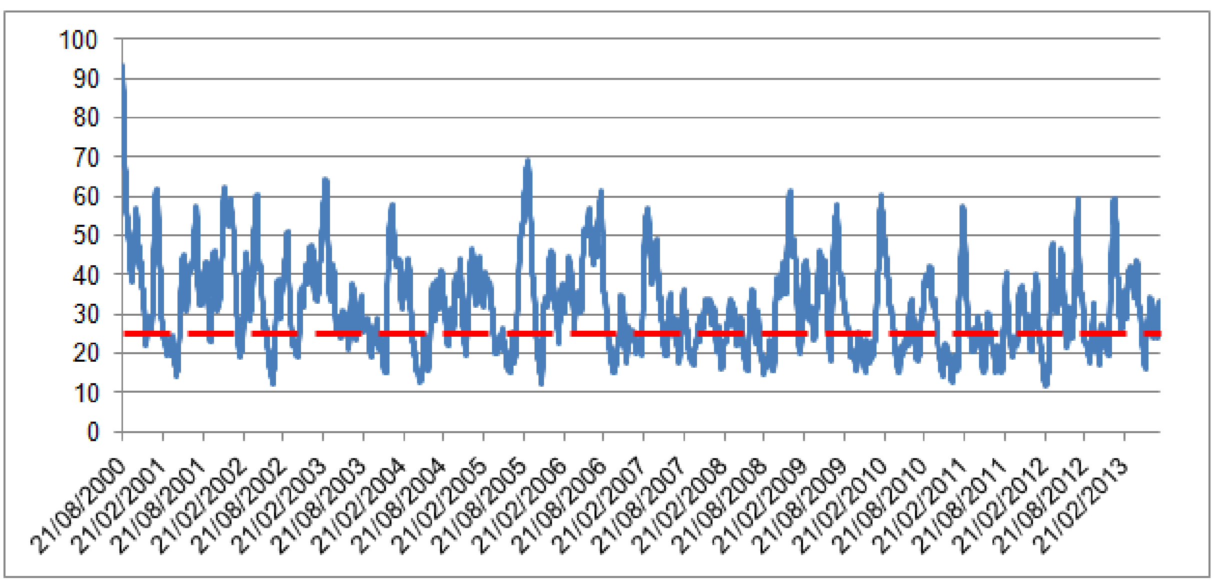
Table C: Comparison: All Indicators: Hedge level as a percentage of the maximum price

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

Source: Compiled by the authors.

Note: Cells with a # after the value illustrates the desired value for each season, whereas the cells with a * after the value illustrates the least desired value for each season.

Figure A: DMI results



Source: Compiled by the authors.