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# Return Volatility Causal Inferences on the Commodity Derivatives Markets

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Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Management

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# Abbreviations

| | |
|---|---|
| ADF | Augmented Dickey Fuller Test |
| AIC | Akaike Information Criterion |
| ALSI | JSE All Share Index |
| ACF | Autocorrelation Function |
| ARCH | Autoregressive Conditional Heteroskedasticity |
| ARMA | Autoregressive Moving Average Model |
| ARIMA | Autoregressive Integrated Moving Average |
| APARCH | Asymmetric Power ARCH |
| BEKK | Baba, Engle, Kraft and Kroner (1990) Model |
| BESA | Bond Exchange of South Africa |
| BFGS | Broyden-Fletcher-Goldfarb-Shanno Algorithm |
| BHHH | Berndt-Hall-Hall-Hausman Algorithm |
| BMM | Block Maxima Model |
| BRICS | Brazil, Russia, India, China, South Africa |
| CAPM | Capital Asset Pricing Model |
| CBOE | Chicago Board of Options Exchange |
| CBOT | Chicago Board of Trade |
| CCC | Constant Conditional Correlation |
| CCH | Chen, Cuny and Haugen (1995) Model |
| CFS | Committee for World Food Security |
| C-GARCH | Classic GARCH |
| CME | Chicago Mercantile Exchange |
| COMEX | Commodity Exchange Incorporated (now merged with NYMEX) |
| CPI | Consumer Price Index |
| DAFF | Department of Agriculture, Forestry and Fisheries of South Africa |
| DAG | Directed Acyclic Graph |
| DCC | Dynamic Conditional Correlation |
| DCE | Dalian Commodity Exchange |
| DM | Diebold and Mariano (2002) Test |
| ECM | Error Correction Model |
| ETFs | Exchange-traded Funds |
| EGARCH | Exponential Generalized Autoregressive Conditional Heteroskedasticity |
| ES | Expected Shortfall |

| | |
|---|---|
| EVA | Extreme Value Analysis |
| EVT | Extreme Value Theory |
| FAO | Food and Agriculture Organisation |
| FIGARCH | Fractionally Integrated ARCH |
| GARCH | Generalized Autoregressive Conditional Heteroskedasticity |
| GCT | Granger Causality Test |
| GED | Generalised Error Distribution |
| GEV | Generalized Extreme Value Distribution |
| GJR GARCH | Glosten, Jaganathan and Runkle GARCH Model |
| GMM | General Method of Moments |
| GPD | Generalized Pareto Distribution |
| G-S MODEL | Garbade and Silber (1983) Model |
| ICE | International Commodity Exchange |
| IGARCH | Integrated Generalized Autoregressive Conditional Heteroskedasticity |
| IMR | Initial Margin Requirement |
| IPI | Industrial Production Index |
| JSE | Johannesburg Stock Exchange |
| KCBT | Kansas City Board of Trade |
| LIFFE | London Interbank Financial Futures Exchange |
| LME | London Metals Exchange |
| MAE | Mean Absolute Error |
| MCMC | Markov Chain Monte Carlo |
| MDH | Mixture of Distribution Hypothesis |
| MF-DCCA | Multi-fractal De-trended Cross-correlation Analysis |
| M-GARCH | Multivariate Generalised ARCH |
| MSE | Mean Square Error |
| NCDEX | National Commodities and Derivatives Exchange |
| NYMEX | New York Mercantile Exchange |
| OLS | Ordinary Least Squares |
| PACF | Partial Autocorrelation Function |
| PAM | Price Asymmetric Model |
| POT | Peak Over Threshold |
| RC | Reality Check Method |
| RMSE | Root Mean Square Error |
| SAFCOM | SAFEX Clearing Company (Pty) Ltd |

| | |
|---|---|
| SAFEX | South African Futures Exchange |
| SAIM | Sequential arrival of information models |
| SAVUSA | South Africa – Vrije University Amsterdam - Strategic Alliances |
| SBC | Schwarz Bayesian Criterion |
| SHFE | Shanghai Futures Exchange |
| SOI | Southern Oscillation Index |
| SSFs | Single Stock Futures |
| SPA | Superior Predictive Ability |
| SV | Stochastic Volatility |
| SVAR | Structural Vector Autoregressive model |
| T-GARCH | Threshold GARCH Model |
| UCT | Universal Coordinated Times |
| VaR | Value at Risk |
| VAR | Vector Autoregressive |
| VECM | Vector Error Correction Method |
| WCE | Winnipeg Commodities Exchange |
| WTIO | West Texas Intermediate Oil |
| ZCE | Zhengzhou Commodity Exchange |

# Abstract

This thesis examined commodity futures on the South African Futures Exchange (SAFEX) from two angles; the investors' perspective and that of the futures exchange. For the former, the research looked at market inefficiencies and resultant arbitrage opportunities while for the latter, extraordinary market movements are examined by exploring how extreme value analysis (EVA) is ideal for exchange risk management and maintaining market integrity. This broadly leads to four empirical contributions to the literature on commodity futures.

Using a variety of time series models, wheat contract anomalies are identified by developing new trading rules whose outcomes are superior to any approach based on chance. Monte Carlo simulation employed in an out-of-sample period after accounting for transaction costs establishes that the trading rules are financially profitable. An examination of information flows across four major markets indicated that the Zhengzhou Commodity Exchange (ZCE) is the most endogenous market, Euronext and the London International Financial Futures Exchange (LIFFE) the most exogenous, while Kansas City Board of Trade (KCBT) is the most influential and sensitive wheat market. SAFEX is a significant receiver of information but does not impact the other markets. Another contribution, analysing maturity effects by incorporating traded volume, change in open interest, and the bid-ask spread while accounting for multicollinearity and seasonality indicates that only wheat supports the so called maturity effect. Lastly, asymmetry is found in long and short positions in SAFEX contracts, and using extreme value theory (EVT) in margin optimization, evidence is found that price limits significantly impact large contract returns.

Several implications arise from these results. SAFEX wheat contract inefficiencies could be attractive to speculators. Wheat margins should be higher nearer maturity. Optimizing margins using EVT could reduce trading costs, increase market attractiveness and liquidity while enhancing price discovery. South Africa should increase wheat production since reducing imports will lower vulnerability to adverse price transmission.

**JEL Classification**: C13, C14, C58, G01, G13, G17

**Keywords**: Futures market; commodities; volatility; seasonality; information flows, margins

# Declaration

This is my original work and has not been presented before for a degree in this or any other University.

……

Chrisbanard Motengwe

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# 1 INTRODUCTION

## 1.1 Background and Context

The African continent has some of the fastest growing emerging market economies on the planet. While seven of the twenty fastest growing economies in the World Bank (2013) rankings are in Africa, there has been slow development of innovative financial platforms on the continent outside of South Africa.[1] Now rated the second biggest economy in Africa after Nigeria, South Africa is the most advanced African economy and has been attracting the largest share of international investment. The South African Futures Exchange (SAFEX), a subsidiary of the Johannesburg Stock Exchange (JSE) is the only fully functional commodity derivatives market in Africa.

The focus of this thesis is risk on the SAFEX market and its management, examined from two angles; the investors and the exchange. For the former, we look at market inefficiencies and the resultant profitable opportunities. The thesis gives insight on whether inefficiencies on SAFEX can be used to generate profits. In the case of the latter, extraordinary market movements are examined exploring how extreme value analysis (EVA) is ideal for exchange risk management and maintaining market integrity.

Futures volatility is a key input in measuring risk, portfolio allocation, pricing of options, derivative valuation, hedging and decision-making. Unexpected price volatility has potential to exert upward pressure on food, energy and metals prices. Volatility impacts on risk management, futures trading, asset allocation and food security, particularly for consumers with low incomes. The food crises associated with the periods 1973-74 and 2007-08 doubled

[1] The 2013 seven fastest growing African economies and their real GDP growth rates are; Sierra Leone (20.1%), South Sudan (13.1%), Ethiopia (10.5%), Botswana (9.3%), Cote d'Ivoire (9.2%), Liberia (8.7%) and Democratic Republic of Congo (8.5%) (World Bank, 2013).

prices over some few months followed by unprecedented price level slumps (Gouel, 2012). Between 2003 and June 2008, food, energy, precious metals and other commodities saw increases in prices beyond 100% (Du, Yu, & Hayes, 2011; Filimonov, Bicchetti, Maystre, & Sornette, 2013; Gilbert, 2010). Price volatility however, presents both challenges and opportunities for derivatives market participants. Investors face difficulties in deciding the market positions or risk management strategies to adopt in the South African commodities context.

Margins are central to risk minimization and market stability. Longin (1999) acknowledges substantial price shifts potentially cause a margin account to be wiped out resulting in a margin call. If an investor reneges on the call, default will result. Warshawsky (1989) suggests futures margins should cover 98% to 99% of futures market price movements. On the other hand, Dutt and Wein (2003) say margins must cover at least 95 % of an asset's price movements.

Mechanisms protecting against futures market failure include margins supported by daily marking-to-market, price limits and futures market circuit breakers (Broussard, 2001). The process of default prevention should however not compromise market liquidity (attributable to excessive margins) as this is detrimental to efficient price discovery. Margins should allow for competitiveness of the exchange while protecting default risk (Cotter, 2001). Ultimately, competitiveness of an exchange is gauged by trading cost levels referred to as the hypothesis of efficient contract design in Brennan (1986).

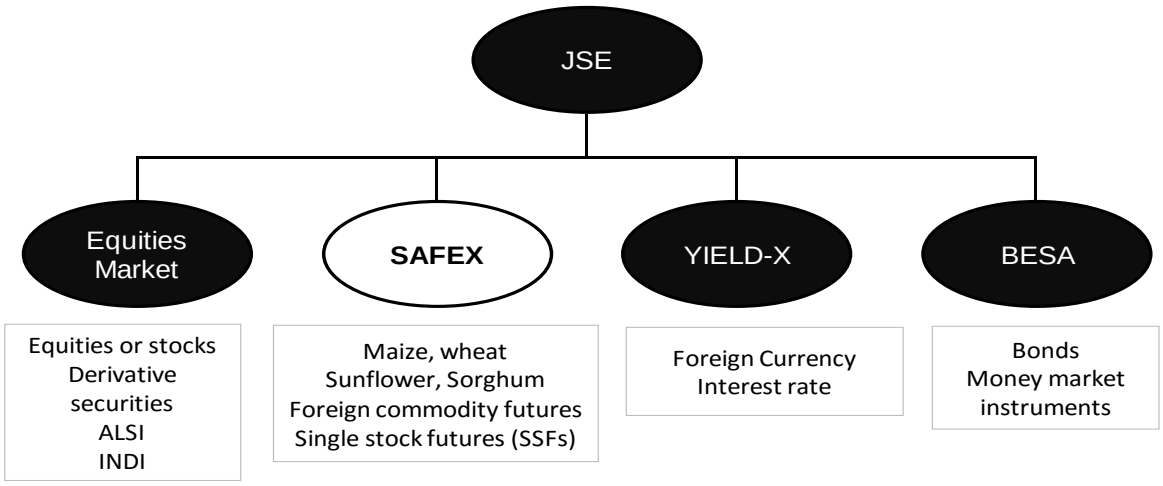
In this thesis, return volatility of selected contracts on SAFEX is examined with focus on market anomalies, seasonality, information transmission and margin exceedances. Further, the behaviour of volatility as contracts approach maturity is examined to find out if the

Samuelson Hypothesis is supported. The thesis also develops trading strategies for the wheat contract to exploit market inefficiencies for financial gain. Information transmission between the SAFEX contract and three major global wheat markets is explored establishing the influence of each market on the others. Finally, the thesis looks at margins on the SAFEX market using extreme value theory with and without price limit events. The focus is on probability of margin exceedance in white maize, yellow maize, wheat, silver and crude oil (WTIO). Exploiting the superior statistical features of extreme value theory, the study suggests an optimal margin approach suitable when contract returns are asymmetric and have price limits.

## 1.2 Overview on the SAFEX market

The Johannesburg Stock Exchange (JSE) was established in 1887 to assist in mobilising funding for mines at the height of the South African "gold rush". As the oldest stock market in Sub-Saharan Africa, JSE is the most advanced and largest exchange on the continent by market capitalisation. Financial markets falling under the JSE are shown in Figure 1.1.

**Figure 1.1: Configuration of JSE Financial Markets[2]**




[2] Source: Adapted from the Johannesburg Stock Exchange's JSE (2010)

Deregulation of the commodity-linked markets in South Africa commenced in the early 1980's (Vink & Kirsten, 2002). Licensing of SAFEX as a derivatives market occurred in 1990. Previously an informal futures market providing a platform for trade in the All Share Index, the gold and industrial indices, SAFEX was licenced in terms of the Financial Markets Control Act in 1990 (JSE, 2010). The commodities free market system came about after the enactment of the Marketing of Agricultural Products Act of 1996 (Adelegan, 2009; Vink & Kirsten, 2002). This opened the door for the trading of agricultural derivatives on SAFEX. White and yellow maize contracts, listed since May 1996, became the largest asset class on SAFEX (Adelegan, 2009). SAFEX was bought by the JSE in 2001.

Official commodity prices are determined on SAFEX by demand and supply economics with bids and offers comprising key inputs for price formation (Vink & Kirsten, 2002). SAFEX is therefore a platform facilitating price discovery and hedging to enable risk management (JSE, 2010). Globally, some of the leading commodity exchanges are the Chicago Mercantile Exchange (CME), established in 1864, and the London Metals Exchange (LME) which was launched in 1877 (Rashid, Winter-Nelson, & Garcia, 2010). Outside of the industrialised world, commodity exchanges started emerging at a faster pace after 1990, supported by information technology advancements. However, outside of South Africa, many economies in Africa have relatively small volumes traded on commodity markets. This study conducts econometric analysis of SAFEX contracts in various classes including agricultural, energy, precious metals and industrial metals.

## 1.3 Problem Statement

Commodity prices experience shocks from time to time impacting on commodity returns (Martin & Anderson, 2011). Over the period 2005 through July 2008, prices for major agricultural commodities increased by about 100%. Metals and energy price increases

amounting to about 228 % and 336% respectively were recorded from 2000 to July 2007 (Gilbert, 2010). The period after September 2007 saw the drastic collapse in oil prices from US$145.00 to US$40.00 per barrel (Du et al., 2011).

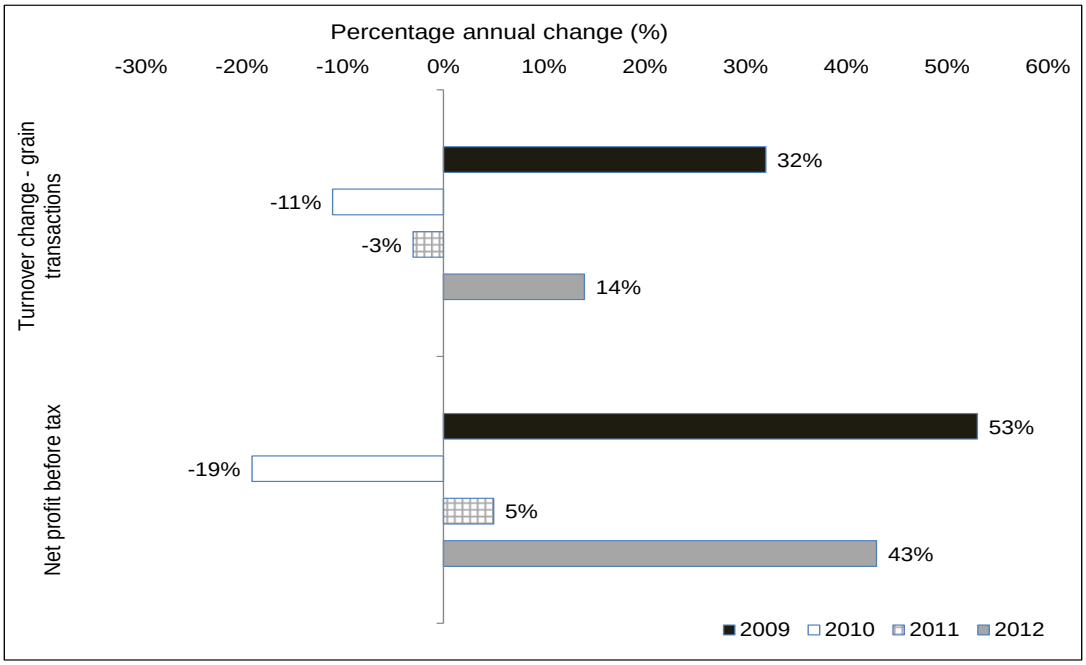
It is thought that international price volatility has an influence on local price volatility (Samouilhan, 2007). There has not been exhaustive investigation in literature on the extent of information transmission between the derivatives markets in South Africa and the global system. While commodity information flows are efficient within developed countries, commodity price volatility flow-through in developing countries is known to vary widely by country (Gilbert, 2010). Piesse and Thirtle (2009) suspect there might be transmission of price increases from the metals and oils to the food commodities.

Unresolved and on-going debates in literature include the nature of the link between speculation and volatility, margin levels and impact of price limits, returns asymmetry and the behaviour of volatility as contracts approach maturity (Gilbert, 2010; Headey & Fan, 2008; Irwin, Sanders, & Merrin, 2009). Thus, this research aims to develop tools and mechanisms to identify factors contributing to commodity return volatility and for anticipating its occurrences. Volatility and its possible links with market fundamentals are major areas of interest if correct market decisions are to be made. In Christoffersen and Diebold (2000), the conclusion is that volatility forecasting using various models missed the global market crash of 1987. Devlin, Woods, and Coates (2011) confirm that the commodity price collapse of mid-2008 took economic forecasters by surprise.

Return variability is a major source of risk in any financial market (Samouilhan, 2007). Commodity prices have been synonymous with “boom and bust” patterns as noted in Gouel (2012) and most markets in literature do not follow the efficient market hypothesis. A

baseline survey on performance of agribusinesses in South Africa is conducted by PriceWaterhouseCoopers (Pvt) Ltd. every year (PwC, 2013). The results of these studies suggest participants in commodity markets have limited tools to predict return volatility to smoothen and sustain profitability. The graph in Figure 1.2 is derived from PwC (2013) and shows significant fluctuation in financial performance in the agricultural commodities industry.

**Figure 1.2: Year-on-year Trends for Agribusinesses (Change in % terms)[3]**




As shown in Figure 1.2, the major agribusinesses in South Africa realised a 32% increase in grain trading turnover in 2009 followed by a decline of 11% in 2010. Average industry net profit in 2009 and 2010 was respectively 53% and -19%. These businesses comprise the majority of the membership of SAFEX, trading on proprietary desks and on behalf of clients. The swings in earnings suggest price and futures return behaviour on SAFEX may not be known in depth. The primary focus of the investigation in this research is return and volatility

[3] The data used for the graph is based on the baseline survey done by PriceWaterhouseCoopers 2013

behaviour, market inefficiencies, causes thereof, and potential impact on market participants on SAFEX.

While SAFCOM (2013) confirms similar margin levels are set for long and short positions, SAFEX contract returns have not been confirmed as symmetric in literature. The impact of price limits on margin-setting and consequently on price discovery on SAFEX is an area not addressed by known previous studies. It is not known in-depth if there is sustainable balance between prudentiality and cost-minimisation on SAFEX and how this might impact exchange competitiveness.

## 1.4 Research Questions

Further to the discussions above, this research addresses a number of questions on futures market anomalies, the behaviour of commodity return and volatility, trading strategy development, information transmission and margin optimisation. Market inefficiencies are investigated in selected contracts while margin adequacy is estimated using extreme value theory. More specifically, the research poses the following questions:

a) Are there market anomalies, inefficiencies and seasonality in the wheat contract on SAFEX? How can such anomalies be exploited for financial gain? How may trade activities be designed to balance risk management and sustainable returns?
b) What are the significant information flows across wheat contracts on SAFEX and three major global futures markets (Zhengzhou Commodity Exchange (ZCE), Euronext/Liffe and Kansas City Board of Trade (KCBT))?
c) Do contracts on SAFEX support the Samuelson Hypothesis whereby volatility increases as time-to-maturity nears? If so, what are the market implications of this market anomaly?

d) Does an understanding of commodity spill-over assist in volatility modelling to account for fundamental factors that drive commodity prices?
e) What is the impact of price limits on margin-setting on the SAFEX market? How suitable is extreme value analysis in generating optimal margins on SAFEX considering that negative and positive returns may be asymmetric?

## 1.5 Purpose and Objectives

The purpose of the study is to develop reliable models for commodity return volatility estimation on SAFEX, taking into account market anomalies and inefficiencies. The study will also look at how contract returns movements could be used in generating optimal margins using extreme value theory. An investigation of commodity price transmission amongst major global wheat markets trading the same underlying asset will be conducted. This will enable the extension of commodity volatility literature on South African markets. Lastly, the purpose of this research is to address volatility-related risk management and offer prescriptions where possible.

The objectives of the study are to develop econometric approaches for commodity derivatives volatility management accounting for its contribution to commodity return. Specifically, the objectives of this research are to:

a) Determine market anomalies and seasonality in the wheat contract with the objective of developing trading rules exploiting inefficiencies for financial gain.
b) Develop models estimating commodity price transmission and information flows between SAFEX and major global futures markets.
c) Determine wheat contract volatility on SAFEX and its spill-overs to or from the major world markets.

d) Investigate if contracts on SAFEX support maturity effects and the implications of this anomaly on futures trading strategy.
e) Determine the impact of price limits on margins on selected SAFEX contracts using extreme value analysis. The study should demonstrate why EVA is superior in margin-setting compared to methods that assume returns follow the normal distribution.

A number of hypotheses were put forward at the beginning of the study, constituting statements about anticipated relationships. This guided the building of arguments for and against expected outcomes. In this process, suggested hypotheses were closely aligned with the objectives of the study given above. H1 to H4 below respectively stand for Hypothesis 1 to Hypothesis 4. Alternative hypothesis are left out as they are assumed to be the converse of each hypothesis.

**H1: The SAFEX wheat contract is not efficient. Market efficiency levels are time-varying and persistent anomalies can be exploited for financial gain.**

**H2: SAFEX wheat prices are influenced by global information flows. Futures contagion may impact price discovery and therefore market efficiency.**

**H3: Major SAFEX contracts support maturity effects consistent with the Samuelson hypothesis**

**H4: Returns on SAFEX are asymmetric, do not follow the normal distribution, and margins for long and short positions should be dissimilar.**

## 1.6 Methodology

Conceptual models for volatilities of major commodity prices and returns are explored in this research. Econometric techniques used in volatility, seasonality and spill-over analysis are the generalised autoregressive conditional heteroskedasticity (GARCH) extensions, cointegration, error correction models, the vector autoregressive model (VAR) and multiple regression. The ordinary least squares approach (OLS) is used in estimating maturity effects in SAFEX contracts. Multiple regression and VAR are used to model volatility spill-overs between SAFEX and global futures markets similar to Jochum (1999) and Samouilhan (2006) or co-integration described in Ai, Chatrath, and Song (2006). Modifications of the vector autoregressive models (VAR) have been used successfully in macroeconomics studies by Bernanke, Boivin, and Eliasz (2005) and those by Banerjee, Marcellino, and Masten (2013). Extreme value theory (EVT) is used in the analysis of SAFEX margins and in estimating the parameters for the generalized extreme value distribution (GEV). Optimal margins are estimated by first generating EVT parameters. The use of these approaches with commodity time series data is described as part of the empirical methodology for respective chapters of the thesis.

## 1.7 Contribution to Knowledge

Local financial market participants require reliable techniques to optimally benefit from changing commodity prices. Empirical studies to date find minimal evidence of speculators' trading activities driving prices (Dwyer, Gardner, & Williams, 2011). Spill-overs of volatility within given commodity classes and across geographical boundaries have been an area of keen interest in literature (Jacks, O'Rourke, & Williamson, 2011). The contributions of this research are in three parts. In terms of empirical contribution, the paper manages to explain commodity return volatility and extreme return behaviour on SAFEX, extending our understanding of the commodities asset class. The thesis makes a theoretical contribution

by developing new trading rules on SAFEX which generate returns net of round-trip trading costs, better than any other trading approach based on chance. Developing the trading strategy exploits market inefficiencies, anomalies and seasonality in the SAFEX wheat contract. Validation of the rule is carried out in the out-of-sample period using Monte Carlo simulation.

The thesis further uses a multiple regression approach for investigating information flows across distinct markets similar to Peiró, Quesada, and Uriel (1998). There is no record in literature of this method being employed to the commodity derivatives class. The methodological approach departs from previous procedures and existing SAFEX literature to estimate return and volatility flows across four markets that include SAFEX, ZCE, Euronext/Liffe and KCBT. The thesis finds SAFEX contract returns have asymmetry in the tails of their distribution to the extent that it is not justifiable to impose similar margins for long and short market positions, as is currently the practice on the exchange. Extreme value analysis (EVA) is found more superior in determining margins that are not similar on opposite sides of the tails, in optimizing the goal of exchange prudentiality, and in minimizing trading costs. EVA achieves all this while avoiding underestimating the likelihood of margin exceedance, if severe market shocks occur. A number of methodologies not previously used with SAFEX data inclusive of the dummy-augmented APARCH, GJR GARCH, VAR, error correction, cointegration and EVT methods are utilised in this study. By providing answers to the gaps in academic knowledge, the research added new insights to literature to generate solutions to challenges facing local commodity market participants.

## 1.8 Motivation

As the means for determining risk, volatility is a crucial element of any investment process. The results of the research have significant importance to a number of derivatives market

participants. Firstly, quantifying price variability aids in projecting profit variation. This study could be used to develop strategies for participating in the markets or for formulating policies to improve commodity markets functionality. Commodity producers' decisions are based on possible prices achievable when facing the markets. Trading participants have to estimate possible buying and selling prices for commodities and the likely margin squeeze. Banks and financiers have to develop pricing assumptions to develop lending products. Processors would require taking hedging positions to aid procurement of raw materials. Consumers require price information to make household budgets while policy makers have to develop safety nets for vulnerable consumers. On the other hand, a review of literature shows that margin exceedances in contracts on SAFEX have not been looked at in depth in both the academic and professional literature and only methodologies assuming normality of returns distribution have been used.

Brooks (2014) concludes that a robust model intuitively describing features of financial asset returns has yet to be found. Commodity derivatives, increasingly becoming popular in balancing and diversifying investment portfolios, are now attracting renewed academic focus. Besides, with Africa being a "treasure trove" of precious natural resources, from arable underutilised land to rare minerals, commodity markets play an integral developmental role on the continent. Understanding the forces driving returns on commodity markets is a critical step in the optimum use of financial resources.

Food security is central to the socio-economic well-being of inhabitants in any economy. Commodity price volatility is taking centre stage given the substantial increase in grain prices experienced over the last one year. The paper builds an in-depth understanding of the extent of market anomalies, inefficiencies, spill-over and contagion across markets and how this shapes the configuration of price risk on the SAFEX market.

SAFEX is still a fairly young futures market. This research has looked at virtually all the available literature produced to-date based on the SAFEX market. A comparison with literature from other markets reveals a number of gaps pertaining to empirical investigations yet to be carried out using returns and volatility data from SAFEX. Firstly, this review could not find any known estimation of seasonality carried out on the wheat contract using parametric approaches. Examples of studies in this area from other markets include Khoury and Yourougou (1993), Fabozzi, Ma and Briley (1994), Xin, Chen and Firth (2005), Karali and Thurman (2010) and Musunuru (2013).

Efficient futures markets are not susceptible to exploitation by employing systematic trading strategies. Regarding possible market anomalies and seasonality in SAFEX contracts, there was ample motivation to find out if trading rules exploiting the inefficiencies could be developed for financial gain. This is possible if significant day-of-the-week, monthly, pre-holiday, post-holiday and other holiday effects are statistically significant. Further, do such trading rules remain profitable after accounting for round-trip trading costs, consistently remaining better than other trading approaches based on chance? The thesis was motivated by the need to answer these questions scientifically and concisely.

The thesis is of interest to global market participants as it addresses an important problem statement on market dependency and information transmission. Firstly, it is critical to understand the nature and behaviour of interactions and dependencies amongst some of the largest wheat futures markets on four continents. A second point is the need to acquire deep insight on how price shocks emanating from any of the markets may adversely impact SAFEX or any of the other markets. Thirdly, it is of interest to find out which of the four markets studied is the most influential and which is the most sensitive, or is vulnerable to be

impacted by the other markets. This guides economic planning at all levels of the value chain. Fourthly, the thesis sought to find out which market has the largest contribution to change in the prices of the other markets and what the implications of the interactions amongst the markets may be. Finally, the study sought to consider what possible policies are open to the South African government, if any, to mitigate any negative consequences from adverse shocks from the other markets.

Further, this study is the first to estimate interaction and dependence involving the SAFEX wheat contract simultaneously with comparable contracts on three major global markets using three distinct estimation approaches. As far as we know, the multiple regression approach of Peiró et al. (1998) has not been applied in literature to agricultural futures located on four continents.

Furthermore, it is of interest to know if the rapid expansion in futures market activity increases both return volatility and information transmission across markets. Such information is paramount in decision-making by central bankers, farmers, national treasury, agro-processors, investors, policy-makers, private sector players and credit providers.

The research was motivated to answer the important research question of whether significant maturity effects exist in selected SAFEX contracts. If this is the case, is the Samuelson hypothesis supported by SAFEX contracts after taking into account the effects of seasonality and multicollinearity? The research also focussed on finding out the implications of maturity effects on trading activities on the futures exchange. Maturity effects studies from other markets were critically analysed guiding the present study including Allen and Cruickshank (2000), Daal and Farhat (2003), Duong and Kalev (2008), Brooks (2012), Chevallier (2012) and Jaeck and Lautier (2015). Existence of maturity effects is of interest to

the futures exchange and clearing house as margins should be higher towards maturity should the Samuelson hypothesis be supported by the data.

Furthermore, literature does not have any record of a study on SAFEX margin estimation using extreme value analysis. Studies on other markets have been carried out using extreme value theory methodologies including Kofman (1992), Booth, Broussard, Martikainen and Puttonen (1997), Adrangi and Chatrath (1999), Longin (1999), Dutt and Wein (2003), Hedegaard (2011) and Hsiao and Shanker (2014). A number of gaps in knowledge therefore exist particularly when one looks at the present approaches used to estimate margins on SAFEX for the day-to-day running of the exchange. Current approaches are based on the assumption that returns data follows the normal distribution. This thesis shows that this is not the case by carrying out empirical analysis on a number of SAFEX contracts. In addition, similar margins are currently applied by SAFEX on the opposite side of the tails, yet there is evidence in this study that positive and negative returns have asymmetry. Is it justifiable therefore to have equal margins for long and short positions in SAFEX contracts with asymmetric returns? Finally, is extreme value analysis more superior and capable of generating margins that are not similar for the opposite tails to optimize margin prudentiality and trading costs? This research was warranted given that most of the above research questions had no answers in literature particularly looking at SAFEX as the only fully functional futures market on the African continent.

## 1.9 Structure of the Thesis

The remainder of the thesis is organized as follows:

Chapter two; *Conceptual Framework.* In this chapter, economic theories and econometric models on futures return volatility are analysed. A broad overview is given on futures markets, causes of volatility, commodity co-movement, futures spill-over, futures margins and extreme value analysis. Empirical evidence on futures risk management, market

anomalies, market contagion and technical trading systems is reviewed. The chapter also gives an overall impression on how econometric models for the four empirical chapters in the thesis are formulated and adopted to the themes of the study.

Chapter three; *A Study of Seasonality in the SAFEX Wheat Market.* This is the first of four chapters in which empirical analysis is carried out. In Chapter three, market inefficiencies and anomalies in the SAFEX wheat contract are investigated using several augmented GARCH models, OLS regression and non-parametric approaches. Both return and volatility seasonality are estimated by studying market anomalies around the day-of-the-week, trading month, pre-holidays, post-holidays, Euronext/Liffe holidays and KCBT holidays. Trading rules are developed to exploit identified market inefficiencies. Monte Carlo simulation validates the rules using the out-of-sample period evaluating possible financial gain after accounting for round-trip trading costs.

Chapter four; *Information Flows in the Wheat Futures Contract.* Information transmission in the wheat contract on SAFEX, ZCE, KCBT and Euronext/Liffe is examined using cointegration analysis, VAR and a multiple regression system. This analysis estimates the most exogenous, most endogenous, sensitive or influential markets amongst the four. The chapter further outlines possible market implications of these results.

Chapter five; *Maturity Effects in Contracts on the SAFEX Market.* The tendency for volatility to increase as contract maturity nears is examined in white maize, yellow maize, wheat, silver and WTIO (crude oil) on the SAFEX market. While accounting for both multicollinearity and seasonality, the analysis also incorporates the effects of traded volume, change in open interest and bid-ask-spread in determining the level of support for the Samuelson hypothesis.

Chapter six; *Margin Adequacy in Contracts on the SAFEX Market.* Extreme value theory is used in the analysis of margins in SAFEX contracts accounting for the impact of price limits. Asymmetry in negative and positive returns is investigated finding if long and short-position margins should be set at the same levels. Margin violation probabilities are generated for a range of margin levels demonstrating the superiority of EVT by comparing theoretical and empirical margin violation curves. Examples of optimal margins set using EVA compared to current SAFEX approaches are presented.

Chapter seven concludes the study and gives ideas for further research.

# 2 CONCEPTUAL FRAMEWORK

## 2.1 Background to Conceptual Framework

Several arguments in literature on commodity volatility are analysed and diverse modelling techniques are looked at in this chapter. Globally, some 85% of all futures contracts and options are traded in the USA (Etula, 2013). As Clapp (2009) notes, out of all the commodity index funds traded on derivative markets, the proportion of agricultural commodities is 30%. Price increases between 2004 and 2008 in major commodities led to food crises in many developing countries (Clapp & Helleiner, 2012). A number of fund managers in the US and elsewhere suffered losses around 2007/2008 resulting from unexpected price volatility. It is confirmed in Brown (2012) that JP Morgan and Chase Private Limited recently lost at least US$3 billion after positioning themselves on the wrong side of the market. Risk management in derivatives trading is more effective if volatility can be understood in depth. Forecasting volatility facilitates trading strategy formulation in anticipation of price shocks. This chapter is about the conceptual framework surrounding commodity volatility and the arguments for this project.

## 2.2 Overview of the Futures Markets

A commodity derivatives market is an exchange where commodity contracts are traded. Contracts may either trade in spot markets or as derivatives of the underlying asset, such as forwards, futures, options or the more complicated swaps. Speculators and investors trade contracts on an exchange with the objective of achieving financial profits. Globally, the USA has the largest futures markets by market capitalisation and in terms of the diverse products traded. Commodity classes on a futures exchange include agricultural, bio-fuels, precious metals, meats and energy products, among others. In the USA, the Chicago Mercantile Exchange (CME) enjoys a market share of approximately 90% of all derivative contracts

(Van Wyk, 2012). Presently there exist some CME-derived contracts traded on SAFEX in Rands terms (Van Wyk, 2012).[4] The underlying assets for these contracts include corn or maize, soybeans, soy oil, gold, platinum, West Texas Intermediate Oil (WTIO) and hard red winter wheat which is predominantly traded on the CME's Kansas City Board of Trade (KCBT).

## 2.3 Price Volatility: Definitions and Overview

Volatility is a measure of price change over time. Tothova (2011) defines volatility as a measure of movement and variation in a given variable. Volatility is therefore a measure of risk in financial markets. In his paper, Pindyck (2004) uses standard deviation of adjusted daily log prices as a working definition of volatility. The above definitions are in agreement with Moledina, Roe, and Shane (2004) who describe volatility as the standard deviation of time series data. Coefficient of variation is also suggested as a measure of volatility (Moledina et al., 2004). Historical volatility, as defined by Tothova (2011) entails price variability of an asset in the past on the basis of observed price movements over time. Koopman, Jungbacker, and Hol (2005) calculate historical volatility using recent known price changes, or the daily return series. Option pricing data is used in literature to compute implied volatility while the sum of squared residuals have been a proxy for realised volatility (Koopman et al., 2005). It is also known that volatility is typically not observed and realised volatility is a good proxy for the actual (Koopman et al., 2005). Implied volatility comprises market participants' expectations on future volatility, and hence is forward-looking (Koopman et al., 2005). Geyser and Cutts (2007) postulate that uncertainty has probable outcomes that are not known while fluctuation relating to volatility is determinable.

[4] South Africa uses the Rand as its currency.

In Symeonidis, Prokopczuk, Brooks, and Lazar (2012), price volatility is an increasing linear function of scarcity. Fluctuating prices lead to an uncertain import bill for commodities in net importing countries. In the case of agricultural commodities, this is a key threat to food security (Tothova, 2011). Net sellers and producers on the other hand, benefit from increased prices (Tothova, 2011). For the case of metals, Symeonidis et al. (2012) found that as the difference between spot prices and futures prices increases, volatility also rises.

## 2.4 Commodity Price Volatility: Causes

Clapp (2009) and Dawson (2014) found demand and supply levels, stocks-to-use ratio, biofuels needs, export restrictions and the fall of the US dollar all impacting contract volatility. For South Africa however, Auret and Schmitt (2008) found the stocks-to-use ratio not influencing maize prices. The most important factors in the case of SAFEX white maize prices were the weather-related Southern Oscillation Index (SOI), the lag of the SAFEX maize prices, the import parity prices and the JSE All Share Index (ALSI) 40 series. Findings by Hennessy and Wahl (1996) were that the amount of rainfall received and temperature levels impacted price variability. Plantier (2013) concurred in finding that the rise and fall of commodity prices was strongly linked to the US Dollar value and the world business cycle. Chen, Rogoff, and Rossi (2010) explored the influence of exchange rate and equity price variation on agricultural commodity prices. Exchange rates in New Zealand, Australia and Canada are useful in predicting major food commodity indices (Chen et al., 2010; Roache, 2010)[5]. Dwyer et al. (2011) and Simons and Rambaldi (1997) say as demand and supply of commodities is inelastic, prices tend to vary substantially whenever disequilibria in the fundamental factors emerges. The short-run inelastic nature of demand and supply is such that any market disturbance has substantial price effects (Gouel, 2012). In Gorton, Hayashi,

[5] The US dollar started falling in 2002 and went down about 27 % by the year 2007. Food value exports from the US increased by 54 % over the same period (Piesse & Thirtle, 2009).

and Rouwenhorst (2013), higher demand for commodities such as metals and oils in China and India was found responsible for price increases in the run up to the global financial crisis in 2007/2008. Some countries put in place trade measures to limit exports thereby precipitating price volatility (Clapp & Helleiner, 2012). Restricting trade in a commodity on the futures markets can cause distortions to the prices (Dwyer et al., 2011; Piesse & Thirtle, 2009; Simons & Rambaldi, 1997).

The prices of energy have been changing rapidly in recent years. Energy, including fuel is a major input in the commodity-producing sectors. The use of biofuels has been found increasing integration between energy and agricultural commodities (Hertel & Beckman, 2011). Ethanol production using food products increased tremendously between 2004 and 2007 with the US registering additional biofuels production of 50 million tons during this time (Abbott, Hurt, & Tyner, 2009; Piesse & Thirtle, 2009). Biofuels appeared to increase demand for food commodities with an adverse impact on prices (Dawson, 2014). USA Gasoline consumption in Saghaian (2010) was estimated at about 140 billion gallons. Inclusion levels for ethanol under the “E10” rule is about 10% and this brought ethanol usage to up to 14 billion gallons in 2010. This was an enormous jump from the 1 billion gallon consumed per year around the late 1990s.

Tang and Xiong (2010) confirmed commodity index investments increased from $15 billion to $200 billion over the period 2003 to 2008. Futures market participants including pension funds, hedge funds and endowment funds increased commodity investment significantly between 2005 and 2008 (Clapp, 2009). The increase in trading by non-commercial participants led to the suspicion that there was unprecedented speculation on commodities markets. Major vehicles of investment into commodities are commodity index funds and exchange-traded funds (ETFs). Bryant, Bessler, and Haigh (2006) identify informed and

uninformed speculators in commodities with the latter hypothesized to cause increased volatility. Further, Stein (1987) finds imperfectly informed but rational speculators fairly capable of destabilizing prices. Excessive speculation was observed to have caused higher wheat prices in Stoll and Whaley (2010). Limited profitable opportunities on the stock markets position commodity derivatives speculation and investment as lucrative (Piesse & Thirtle, 2009).

To the contrary, Dwyer et al. (2011) suggested commodity volatility is attributable to fundamental factors more than speculative activities. Janzen, Smith, and Carter (2013) concluded speculators in index commodity investments had no significant bearing on cotton prices in the USA. Adam and Fernando (2006) found that in general, speculation does not generate persistent price bubbles. Devlin et al. (2011) found speculation had a minimal causal link with high commodity volatility over the recent past. In fact, Filimonov et al. (2013) welcomes commodity financialization as it pulls prices nearer fundamentals. Financialization also provides liquidity to the futures markets while providing mechanisms for transferring risk to participants willing to assume it (Filimonov et al., 2013). The high demand for speculation during significant volatility periods is superseded by higher hedging requirements of commercial market participants (Chang, Chou, & Nelling, 2000). Tadesse, Algieri, Kalkuhl, and von Braun (2013) propose a more balanced approach in assessing speculation. Increased liquidity emanating from speculators helps price discovery whilst herd mentality from speculation may cause prices to drift from their fundamental values (Tadesse et al., 2013).

The views in literature on trading behaviour of market participants are not in agreement and as such, futures market speculation still requires further exploration. Some econometric studies on speculation compared the positions of market participants categorised between

commercial and non-commercial investors. Non-commercial role-players are generally regarded as speculators.

## 2.5 Commodity Return Volatility Theories

### *2.5.1. Samuelson Effect*

The first theory for this project is given in Samuelson (1965). Price variability rises the closer to maturity a futures contract gets, according the Samuelson hypothesis (Duong & Kalev, 2008; Samuelson, 1965). Also called the maturity effect, this phenomenon has been investigated in many studies involving futures contracts (Anderson, 1985; Castelino & Francis, 1982; Chatrath, Adrangi, & Dhanda, 2002; Duong & Kalev, 2008; Goodwin & Schnepf, 2000; Hennessy & Wahl, 1996; Karali & Thurman, 2009, 2010; Kenyon, Kling, Jordan, Seale, & McCabe, 1987; Milonas, 1986b; Yang & Brorsen, 1993). In Milonas (1986a), 10 out of 11 futures contracts examined confirmed the inverse relationship between volatility and time remaining before maturity of the contracts. Included in the study were agricultural futures, metals and financial futures.

### *2.5.2. Mixture of Distribution Hypothesis*

The mixture of distribution hypothesis (MDH) states that trading returns and volume in a given financial market are both influenced by common latent events or variables (Andersen, 1996). In Epps and Epps (1976), the MDH was explained as the dependence of the log of price change of a traded asset on the volume traded. Volume and volatility are expected to be positively related as they are understood to have common causal variables (Brooks, 1998). The rate of information flow doctrine suggests volume rises more with price rises than price decreases (Brooks, 1998). Andersen (1996) investigated return volatility and trading volume relationships within the context of the MDH. In this study, it was found return volatility was significantly related to trading volume, number of transactions, the bid-ask spread and

market liquidity. Bessembinder and Seguin (1993) investigated linkages between trading volume, market depth, open interest and return volatility. The study involved agricultural commodities, minerals and the exchange rate series. Unexpected volume shocks were found more influential on return volatility than expected shocks (Bessembinder & Seguin, 1993). Return volatility and open interest were found to be negatively linked in Bessembinder and Seguin (1993). The MDH was found to hold in that study.

A key finding in Lamoureux and Lastrapes (1990) was volatility persistence in GARCH reduced drastically if volume is included in the variance equation. Volume can thus be viewed as a barometer for information flow (Lamoureux & Lastrapes, 1990). Kyle (1985) examined the link between volume traded and stock return variance. Findings were that there existed uninformed liquidity traders and investors with private information, or insiders, who maximise monopoly power on information. Rather than use fundamental information, noise traders execute more trades in higher volume or liquid markets (Choudhry, 2000). Specialists and discretionary liquidity traders typical execute trades during active trading times characterized by high market liquidity and high volumes. On the other hand, informed traders and random liquidity traders are the more dominant participants during inactive financial market periods (Barclay, Litzenberger, & Warner, 1990).

### *2.5.3. Sequential Arrival of Information Models (SAIM)*

Sequential arrival of information models (SAIM) were analysed in Bessembinder and Seguin (1993). The SAIM doctrine says information reaches different types of traders consecutively (Bessembinder & Seguin, 1993). As it were, not all traders receive information at the same time (Chiang, Qiao, & Wong, 2010). In terms of rank and order, informed traders secure information first while uninformed traders obtain information last. As such, the uninformed traders are not able to determine the full extent of information in existence and how much

trading is informed or not informed. In Kyle (1985) the three types of traders in the market include the single risk neutral insider, competitive risk market makers and random noise traders. Kyle (1985) contends private information is incorporated in prices in market trades during the day. In the gradual information dissemination process, intermediate equilibria are reached first leading up to subsequent equilibrium in prices (Brooks, 1998). Final equilibrium is only realized when all traders have reacted to the signals of information (Chiang et al., 2010). In a mathematical sense, volatility may take the pattern of lags matching sequential responses by traders.

### *2.5.4. Returns and Volatility Theories*

Etula (2013) suggested commodity returns on the futures markets are influenced by systematic factors and commodity specific factors. Positive unexpected return increase is associated with a decrease in price volatility (Bessembinder & Seguin, 1993; Bryant et al., 2006; Glosten, Jagannathan, & Runkle, 1993b). Tang and Xiong (2010) found positive correlation between oil prices and rolling returns for commodities that include copper, live cattle and soybeans. Roache (2010) suggested there is a weak relationship between return volatilities and financialization or speculation. Gilbert (2010) assessed the trading activities of index investors and found their trading patterns influencing returns for soybeans but neutral on maize, soybean oil and wheat. Glosten et al. (1993b) found a negative relation linking conditional expected monthly return and the conditional variance of this return. The decrease in share price alters a firm's capital structure and raises leverage levels (Glosten et al., 1993b). Increased price fluctuation then derives from this higher leverage (Glosten, Jagannathan, & Runkle, 1993a).

Brooks (2014) explains conditional variance of return, given the variable or condition $x$ is satisfied, using the relation:

$$Var(r_t|x) = E\left(\left[r_t - E(r_t|x)\right]^2|x\right) \quad (2.1)$$

where $r_t$ are daily returns. Many authors agree that $E(r_t)$ should be zero (Brooks, 2014). Thus, $Var(r_t)$ can be compared to $E\left[r_t^2\right]$. In most econometric modelling applications, the square of the returns is a proxy for daily volatility (Auer, 2014). However, Andersen and Bollerslev (1998) acknowledge squared daily returns are not as good a measure of volatility when compared to estimations involving intra-day data. The square of hourly returns added up together for the entire day makes a better variance measure as more observations are incorporated.

In Day and Lewis (1992) conditional excess return has the relation

$$R_{Mt} - R_{Ft} = \lambda_0 + \lambda_1 h_t + \varepsilon_t \quad (2.2)$$

$R_{Mt}$ is the return on market portfolio and $R_{Ft}$ is the risk-free rate. The conditional standard deviation of return and the random error are $h_t$ and $\varepsilon_t$ respectively. The theoretical conclusion from the examination of the above is there is a negative relation between returns and unexpected price volatility (Day & Lewis, 1992). In the variance equation, Day and Lewis (1992) make use of an extension of the GARCH to include implied volatilities as follows:

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + \delta \sigma_{t-1}^2 \quad (2.3)$$

Implied volatilities given in the lagged terms $\sigma_{t-1}^2$ were found not adding substantial information in the modified variance relation above (Day & Lewis, 1992).

### *2.5.5. Capital Asset Pricing Model (CAPM)*

In Bollerslev, Engle, and Wooldridge (1988), return of an asset above risk-free rate has a proportional relationship with non-diversifiable risk. This risk is calculated as the covariance

of asset return to assets in a market portfolio. Kim and Rogers (1995) postulate the CAPM may be modelled linearly in terms of risk using the GARCH-M approach as shown below

$$R_t^i = \gamma_0 + \gamma_1 h_t^{1/2} + \gamma_2 DL_t + \theta\varepsilon_{t-1} + \varepsilon_t \quad (2.4)$$

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 DL_t + \delta_2 DS_t \quad (2.5)$$

$R_t^i$ denotes the return while $h_t$ is the conditional variance (Kim & Rogers, 1995). A post-announcement dummy is given as $DL_t$, the seasonal dummy is $DS_t$ while the error is represented in $\varepsilon_t$ (Kim & Rogers, 1995).

### *2.5.6. Cost of Carry Model*

The futures price is higher than the spot price by an excess measured as the cost of carry in Tse (1995) as given in the relation:

$$f_t = S_t \exp[(r-d)T_t] \quad (2.6)$$

The futures price is $f_t$ while the spot price is $S_t$. Tse (1995) explains that the risk-free rate and dividends are respectively given by $r$ and $d$. $T_t$ stands for the time to maturity. Taking on logs, the relationship becomes:

$$\log f_t = \log S_t + (r-d)T \quad (2.7)$$

If we let

$$r_d = r - d \quad (2.8)$$

Then we have the relation

$$z_t = \log S_t - \log f_t + r_d T_t \quad (2.9)$$

Informational efficiencies surrounding a financial market are benchmarked on the extent to which spot and futures returns are completely correlated (Brooks, Rew, & Ritson, 2001). Futures prices are in the majority of cases ahead of spot prices on account of the higher

liquidity levels associated with the former (Brooks et al., 2001). Violation of the cost of carry occurs as a result of infrequent trading, transaction costs and some delays in the computation of an index representing the futures price. Plausible assumptions are made as in Tse (1995) and Brooks et al. (2001), for example that respectively $d = 0.86\%$ and $r$ is equivalent to the 3-month UK Treasury Bill (TB) rate.

In Crain and Lee (1996) it was concluded that futures prices for wheat have causality on spot prices within USA markets. Fedderke and Joao (2001) used the unrestricted VAR method to ascertain price discovery between the JSE All Share Index, which represented the spot market and the SAFEX All Share Index in the futures market. Findings were that the futures market led the spot market for all time intervals longer than two minutes and there was bi-directional price leadership and discovery (Fedderke & Joao, 2001). Strydom and McCullough (2013) investigated price discovery between SAFEX white maize prices and white maize spot prices. The error correction model (ECM) and the vector error correction model (VECM) enabled long-run cointegration relationships to be determined (Strydom & McCullough, 2013). Contrary to a number of similar studies in literature, price discovery was found to occur in the spot white maize market (Strydom & McCullough, 2013). The reasons given for the spot price leading the futures price include inadequacy of liquidity and possible inefficiencies in the futures market (Strydom & McCullough, 2013). The spot white maize market in South Africa may have been enjoying higher liquidity levels than the futures market (Strydom & McCullough, 2013).

### *2.5.7. Price Discovery*

In literature, tests have been carried out comparing futures and spot prices to find out in which market price discovery occurs. Fedderke and Joao (2001) examined price discovery in the South African markets with focus on the stock index futures and the underlying JSE

equities. Fedderke and Joao (2001) suggested in the majority of cases, futures tend to be more efficient than spot prices. The reasons given for this include the lower transaction costs in futures markets, the higher trading volumes and the lower capital requirements to trade on futures markets compared to spot markets. The VAR approach which included testing for cointegration was used in Fedderke and Joao (2001). The study found futures prices leading spot prices. In Moosa (2002), price discovery is examined using the Garbade and Silber (1983) (G-S) model, taking the form

$$P_t^A = C_B + (1 - d_B)P_{t-1}^A + d_B P_{t-1}^B + \lambda_{t1} \quad (2.10)$$

$$P_t^B = C_A + (1 - d_A)P_{t-1}^B + d_A P_{t-1}^A + \lambda_{t2} \quad (2.11)$$

Where $P_t^A$ and $P_t^B$ are the logs of the spot and futures prices respectively. The constants $C_A$ and $C_B$ capture secular price trends and persistent differences between spot and futures prices. Error terms in the relation are $\lambda_{t1}$ and $\lambda_{t2}$. A parameter $\tau$ used to measure and explain price discovery is defined in the G-S model with the relation

$$\tau = d_B / (d_A + d_B) \quad (2.12)$$

Analysis by Moosa (2002) using the model above found 60% of price discovery taking place in the futures market. In Frino and West (2003) the tendency is for price discovery to occur in the least-transaction-cost market first.

### *2.5.8. Life-cycle Model of Household Spending Behaviour*

The model hypothesizes that when asset prices are increasing, higher levels of wealth emerge, leading to higher consumption levels in the economy (Ando & Modigliani, 1963; Sariannidis, 2011). The linkages that hold this life-cycle structure together include the financial markets themselves, the per capita income and its changes and the economic growth that happens in the bigger economy (Ando & Modigliani, 1963; Sariannidis, 2011).

### *2.5.9. Volatility Feedback Hypothesis*

This hypothesis was advanced by Campbell and Hentschel (1992) and Braun, Nelson, and Sunier (1995). The hypothesis states that a rise in asset volatility increases required asset returns with the effect of lowering asset prices. In the feedback effect, Campbell and Hentschel (1992) find asymmetry with feedback amplifying large negative asset returns more than large positive returns. The result is there are negatively skewed asset returns which enhance the likelihood of market crashes. The feedback effect is also observed to be more significant when volatility is high.

### *2.5.10. Information Availability Theory*

In Foster and Viswanathan (1990) the informed trader is assumed to have much more information than the liquidity traders especially on Mondays. However, Mondays are observed to have higher trading costs and the highest price change variance levels, but with lower volume than Tuesdays. Such effects have been more significant in assets with higher levels of discretionary trading. Variations in inter-day traded volume, trading costs and price changes are largest for the most-actively traded, high-profile assets.

### *2.5.11. Settlement Period Hypothesis*

Going by the theory in Agrawal and Tandon (1994), if there is a two-day settlement period, Thursdays are bound to have higher returns than the other days of the week. Settlement times have the duration from the period of trading to payment and higher returns for Thursdays are possible as there is need to compensate for forgone returns over the weekend (Agrawal & Tandon, 1994). While purchase and payment for these contracts occurs at market close on Wednesday, cash settlement and receiving of the related payment only happens on Monday (Agrawal & Tandon, 1994).

## 2.6 Commodity Volatility Modelling

### *2.6.1. The Autoregressive Moving Average (ARMA) Model*

The ARMA(p,q) is given in Du and Wang (2004) as

$$Y_t = X_t^{'}\beta + \sum_{1=1}^{p}\phi_i Y_{t-i} + \varepsilon_t + \sum_{j=1}^{q}\theta_j \varepsilon_{t-j} \quad (2.13)$$

Explanatory variables are given in the vector $X_t^{'}$ while lagged dependent variables are represented by $Y_{t-i}$, which also captures the autoregressive or AR part of the relation (Du & Wang, 2004). Lagged errors embody the moving average of MA component and are represented by $\varepsilon_{t-j}$. Parameters to be estimated include $\beta$, $\phi_i$ and $\theta_j$. Goodness of fit criterion that include the MSE, AIC and SBC are applied in determining the ideal values of $p$ and $q$ (Du & Wang, 2004).

### *2.6.2. The ARCH Model*

Time series data can be tested for the presence of the ARCH effect using the Portmanteau (Q) test or the LaGrange Multiplier test (Du & Wang, 2004). When ARCH effects are detected, it is logical to do away with the ARMA model and proceed to the ARCH or GARCH (Jordaan, Grove, Jooste, & Alemu, 2007). Alternatively, the tests of heteroskedasticity are suggested in Sariannidis (2011) using the autocorrelation function (ACF) and partial autocorrelation function (PACF) and the Ljung-Box statistics (Sariannidis, 2011). Where heteroskedasticity is detected, this qualifies the application of the ARCH and GARCH approaches. The ARCH operates under assumptions of changing conditional variance leaving the unconditional variance constant (Bollerslev, 1986). The ARCH model, in Engle (1982) is as follows:

$$R_t = \mu + \varepsilon_t \quad (2.14)$$

The return of a financial series is given by $R_t$ and $\varepsilon_t$ is given in:

$$\varepsilon_t = \sqrt{h_t} z_t, \quad z_t \sim D(0,1) \tag{2.15}$$

The $z_t$ term comprises white noise. The variance equation in Engle (1982) represents the ARCH(q) given by:

$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{2.16}$$

A key condition is that $\omega > 0$ and $\alpha_j \geq 0$ (Engle, 1982). Brooks (2014) contends that financial data is unlikely to be characterised by constant variance hence the unattractiveness of the ARCH when compared to the GARCH.

### *2.6.3. GARCH Model*

Bollerslev (1986) developed the GARCH from the ARCH. The GARCH model is given in Bollerslev (1986). Firstly, $\varepsilon_t$, the discrete-time stochastic series in Bollerslev (1986) is given in the information space $\psi_{t-1}$ as follows:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{2.17}$$

The GARCH(p,q) variance equation for $p \geq 0$ and $q > 0$ is

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2.18}$$

$$\alpha_0 > 0, \quad \alpha_i \geq 0, \quad i = 1, \ldots\ldots q \tag{2.19}$$

$$\beta_i \geq 0, \quad i = 1, \ldots\ldots p \tag{2.20}$$

In this case $h_t$ stands for variance of $\varepsilon_t$ conditional on information up to $t$ period. Lagged conditional variances are allowed as part of the GARCH model (Bollerslev, 1986). The ARCH and GARCH are applied to volatility modelling in (Jordaan et al., 2007; Just & Pope, 2003; Moledina et al., 2004). On SAFEX, Jordaan et al. (2007) found the prices of maize and sunflower seed to be significantly volatile and time-varying. The use of GARCH was therefore fairly appropriate (Jordaan et al., 2007).

To analyse commodity co-movement, Deb, Trivedi, and Varangis (1996) modelled prices using the univariate and multivariate GARCH. Their regression also captured the effect of common macroeconomic variables whose effect they wanted to filter out first before looking at the volatility terms. Deb et al. (1996) carried out the regression

$$\Delta p_{it} = \sum_{j=0}^{j} a_{ij}\Delta x_{t-j} + \rho_i \Delta p_{i,t-1} + \varepsilon_{it} \tag{2.21}$$

$$i = 1,....., M \text{ and } t = 1,....., T \tag{2.22}$$

Above, $\Delta p_i$ stands for change of the logarithm of the price of $i^{th}$ commodity and $\Delta$ is the difference operator. The common set of macro variables are all included in $x$ (Deb et al., 1996). The macro variables used included logarithm of the Consumer Price Index (CPI), industrial production, exchange rate, stock prices, money stock and interest rates. In the multivariate GARCH*(p,q)* model, Deb et al. (1996) specify the relation as given by

$$H_t = C^* + \sum_{k=1}^{K}\sum_{i=1}^{q} A'_{ik}\,\varepsilon_{t-i}\varepsilon'_{t-i}\,A_{ik} + \Sigma\Sigma G'_{ik}\,H_{t-1}G_{ik} \tag{2.23}$$

In the relation above, $\varepsilon_{it} = \eta_{it}\sqrt{h_{it}}$ , with $h_{it}$ as the conditional variance. Deb et al. (1996) define $H_t : (mxm)$ as a time-varying conditional covariance matrix. *A* and *G* are constants and $\varepsilon_t \left| \Omega_{t-1} \sim N(0, H_t) \right.$ in time $t$ and $\Omega_{t-1} = \{\varepsilon_{it-1}, \varepsilon_{it-2}, ..... \}$. $\Omega_{t-1}$ is the conditional information set at $t-1$ (Deb et al., 1996). French, Schwert, and Stambaugh (1987) used the GARCH-in-mean to investigate the relation between expected risk premiums and volatility levels in the time series data for the S&P 500.

The GARCH class of approaches are capable of volatility clustering modelling (Choudhry, 2000; Kim & Rogers, 1995). Although the ARCH/GARCH set of models continue to be some of the leading techniques for the second moments, they also have limitations (Brooks, 2014).

The shortcomings occur when modelling the fat tails that characterise financial data (Brooks, 2014). Fat tails give financial time series the leptokurtic character. The GARCH models also ignore the negative correlation between current and future volatility as found out by researchers (Nelson, 1991). Persistence of conditional volatility in ARCH/GARCH and several extensions has also been known to be difficult to ascertain as some contradictions usually occur (Nelson, 1991). The GARCH approach also requires rigid parameter restrictions which do not reflect the reality of some data (Nelson, 1991). An assumption of normality of errors is listed in Serra (2011) as an important downside to the GARCH.

### *2.6.4. GARCH-M Model*

In the mean equation, Nelson (1991) states the GARCH-M or GARCH-in-mean has the relation:

$$R_t = a + b\sigma_t^2 + \xi_t \tag{2.24}$$

$R_t$ denotes returns series and $\sigma_t^2$ is the conditional variance of $R_t$. Engle, Lilien, and Robins (1987) point to the trade-offs in the GARCH-M which involves risk and return. The variance equation is basically similar to that of the GARCH model (Auer, 2014). This model is said to maintain consistency with portfolio theory in Auer (2014) with higher risk matching higher return. In the case of three or more markets, an extension of the GARCH-M, which enables determination of linkages amongst these markets, is presented in Hamao, Masulis, and Ng (1990) as

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \varepsilon_{t-1} + \varepsilon_t \tag{2.25}$$

In the variance equation, we have

$$h_t = a + bh_{t-1} + c\varepsilon_{t-1}^2 + dD_t + f_1 X_{1t} + f_2 X_{2t} \tag{2.26}$$

$R_t$ is the return at time *t*. Typically, $R_t$ is return calculated from open-to-close, close-to-close or close-to-open prices. $D_t$ is a daily dummy or Monday dummy in Hamao et al. (1990). An MA(*1*) process is captured in $\varepsilon_{t-1}$, such that the model becomes an MA(*1*)-GARCH(*1,1*)-M.

Exogenous variables from to foreign markets are included in the variance relation. This is achieved by including $X_{it}$, which are squared residuals emanating from the MA(*1*)-GARCH(*1,1*)-M models of the two foreign markets that are compared with the first market in the set. The basic idea is to check the incremental effect that occurs after introducing sequentially, $f_1(X_t)$ followed by $f_2(X_t)$. A relation taking account of conditional mean spill-over, extending from the above is

$$R_t = \alpha + \beta h_t + \delta D_t + \phi Y_t + \gamma \varepsilon_{t-1} + \varepsilon_t \tag{2.27}$$

$$h_t = a + b h_{t-1} + c\varepsilon_{t-1}^2 + dD_t + fX \tag{2.28}$$

In the above, *Y* is the conditional mean in the open-to-close, close-to-close or close-to-open sessions, as the case may be.

### *2.6.5. T-GARCH Model*

The variance equation for the T-GARCH model is given in Auer (2014) as

$$h_t = \delta + \sum_{k=1}^{p} \xi_k \varepsilon_{t-k}^2 + \sum_{l=1}^{q} \eta_l h_{t-l} + \sum_{v=1}^{r} \lambda_v T_{t-v} \varepsilon_{t-v}^2 \tag{2.29}$$

The element of asymmetry is measured to determine if negative shocks might tend to associate with higher volatility (Auer, 2014). As such, $T_{t-v}$ is a dummy taking the value 1 if $\varepsilon_{t-v} < 0$ and *0* if $\varepsilon_{t-v} \geq 0$. When $\lambda_v > 0\ (\lambda_v < 0)$, negative (positive) shocks are more influential on conditional variance than positive (negative) shocks (Auer, 2014).

### *2.6.6. GJR GARCH Model*

GJR GARCH is the acronym for the authors in Glosten et al. (1993a). It has been acknowledged the model is able to test asymmetric information but includes the fewest number of variables possible within the GARCH family (Sariannidis, 2011). Glosten et al. (1993a) proposed the GRJ GARCH which takes the form

$$Y_t = X_t^{'}\theta + u_t \tag{2.30}$$

$X_t^{'}$ represents a vector of exogenous variables and $Y_t$ is the dependent variable in the mean equation. The error term is given in $u_t$ while $\theta$ stands for the parameters to be estimated. The variance equation is given in Glosten et al. (1993a) as follows:

$$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + a_2 u_{t-1}^2 + a_3 S_{t-1}^{-} u_{t-1}^2 \tag{2.31}$$

The following condition holds

$$u_t \sim GED\left(0, \sigma_t^2\right) \tag{2.32}$$

GED, in Glosten et al. (1993b) is the acronym for generalised error distribution. In the relations above, $\sigma_t^2$ is the conditional variance while $u_t^2$ is the unconditional variance. $S_t^{-} = 1$ when $u_{t-1} < 0$ while $S_t^{-} = 0$ elsewhere. If $a_3 > 0$, then leverage exists (Glosten et al., 1993a). Positive variance is assured in the case where $a_o \geq 0, a_1 \geq 0, a_2 \geq 0$ and $a_2 + a_3 > 0$. If $Y_t - \hat{Y}_t < 0$, then $u_t < 0$ and then $S_t^{-} = 1$, which is the case that has bad news (Engle & Ng, 1993; Sariannidis, 2011). In that case, the variance relation modifies to:

$$\sigma_t^2 = a_0 + a_1\sigma_{t-1}^2 + \left(a_2 + a_3\right)u_{t-1}^2 \tag{2.33}$$

For the above, if $a_3 > 0$ bad news will have more impact on volatility. If however $a_3 \neq 0$, news impacts on volatility in an asymmetrical manner (Glosten et al., 1993b). Otherwise, good news is associated with $u_{t-1} > 0$ (Engle & Ng, 1993; Sariannidis, 2011). The asymmetric leverage is characterised by this model with downside shocks inclined to have larger influence on volatility than positive shocks (Wei, Wang, & Huang, 2010).

### *2.6.7. Asymmetric Bivariate EGARCH*

The asymmetric bivariate EGARCH is used in a number of studies involving transmission of volatility from one market to another (Bhar, 2001; Bhar & Nikolova, 2009; Booth, Martikainen,

& Tse, 1997; Reyes, 2001; Yang & Doong, 2004). The approach allows for comparison and accounting for the relative impacts of good and bad news. Good news results in market advances while bad news causes retreat of prices and the EGARCH allows the asymmetric tests of either effect (Booth, Martikainen, & Tse, 1997). The form taken by EGARCH in Booth, Martikainen, et al. (1997) is

$$R_{it} = \beta_{i0} + \sum_{j=1}^{2} \beta_{ij} R_{j,t-1} + \varepsilon_{it}, \quad i = 1,...,2 \tag{2.34}$$

$$\varepsilon_t | \Omega_{t-1} \sim Student - t(0, H_t, v) \tag{2.35}$$

$$\sigma_{it}^2 = \exp\{\alpha_{i0} + \sum_{j=1}^{2} \alpha_{ij} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\} \tag{2.36}$$

$$f_j(z_{j,t-1}) = |z_{j,t-1}| - E(|z_{j,t-1}|) + \delta_j z_{j,t-1}, \quad j = 1,.....2 \tag{2.37}$$

$$\sigma_{ijt} = \rho_{ij}\sigma_{it}\sigma_{jt} \text{ for } i = 1,...,2 \text{ and } i \neq j \tag{2.38}$$

$R_{it}$ refers to return in the $i^{th}$ market at time $t$. The information space at *t-1* is given in $\Omega_{t-1}$. The conditional variance is given as $\sigma_{it}$ while the conditional covariance has the form $\sigma_{ijt}$. Booth, Martikainen, et al. (1997) explains that $\mu_{it}$, the conditional mean, comes from the following expression

$$\varepsilon_{it} = R_{it} - \mu_{it} \tag{2.39}$$

while

$$E(|z_{it}|) = \left(2/\pi\right)^{1/2} (\Gamma(v-1)/2)/\Gamma(v/2) \tag{2.40}$$

and

$$z_{it} = \varepsilon_{it} / \sigma_{it} \tag{2.41}$$

The standardized innovation is denoted by $z_{it}$ (Booth, Martikainen, et al., 1997). $H_t$ is the matrix for the vector error (Booth, Martikainen, et al., 1997). Volatility spill-over is given in the

term $\sum_{j=1}^{2}\alpha_{ij} f_j\left(z_{j,t-1}\right)$ and the volatility persistence is given in $\gamma_i \ln\left(\sigma_{i,t-1}^2\right)$ (Booth, Martikainen, et al., 1997). The asymmetry relation is obtained from the following derivative

$$\partial f_j\left(z_{jt}\right) \Big/ \partial z_{jt} = \begin{Bmatrix} 1+\delta_j, & z_j > 0 \\ -1+\delta_j, & z_j < 0 \end{Bmatrix} \tag{2.42}$$

The size effect is measured by $\left|z_{j,t-1}\right| - E\left(\left|z_{j,t-1}\right|\right)$ while the sign effect is given by the term $\delta_j z_{j,t-1}$(Yang & Doong, 2004). The half-life, which is defined as the time taken for a shock to have half of its original impact is given in Bhar (2001) as

$$HL = \frac{\ln(0.5)}{\ln|\gamma_i|} \tag{2.43}$$

The BHHH[6] algorithm developed by Greg Koutmos is used to resolve the bivariate EGARCH system of equations (Reyes, 2001). The advantages of the EGARCH are outlined in Reyes (2001) and include the unique ability to directly determine volatility spill-over and the need not to give any parameter restrictions. The log of conditional variance is used ensuring positive variance. The EGARCH is also one of the most appropriate approaches for modelling indices from different markets. The asymmetric information included in the system has enabled the EGARCH to give the best returns and volatility predictions (Reyes, 2001). On the downside, Glosten et al. (1993b), Engle and Ng (1993) and Sariannidis (2011) argue that the EGARCH has the propensity to overstate conditional variability.

The multivariate EGARCH allows comparison of three or more markets simultaneously. Multivariate EGARCH is given in Koutmos and Booth (1995) as follows:

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3}\beta_{i,j}\varepsilon_{j,t-1} + \varepsilon_{i,t} \tag{2.44}$$

[6] BHHH algorithm is a computerized EGARCH program developed by Greg Koutmos.

The mean relation is true for $i, j = 1,2,3$. A variance relation taking account of cross-market linkages is specified as

$$\sigma_{i,t} = \exp\left\{\alpha_{i,0} + \sum_{j=1}^{3}\alpha_{i,j} f_j\left(z_{j,t-1}\right) + \gamma_i \ln\left(\sigma_{i,t-1}^2\right)\right\} \tag{2.45}$$

$$f_j\left(z_{j,t-1}\right) = \left(\left|z_{j,t-1}\right| - E\left(\left|z_{j,t-1}\right|\right) + \delta_j z_{j,t-1}\right) \tag{2.46}$$

$$\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \tag{2.47}$$

In the relations above, $i, j = 1,2,3$ and $i \neq j$. $R_{it}$ is the close-to-close or close-to-open return at *t.* The conditional mean and conditional variance are given in $\mu_{i,t}$ and $\sigma_{i,t}^2$. Conditional covariance is defined in $\sigma_{i,j,t}$ and the innovation at time *t* is $\varepsilon_{i,t}$. Further,

$$\varepsilon_{i,t} = R_{i,t} - \mu_{i,t} \tag{2.48}$$

Standardized residuals, as before, are defined as

$$z_{i,t} = \varepsilon_{i,t} \Big/ \sigma_{i,t} \tag{2.49}$$

Asymmetry occurs if $\delta$ is significant. The size effect is given in $\left|z_{j,t}\right| - E\left(\left|z_{j,t}\right|\right)$. Research by Engle and Ng (1993) involving market news and using the EGARCH approach found that negative shocks influence volatility more than positive shocks. This asymmetric response to news is characterised by rising volatility in response to bad news and declining volatility when good news is received in the market (Nelson, 1991).

### *2.6.8. C-GARCH Model*

The specification for the Classic GARCH or the C-GARCH is given by Engle and Lee (1993), McMillan and Speight (2001) and Auer (2014) as

$$r_t = a_0 + \sum_{i=1}^{m} a_i r_{t-i} + \sum_{i=1}^{n} b_i \varepsilon_{t-i} + \varepsilon_t \tag{2.50}$$

$$h_t^2 = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta_1\left(h_{t-1}^2 - q_{t-1}\right) \tag{2.51}$$

The term $q_t$ is defined in McMillan and Speight (2001), Kang, Kang, and Yoon (2009) and Auer (2014) as

$$q_t = \omega + \rho q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}^2\right) \tag{2.52}$$

Auer (2014) describes $q_t$ as the classic long-term volatility. The past forecast error is given in $\left(\varepsilon_{t-1}^2 - h_{t-1}^2\right)$ while $\alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta_1\left(h_{t-1}^2 - q_{t-1}\right)$ is the transitory element of volatility (Auer, 2014). $h_t^2 - q_t$ is the short-run component of conditional variance (McMillan & Speight, 2001). Movement of $q_t$ has magnitude corresponding to past forecast error $\varepsilon_{t-1}^2 - h_{t-1}$ (Kang et al., 2009). There is need for the restriction $0 < \alpha + \beta_1 < \rho < 1$ for the transitory component to be less persistent than the permanent component (Kang et al., 2009; McMillan & Speight, 2001). The C-GARCH model essentially decomposes volatility into the long-run and short-run components (Auer, 2014; Kang et al., 2009; McMillan & Speight, 2001). Wei et al. (2010) found the C-GARCH and FIGARCH more accurate in forecasting long-memory than the GARCH and the IGARCH approaches.

### *2.6.9. FIGARCH Model*

The GARCH is known to be more suitable for modelling short-term volatility as opposed to long-term volatility (Wei et al., 2010). To handle long-term volatility, (Baillie, Bollerslev, & Mikkelsen, 1996) and Andersen and Bollerslev (1997) used the fractionally integrated ARCH or the FIGARCH $(1, d, 1)$. A slow decay rate is characteristic of the variance relation

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \left[1 - (1 - \beta L)^{-1}(1 - \varphi L)(1 - L)^d\right]\varepsilon_t^2 \tag{2.53}$$

$$0 \le d \le 1,\ \omega > 0,\ \phi, \beta < 1 \tag{2.54}$$

$d$ is a fractional integration parameter and *L* is the lag operator (Baillie et al., 1996). Complete persistence of integrated volatility occurs when *d=1*. The so-called glossary of the various GARCH models in literature was developed in Bollerslev (2008).

### *2.6.10. Multivariate Generalised ARCH (M-GARCH)*

Multivariate GARCH models which usually involve at least three sets of time series data have been used in a number of financial markets studies (Bollerslev, 1990; Karolyi, 1995; Kearney & Patton, 2000; Worthington & Higgs, 2004). In Bollerslev (1990) the M-GARCH is given as

$$R_{it}^{'} = \varepsilon_{it}^{'} \tag{2.55}$$

$$i = 1,2 \tag{2.56}$$

$$R_{it}^{'} = \begin{bmatrix} R_{1t} \\ R_{2t} \end{bmatrix} \tag{2.57}$$

$$\varepsilon_{it}^{'} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{2.58}$$

$$\varepsilon_{it}^{'} \left| \psi_{t-1} \sim N(0, H_t) \right. \tag{2.59}$$

Conditional variance matrix is given by

$$H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} \tag{2.60}$$

Bollerslev (1990) has the conditional variance equation as

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} C_{11} \\ C_{12} \\ C_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} X \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ (\varepsilon_{1,t-1})(\varepsilon_{2,t-1}) \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} X \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \tag{2.61}$$

$$a, b \geq 0 \text{ and } C \geq 0 \tag{2.62}$$

The above relation can also be represented as

$$(vech)H_t = C + A\varepsilon + BH_{t-1} \tag{2.63}$$

In the above, $H_t, C, A, \varepsilon$ and $B$ are vectors as represented above. As there are 21 coefficients, one proposal in Bollerslev (1990) is restricting to zero all off-diagonal elements. The conditional variance equations then become

$$h_{11,t} = C_{11} + a_{11}\varepsilon_{1,t-1}^2 + b_{11}h_{11,t-1} \tag{2.64}$$

$$h_{22,t} = C_{22} + a_{33}\varepsilon_{2,t-1}^2 + b_{33}h_{22,t-1} \tag{2.65}$$

$$h_{12,t} = \rho_{12}x\left(h_{11,t}xh_{22,t}\right)^{1/2} \tag{2.66}$$

This assumes correlation $\rho_{12}$ is constant (Bollerslev, 1990). Parameters to be estimated now reduce to $(a_{11}, a_{33}, b_{11}, c_{11}, c_{22}, \rho)$. In Engle and Kroner (1995) a model has been given for the interdependence of three markets or data series. In the BEKK[7] approach, testing for the ARCH is carried out using the residuals from the mean equation

$$R_{it} = \mu_i + \alpha R_{i,t-1} + \varepsilon_{it} \tag{2.67}$$

The BEKK model is therefore represented as

$$H_{t+1} = C'C + A'\varepsilon_t\varepsilon_t'A + B'H_tB \tag{2.68}$$

Vectors *A, B* and *C* are defined as

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}, C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \tag{2.69}$$

*A* expresses the link between conditional variance and lagged square error terms. *B* defines the link between current and previous conditional variance terms. Zeros have been used as restrictions in the upper triangle of *C*. If we assume normal distribution of the errors, the likelihood function is

[7] BEKK are the initials from Baba, Engle, Kraft and Kroner (1990) unpublished manuscript from the University of California, San Diego. The published paper with the same title by two of the four authors is Engle and Kroner (1995).

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H| + \varepsilon_t^{'} H_t^{-1}\varepsilon_t\right) \tag{2.70}$$

$\theta$ stands for estimated parameter vector while *T* is the number of observations. Engle and Kroner (1995) suggest using the BFGS algorithm to generate the estimate of the variance-covariance matrix in the BEKK. The simplex algorithm is used for the initial iterations.

### *2.6.11. VAR (1)-GARCH (1,1)*

The VAR(1)-GARCH(1,1) is suitable for examining spill-overs between markets and is given in Arouri, Jouini, and Nguyen (2012) as

$$Y_t = \mu + \phi Y_{t-1} + \varepsilon_t \tag{2.71}$$

$$\varepsilon_t = D\eta_t \tag{2.72}$$

In a bivariate relation, $Y_t$ defines returns as follows

$$Y_t = \left(r_t^A, r_t^B\right) \tag{2.73}$$

For returns in markets A and B respectively. Further,

$$D_t = diag\left(\sqrt{h_t^A}, \sqrt{h_t^B}\right) \tag{2.74}$$

Conditional variances are denoted as $h_t^A$ and $h_t^B$, thus we have the relations

$$h_t^A = C_A^2 + \beta_{A1}^2 h_{t-1}^A + \alpha_{A1}^2\left(\varepsilon_{t-1}^A\right)^2 + \beta_{A2}^2 h_{t-1}^B + \alpha_{A2}^2\left(\varepsilon_{t-1}^B\right)^2 \tag{2.75}$$

$$h_t^B = C_B^2 + \beta_{B1}^2 h_{t-1}^B + \alpha_{B1}^2\left(\varepsilon_{t-1}^B\right)^2 + \beta_{B2}^2 h_{t-1}^A + \alpha_{B2}^2\left(\varepsilon_{t-1}^A\right)^2 \tag{2.76}$$

Where $\eta_t = \left(\eta_t^A, \eta_t^B\right)$ are i.i.d random vectors.

### *2.6.12. Stochastic Volatility (SV)*

In Koopman et al. (2005), stochastic volatility is represented as

$$R_n = \mu + \sigma_n \varepsilon_n \tag{2.77}$$

$$\varepsilon_n \sim NID(0,1), \quad n = 1,\ldots\ldots., N \tag{2.78}$$

$$\sigma_n^2 = \sigma_n^{*2} \exp(h_n) \tag{2.79}$$

$$h_{n+1} = \phi h_n + \sigma_n \eta_n \tag{2.80}$$

$$\eta \sim NID(0,1), \quad h_1 \sim NID\left(0, \sigma_n^2 / \left\{1-\varphi^2\right\}\right) \tag{2.81}$$

$R_n$ is the mean of the asset and the residuals are denoted by $\sigma_n \varepsilon_n$. The conditional variance is $h_n$ while the unconditional variance is $\sigma_n \eta_n$. The parameters to be estimated include $\mu$ and $\phi$. To estimate the parameters in a stochastic volatility system, Koopman et al. (2005) made use of importance sampling and the Monte Carlo simulations. An advantage of stochastic volatility in Soriano and Climent (2005) is that the model has separate errors, $\varepsilon_t$ in the mean levels and $\eta_t$ in the variance equation. A downside to SV however is its specification as not following a normal distribution unlike GARCH where there is conditional normality (Soriano & Climent, 2005).

A multivariate stochastic volatility model in Tanizaki and Hamori (2009) has the relation

$$r_t^j = z_t^j \alpha^j + \exp\left(1/2\, h_t^j\right) \varepsilon_t^j \tag{2.82}$$

$$h_t^j = x_t^j \gamma^j + \delta^j h_{t-1}^j + \eta_t^j \tag{2.83}$$

$$\varepsilon_t^j \sim N(0,1) \text{ and } \eta_t^j \sim N\left(0, \sigma^{j2}\right) \tag{2.84}$$

In the case of 3 markets, $j = 1,2,3$. The deterministic component of returns containing *1xk*$_1$ exogenous variables is captured in $z_t^j \alpha^j$. Parameters to be estimated are included in the set $\left(\alpha^j, h_t^j, \gamma^j, \delta^j\right)$. Estimation of $B_n$ and $\theta$ where $B_n = (h_0, h_1, \ldots\ldots, h_n)$ and $\theta = \left(\alpha', \gamma', \delta, \sigma\right)$ is achieved using non-linear Gaussian state space modelling. In that process, the Markov Chain Monte Carlo (MCMC) approach that uses a Bayesian methodology generates the

required parameters. The spill-over term, $z_t^j$ takes the value $\tilde{r}_t^{j'}$ and $r_{t-1}^j$ where $\tilde{r}_t^{j'}$ is the most recent % change for country $j$`. The most recent returns by country are taken to ascertain the spill-over intensity. $x_t^j$ takes terms that may include the set $\left(H_t^j, d_t^j, d_t^{j'}, d_t^{j``}, \tilde{h}_t^{j'}, \tilde{h}_t^{j''}, Mo_t, Tu_t, We_t, Th_t, Fr_t\right)$. Holidays are captured in the dummy $H_t^j$. The most-recent volatility from country $j'$ is $\tilde{h}_t^{j'}$ while $\tilde{h}_t^{j''}$ is the available most-recent volatility data out of country $j''$. Asymmetry is captured in $d_t^j$ terms. Thus, $d_t^j = 1$ when $r_{t-1}^j$ is negative, and zero otherwise. $d_t^{j'} = 1$ when $\tilde{r}_t^{j'}$ is less than zero, and zero otherwise. In the same way, the term $d_t^{j''} = 1$ when $\tilde{r}_t^{j''}$ is negative, and zero otherwise.

### *2.6.13. Granger Causality*

In Brooks (1998), a Granger Causality system takes the form

$$X_t = A(L)X_t + B(L)Y_t + \varepsilon_{x,t} \tag{2.85}$$

$$Y_t = C(L)X_t + D(L)Y_t + \varepsilon_{Y,t} \tag{2.86}$$

$$t = 1,2,\ldots\ldots\ldots,T \tag{2.87}$$

$A(L)$, $B(L)$, $C(L)$ and $D(L)$ are lag operators in polynomial terms that are stationary. $\varepsilon_{X,t}$ and $\varepsilon_{Y,t}$ are residuals which are identically and independently distributed with zero mean and constant variance (Brooks, 1998). Causality of *X* by *Y* occurs when coefficients in the lag polynomial *B(L)* are not statistically similar to zero. *X* causes *Y* when the lag polynomial *C(L)* have coefficients that are not jointly equal to zero. Where both lag polynomials *B(L)* and *C(L)* are not jointly significantly different from zero, causality has bidirectional form.

### *2.6.14. ECM and VECM*

Long-run relationship testing can be carried out regardless of time series data not being stationary (Zhang & Wei, 2010). A cointegration test involving two series is carried out in Zhang & Wei (2010) using the following relation

$$P_t^A = \omega_1 + \delta_1 * P_t^B + \varphi_{1t} \tag{2.88}$$

$$P_t^B = \omega_2 + \delta_2 * P_t^A + \varphi_{2t} \tag{2.89}$$

$P_t^A, P_t^B$ are prices in logs for assets *A* and *B*. If $\varphi_1, \varphi_2$ are stationary, then there is cointegration between the prices of assets *A* and *B*. Strydom and McCullough (2013) applied the ECM and the VECM to study cointegration between spot and futures prices for white maize on SAFEX. Long-range cointegration was confirmed under the study. The ECM may go both directions requiring the use of the following two equations:

$$\Delta S_t = \alpha_1 + \alpha_S \hat{\varepsilon}_{t-1} + \sum_{i=1} \alpha_{11}(i) \Delta S_{t-1} + \sum_{i=1} \alpha_{12}(i) \Delta F_{t-1} + \varepsilon_{St} \tag{2.90}$$

$$\Delta F_t = \alpha_2 + \alpha_F \hat{\varepsilon}_{t-1} + \sum_{i=1} \alpha_{21}(i) \Delta S_{t-1} + \sum_{i=1} \alpha_{22}(i) \Delta F_{t-1} + \varepsilon_{Ft} \tag{2.91}$$

Spot prices and futures prices are denoted by $S_t$ and $F_t$ respectively. The speed of adjustment is represented by the coefficients $\alpha_S$ and $\alpha_F$. The key condition $\alpha_S, \alpha_F \neq 0$ holds where contegration exists (Strydom & McCullough, 2013). The use of the Johansen VECM variation suggests the possibility of having *x-1* cointegrating relationships given $x$ non-stationary variables (Strydom & McCullough, 2013). With two variables under study, the rank of association would be less than or equal to one. In Strydom and McCullough (2013) the AIC and SIC are used for lag length determination of the VECM system. The leading tests for some cointegration relationship include the Trace test and the Maximum Eigenvalue Test.

## 2.7 Commodity Price and Return Co-movement

Sariannidis (2011) lists four factors that support the co-movement of prices of two or more asset series. The factors include financial markets integration, internationalization, interdependence and technological advances (Sariannidis, 2011). Co-movements in prices and returns have been studied among commodity classes and between asset classes, for example, the equities and the commodity futures markets. Energy commodities and agricultural derivatives were observed to move together from the year 2006 in Abbott et al. (2009). In Hertel and Beckman (2011) price correlation between crude oil and maize increased from -0.26 for the period 1988 to 2005 to 0.8, calculated for the years 2006 to 2008. Ai et al. (2006) find that co-movements in commodity prices are not excessive. Observed co-movements are a result of demand and supply factors (Ai et al., 2006). Thus, the fundamentals for different commodities are more related than may have been assumed (Ai et al., 2006).

Gorton et al. (2013) acknowledge commodities as a unique investment channel to diversify systematic risk in portfolios involving other asset classes. This part of risk is not supposed to be diversifiable. During the beginning phase of a recession when equities are collapsing, commodities usually perform much better. These findings concur with those of Chance and Brooks (2009). Plantier (2013) suggested holdings in commodities, especially gold, have been thought of as a hedge against inflation. In Saghaian (2010), using Granger Causality and Directed Acyclic Graph (DAG) approaches, it was concluded that energy class commodities' causal impact on agricultural prices is mixed. This thesis carries out information transmission estimation involving diverse global futures markets to determine if there is any co-movement and information flows.

## 2.8 Commodity Price Spill-overs

Spill-overs involve gradual transmission of price or volatility effects from one financial market to a foreign financial market (Kaminsky, Reinhart, & Vegh, 2003). Key factors instrumental in volatility spill-over between two or more futures markets in Baele (2005) included trade integration and extent of futures market development. Collins and Biekpe (2003) on the other hand explain interdependence as some correlation between any given markets which stays relatively constant over time. In Duong and Kalev (2008), interdependence means two or more financial markets or contracts have some cross-market linkages. Financial markets contagion has been defined in Collins and Biekpe (2003) as the passing over of market disturbances across two or more markets. Bekaert, Ehrmann, Fratzscher, and Mehl (2011) and Bekaert and Harvey (2003) posit that contagion is correlation between markets in excess of that explained by fundamental economic factors. In the wake of market crises or financial shocks, Soriano and Climent (2005) found contagion leading to a rise in cross-correlations between two or more markets. Kaminsky et al. (2003) agreed with this finding saying contagion entailed immediate effects significantly impacting different markets when a financial crisis or shock occurs in one of them.

Financial contagion also means the state of market linkages is modified during times of market turbulence (Bonfiglioli & Favero, 2005). Contagion has been attributed to trade associations and financial links between markets (Boshoff, 2006; Collins & Biekpe, 2003). Investor behaviour is the other key factor promoting contagion (Boshoff, 2006; Collins & Biekpe, 2003). As an example, investors could exit a market in decline by selling off assets to some emerging markets or to a group of active investors. Such action could influence markets one way or another in the same way as the effect of information asymmetries (Collins & Biekpe, 2003).

In their description of “fast and furious” contagion, Kaminsky et al. (2003) posited that three elements have to exist simultaneously in an “unholy trinity”. Firstly a surprise announcement is made, then secondly, a surge in capital flows occurs. The third element of the trinity is the existence of leveraged common creditors participating in the different markets involved in the financial contagion. Boshoff (2006) explained that the need arises for topping up margins when asset prices fall in a given market with the result that liquidation of other financial holdings elsewhere occurs. Asymmetries are typically known to promote “herd behaviour”. One simple way of ascertaining contagion is to observe the strengthening correlation in prices of two markets experiencing market disturbances. Using an econometric specification based on the GMM approach, Baele (2005) measured contagion using the relation:

$$e_{i.t} = b_1 + (b_2 + b_3 D_t)\hat{e}_{EU,t} + (b_4 + b_5 D_t)\hat{e}_{US,t} + u_{i,t} \qquad (2.92)$$

Orthogonalized residuals in the model for the EU and the US returns are respectively $\hat{e}_{EU,t}$ and $\hat{e}_{US,t}$. When the two dummies $D_t$ are both equal to *one,* there is high volatility, otherwise they assume the value zero. The parameters $b_3$ and $b_5$ respectively measure additional regional and international contagion during crisis periods (Baele, 2005). Contagion was found by Baele (2005) to be flowing from the US to several markets in the European area particularly during times of high market volatility.

In the study of price discovery in the white maize contract between SAFEX and its underlying spot market, Strydom and McCullough (2013) suggested the influence of the CME market may have been causing the spot market to lead the futures. Van Wyk (2012) earlier conducted a spill-over study in which it was concluded spill-over from the CME to the SAFEX maize was not significant statistically. Mensi, Beljid, Boubaker, and Managi (2013) examined spill-over from the S&P 500 index to a number of commodity indices using the VAR-GARCH method. Daily returns for various indices for the period January 2000 to December 2011

were positioned as dependent variables in the main GARCH equation. Significant spill-over between the S&P 500 index and commodity indices was confirmed (Mensi et al., 2013). Bhar and Nikolova (2009) investigated spill-over of return volatility among BRIC countries and the world financial markets with the bivariate EGARCH framework. Major equity indices in Brazil, Russia, India and China provided the variables of interest (Bhar & Nikolova, 2009). The objective was to ascertain the extent of integration of the BRIC countries with the world financial markets (Bhar & Nikolova, 2009). India emerged with the highest levels of regional and global integration. On the other hand, China was found to have a negative relationship with global market returns, positioning it as ideal for investment diversification (Bhar & Nikolova, 2009).

Using the Bayesian multivariate framework, Sujithan, Avouyi-Dovi, and Koliai (2014) demonstrated spill-over of volatility from cocoa to wheat and coffee, as well as from maize to cocoa and to wheat. On the other hand, soybean price shocks were shown to reduce cocoa and sugar volatility. The spill-over phenomenon did not appear to show any uniform pattern amongst the various commodities studied (Sujithan et al., 2014). In a study of interdependencies between fossil fuel oil and biofuels, Busse, Brümmer, and Ihle (2010) used the Markov-switching vector error correction approach. Crude oil prices were found to have pass-through into biodiesel prices. Biodiesel prices have an influence on rapeseed oil prices (Busse et al., 2010). In Nazlioglu, Erdem, and Soytas (2013) volatility transmission was investigated between the oil market and agricultural commodities including maize, wheat, soybeans and sugar. The data covered the period 1986 to 2011, and was split into two samples, the pre-crisis period (1986-2005) and the post-crisis period (2006-2011) (Nazlioglu et al., 2013). Oil price volatility spilled into all the agricultural commodities other than sugar in the post-crisis period (Nazlioglu et al., 2013).

In spill-over studies by Du et al. (2011), the bivariate stochastic volatility (SV) approach was used to investigate volatility spill-over. Findings were that there exists transmission of volatility across maize, wheat and crude oil prices. Du et al. (2011) investigated spill-over between pairs of commodities with observed returns given as

$$Y_{it} = \Delta \log P_i = \log P_{i,t} - \log P_{i,t-1} \tag{2.93}$$

Spill-over is defined by using the relations

$$Y_t = \Omega_t \varepsilon_t, \quad \varepsilon_t \sim \overset{iid}{N}(0, \sum_{\varepsilon}) \tag{2.94}$$

$$V_{t+1} = \mu + \phi(V_t - \mu) + \eta_t, \quad \eta_t \sim N(0, \sum_{\eta}) \tag{2.95}$$

In Equations 2.97 and 2.98, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$, $\mu = (\mu_1, \mu_2)'$ and $V_t = (V_{1t}, V_{2t})'$. The term $V_t$ represents the instantaneous volatility vector which is assumed to follow a mean-reverting configuration while $\mu$ is the mean return. Du et al. (2011) define $\Omega_t$ as follows

$$\Omega_t = \begin{pmatrix} \exp(v_{1t})/2 & 0 \\ 0 & \exp(v_{2t})/2 \end{pmatrix}, \tag{2.96}$$

Then,

$$\sum_{\varepsilon} = \begin{pmatrix} 1 & \rho_{\varepsilon} \\ \rho_{\varepsilon} & 1 \end{pmatrix} \tag{2.97}$$

and

$$\sum_{\eta} = \begin{pmatrix} \sigma_{\eta 1}^2 & 0 \\ 0 & \sigma_{\eta 2}^2 \end{pmatrix} \tag{2.98}$$

Further, in a bivariate stochastic volatility (SV) framework, spill-over is given by

$$\phi = \begin{pmatrix} \phi_{11} & 0 \\ \phi_{21} & \phi_{22} \end{pmatrix} \tag{2.99}$$

The model requires prior specification of the distribution of the unknown parameters, which are:

$$\Theta' = \left\{\mu_1, \mu_2, \rho_\varepsilon, \phi_{11}, \phi_{12}, \phi_{21}, \sigma_{\eta 1}, \sigma_{\eta 2}\right\} \quad (2.100)$$

These parameters are typically assumed mutually independent and are either given beforehand or are selected as hypothetical values in a simulation process (Du et al., 2011).

In general, volatility spill-over is enhanced by trade links between markets, financial markets synchronisation and the activities of respective financial traders in two given markets (Van Wyk, 2012). Selected procedures from the above equations are applied to the commodity derivatives markets in this study. KCBT, Euronext/Liffe and ZCE are used as proxies for the world commodity markets given they are some of the largest such futures exchanges. The analysis investigates if the "spill-over coefficient" between SAFEX and the other 3 markets is significant and positive or negative.

## 2.9 Co-movement and Spill-over Empirical Evidence

Deb et al. (1996) consider co-movement of unrelated futures contracts such as agricultural, mineral-based or energy derivatives (Deb et al., 1996). Nine commodities were considered within the USA markets. Weak evidence of co-movement was found. The basic logic for co-movement is that contracts may be jointly affected by common business cycles or what is referred to as "fad" or "herd" behaviour (Deb et al., 1996). Thus, investors may become bullish, for example on "many" commodity products at the same time for no defendable reason. Janzen et al. (2013) found fairly little evidence of price co-movement when cotton prices were modelled against those of other commodities traded in the USA. It was the conclusion of Janzen et al. (2013) that other cotton market factors had more significant influence on cotton prices. Spikes in prices showed a close link to cotton supply disruptions.

Price spill-over was studied in Samouilhan (2006) focussing on equity markets in South Africa and the UK. Spill-over of volatility onto the JSE market from the London Stock Exchange was found to be significant (Samouilhan, 2006). Van Wyk (2012) examined

information transmission between the CBOT maize contract and the SAFEX white and yellow maize futures. It is imperative to point out there are several CME contracts traded on SAFEX for cash settlement, a factor which may increase integration of the two markets. The EGARCH approach was used in Van Wyk (2012) finding volatility spill-over in maize traded on CME and SAFEX not substantial.

Jochum (1999) investigated whether spill-overs from major world stock exchanges influence the Swiss Stock Market. Findings were that asset risk on the Swiss Stock Market is a function of the covariance with major global financial markets. Mensi et al. (2013) used the VAR-GARCH to determine spill-over effects between S&P 500 series and selected commodity market indices. Substantial pass-through between the S&P 500 and the commodity indices was found. Methodologies proposed in the study include BEKK[8] parameterization, constant conditional correlation (CCC) and dynamic conditional correlation (DCC). To compare the spot and futures market on the Nikkei Stock Exchange, Tse (1995) used the error correction method finding spill-over between the spot index and the corresponding futures price significant.

Li and Lu (2012) studied cross-correlations of futures prices in the US and China. Using the multi-fractal de-trended cross-correlation analysis (MF-DCCA), the study analysed soybeans, soymeal, wheat and maize finding soybeans and soymeal exhibiting persistent cross-correlation. Maize and wheat prices in the two countries had anti-persistent cross-correlations. In a study that used the Bayesian multivariate framework, Sujithan et al. (2014) included in his model US industrial production index (IPI), biofuel prices and maize, wheat, coffee and sugar prices. US IPI was found to impact negatively on the volatility of coffee and sugar prices, while corn and wheat volatilities were negatively linked to crude oil prices.

[8] BEKK, is an acronym for the authors Baba, Engle, Kraft and Kroner after their paper written in 1990

Auffhammer, Berck, and Hausman (2012) investigated the maize and soybeans price responsiveness to additional ethanol production, implying increased diversion of crops from food to biofuels use. Maize and soybeans are key raw materials in ethanol production. It was found that a 1 % reduction in area under maize (corresponding to 1 million acres) switched from food to biofuels resulted in a 1% increase in the maize price (Auffhammer et al., 2012).

## 2.10 Market Concentration and Trading Patterns

Streeter and Tomek (1992) suggested market concentration by relatively few large participants tends to promote price volatility. Goodwin and Schnepf (2000) examined determinants of price volatility for maize and wheat. Findings were that futures market activities, behaviour of market participants, stocks-to-use ratio and production conditions impacted price variability (Goodwin & Schnepf, 2000). Peck (1981) posits that speculation increases liquidity on the futures market making it easier for commercial market participants to take hedging positions. The implication is speculation must be related to price variability (Peck, 1981). Streeter and Tomek (1992) found speculative activities in the soybeans futures market negatively impacting price variability. In that study, it was concluded market concentration by a few large participants raises price volatility. Findings by Goodwin and Schnepf (2000) are maize price variability is positively impacted by market concentration while in the case of wheat variability, the influence is negative. The study also concludes scalping levels positively impact price variability. The ratio of volume to open interest was used as a proxy for scalping. Goodwin and Schnepf (2000) also concluded day trading volumes were associated with higher price volatility. Dawson (2014) argues speculation may potentially impact volatility if it comprises a large proportion of traded volume. Feedback trading is when noise traders buy as prices increase and sell when prices drop (Dawson, 2014).

## 2.11 Financial Markets Anomalies

The day-of-the-week effect has been studied in Agrawal and Tandon (1994), Choudhry (2000) and Auer (2014) using the following modified GARCH model

$$y_t = \delta_1 D_{1t} + \delta_2 D_{1t} + \delta_1 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} + \delta_5 D_{5t} + \varepsilon_t \quad (2.101)$$

$$\varepsilon_t | \psi_{t-1} \sim student, t.(0, h_t, v) \quad (2.102)$$

The related variance equation is

$$h_t = \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + \gamma_4 D_{4t} + \gamma_5 D_{5t} + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \quad (2.103)$$

The daily return is $y_t$ and the daily dummies are $D_{1t,}.....,D_{5t}$ (Auer, 2014; Choudhry, 2000). $\varepsilon_t$ are the unconditional residuals, $\psi_{t-1}$ is past information and $h_t$ is conditional variance (Choudhry, 2000). Unconditional variance follows the student-*t* distribution with $v$ degrees of freedom (Choudhry, 2000). Agrawal and Tandon (1994) found daily seasonality in the stock markets of all 18 countries examined. From the same sample of countries, the weekend effect was found in 9 countries. For the equity markets, negative returns were typically found for Mondays while Fridays generally had the largest returns (Agrawal & Tandon, 1994). Returns had the highest variance on Mondays. Other anomalies found by Agrawal and Tandon (1994) include large returns prior to holidays in December, inter-holiday high returns and much higher returns in January than the other months of the year. The turn-of-the-month phenomenon causes returns to be higher in the first half of a given trading month beginning with the last trading day of the previous month (Agrawal & Tandon, 1994). Cumulative returns of the first 4 days (starting from the last trading day of the previous month) exceeded entire monthly returns (Agrawal & Tandon, 1994).

Various hypotheses have been given in literature as to the reasons for the occurrence of market anomalies and seasonal effects. One explanation is centred around settlement

procedures, which differ for various markets depending on the timeframes to settle trades (Agrawal & Tandon, 1994). As an example, the settlement period in South Africa is five days. A buy on Friday followed by selling on Monday requires cash to be paid for the buy the next Friday. Cash for the sell is only received the next Monday. The high returns on Monday (if they occur), will be for compensating for the 3 days difference between the cash payment and the cash receipt (Agrawal & Tandon, 1994). However, Agrawal and Tandon (1994) have conceded the settlement procedures have generally not been very strong as an explanation of daily stock market seasonality. One explanation for high variances in returns on Mondays is increased availability of information, public and private which causes high volatility (Agrawal & Tandon, 1994).[9] The turn-of-the-month effect is caused by seasonality of cash availability within firms and by individuals (Agrawal & Tandon, 1994).

Following detection of possible anomalies, a trading rule may be developed. The trading results using the rule are compared to the passive or buy-and-hold trading strategy. Tests are then carried out on the equality of means and variances between the competing investment strategies. In Kruskal and Wallis (1952) a non-parametric $\chi^2$ test statistic is used for testing differences in returns. The Brown-Forsythe modified Levene's statistic is used for testing the equality of variances (Lucey & Pardo, 2005). Another test is outlined in Jobson and Korkie (1981) which however tends to be weak in the presence of heavy-tailed data (Auer & Schuhmacher, 2013; Ledoit & Wolf, 2008). The Memmel (2003) and Jobson and Korkie (1981) approaches assume returns are normally distributed and serially uncorrelated. The procedure in Ledoit and Wolf (2008) considers returns from two investment strategies, say, $r_{ti}$ and $r_{tn}$. Stationarity is a pre-condition for this test and the return distributions for the returns are

[9] Weekends largely release the private information.

$$\mu = \begin{pmatrix} \mu_i \\ \mu_n \end{pmatrix} \tag{2.104}$$

$$\Sigma = \begin{pmatrix} \sigma_i^2 & \sigma_{in} \\ \sigma_{in} & \sigma_n^2 \end{pmatrix} \tag{2.105}$$

The difference between the Sharpe ratios of the strategies is:

$$\Delta = Sh_i - Sh_n = \frac{\mu_i}{\sigma_i} - \frac{\mu_n}{\sigma_n} \tag{2.106}$$

An estimator of the above expression is given by Ledoit and Wolf (2008) as

$$\hat{\Delta} = \hat{S}h_i - \hat{S}h_n = \frac{\hat{\mu}_i}{\hat{\sigma}_i} - \frac{\hat{\mu}_n}{\hat{\sigma}_n} \tag{2.107}$$

A test is carried out using a bootstrap inference process and a symmetric studentized confidence interval with the null hypothesis being $H_o : \Delta = zero$ (Auer & Schuhmacher, 2013; Ledoit & Wolf, 2008). The bootstrap approach in Politis and Romano (1992) and Politis and Romano (1994) is used. Rejection of the null occurs when the *1-*$\alpha$ bootstrap confidence interval for $\Delta$, excludes zero

$$\hat{\Delta} \pm z^*_{|.|,1-\alpha} S\left(\hat{\Delta}\right) \tag{2.108}$$

$S\left(\hat{\Delta}\right)$ is the standard error for $\hat{\Delta}$ defined above. The $z^*_{|.|,\lambda}$ is the $\lambda$ quartile for

$$\delta\left(\left|\hat{\Delta}^* - \hat{\Delta}\right| \Big/ S\left(\hat{\Delta}^*\right)\right) \tag{2.109}$$

where $\delta(X)$ represents the distribution of the given variable *X* (Ledoit & Wolf, 2008).

## 2.12 Forecasting in Financial Markets

Market predictions carried out with time series data are in two categories, out-of-sample and in-sample forecasts (Moholwa, 2005; Wei et al., 2010). One way of conducting out-of-sample forecasting is to hold back about one third of the sample and compare forecasting results

with the actual data (Moholwa, 2005). A suitable model needs to be selected for use in the forecasting process. Some criteria used to select the best model in Fildes and Petropoulos (2013) included assessing predictability, trend and seasonality. In models such as ARIMA, the final specifications of the model are arrived at using the AIC and BIC criteria (Fildes & Petropoulos, 2013). In terms of evaluation of predictions, the root-mean square error (RMSE) and the mean absolute error (MAE) are essential measures (Tse, 1995). The lower these parameters are, the better the forecast quality. Leading evaluation tests for forecasts are the Superior Predictive Ability (SPA) test, the Diebold and Mariano (2002) or DM test and the Reality Check or RC test of White (2000). Several equations and definitions of loss functions are given below

$$MSE = n^{-1} \sum_{t=1}^{n} \left( \sigma_t^2 - \hat{\sigma}_t^2 \right)^2 \tag{2.110}$$

$$MAE = n^{-1} \sum_{t=1}^{n} \left| \sigma_t^2 - \hat{\sigma}_t^2 \right| \tag{2.111}$$

The number of forecast observations is denoted as $T$. $\sigma_t^2$ is the forecast volatility for day *t* and $\hat{\sigma}_t^2$ is the actual volatility on day *t* (Kang et al., 2009). The MSE extension capturing heteroskedasticity is given in Wei et al. (2010) as

$$HMSE = n^{-1} \sum_{t=1}^{n} \left( 1 - \sigma_t^2 / \hat{\sigma}_t^2 \right)^2 \tag{2.112}$$

On the other hand, when MAE is adjusted for heteroskedasticity, we get

$$HMAE = n^{-1} \sum_{t=1}^{n} \left| 1 - \sigma_t^2 / \hat{\sigma}_t^2 \right| \tag{2.113}$$

The QLIKE, which resembles the loss in a Gaussian likelihood is given in

$$QLIKE = n^{-1} \sum_{t=1}^{n} \left( \ln\left( \hat{\sigma}_t^2 \right) + \sigma_t^2 / \hat{\sigma}_t^2 \right) \tag{2.114}$$

Mincer and Zarnowitz (1969) regressions alternatively give a loss function, $R^2LOG$, defined as

$$R^2LOG = n^{-1}\sum_{t=1}^{n}\left[\ln\left(\sigma_t^2/\hat{\sigma}_t^2\right)\right]^2 \quad (2.115)$$

The number of data points estimated in the above is *n* (Wei et al., 2010). Out-of-sample forecasting may be evaluated with the root square mean error (RSME) in Mohammadi and Su (2010) as follows:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} e_t^2} \quad (2.116)$$

A more comprehensive description of the Superior Predictive Ability (SPA) test is given below.

### *2.12.1. Superior Predictive Ability (SPA) test*

The SPA test is formulated in Hansen (2001) and Hansen (2005). SPA is comparable to the Reality Check (RC) method for data snooping. Modifications from the RC include application of studentized statistics and sample-dependent null distribution approaches (Hansen, 2005). The strengths of the SPA include its ability to compare more than two models at the same time and its past record for accuracy (Wei et al., 2010). SPA is also less sensitive to the inclusion of poor and irrelevant alternative forecasting models to the pool of approaches examined (Hansen, 2005). A benchmark model is compared to new competing models using the equation

$$X_{t,l}^{(0,i)} = L_{t,l}^{(0)} - L_{t,l}^{i} \quad (2.117)$$

$L_{t,l}^{(0)}$ is the loss function for the benchmark model $M_0$ (Hansen, 2001). The competing model $M_i$ has the loss function $L_{t,l}^{(i)}$ for $i = 1,....,.k$ (Hansen, 2001; Wei et al., 2010). In Wei et al. (2010), the null hypothesis, which states that $M_0$ is not outperformed is given as

$$H_0 : \max_{i=1,.....,k} E\left(X_{t,l}^{(0,i)}\right) \leq 0 \quad (2.118)$$

The stationary bootstrap of Politis and Romano (1994) and the p-value provided in Koopman et al. (2005) are used to compare the competing model and the rival model. The forecast performance is evaluated based on a bootstrap approach for constructing the SPA table (Wei et al., 2010).

Hansen (2005) provides the studentized statistic for evaluating the null as follows

$$T_n^{SPA} \equiv \max\left[\max_{k=1,\ldots,m} \frac{n^{1/2}\overline{X}_k}{\hat{\omega}_k}, 0\right] \tag{2.119}$$

The estimator for $\hat{\omega}^2$ is

$$\omega_k^2 \equiv \mathrm{var}\left(n^{1/2}\overline{X}_k\right) \tag{2.120}$$

In Hansen (2005) $\overline{X}_k$ for $k = 1,\ldots\ldots,m$ is the mean of the set $X_{t,l}^{(0,i)}$ terms defined above. Hansen (2001) prescribes a bootstrap procedure for obtaining $\omega_k$ and the p-value of the SPA test statistic. Using the SPA method, Wei et al. (2010) found the non-linear GARCH approaches more robust in long-run forecasting compared to the linear GARCH models.

### *2.12.2. Diebold and Mariano (DM) test*

The DM test is given in the paper by Diebold and Mariano (2002). The test is able to compare two forecast sets from different models (Kang et al., 2009). If forecast errors in the two models are $e_{1t}$ and $e_{2t}$, the test is expressed as

$$E[d_t] = 0 \tag{2.121}$$

$$d_t = g(e_{1t}) - g(e_{2t}) \tag{2.122}$$

The mean of $d$ is given by

$$\overline{d} = n^{-1}\sum_{t=1}^{n} d_t \tag{2.123}$$

Variance of $d$ in Diebold and Mariano (2002) is asymptotic and defined as

$$V\left(\bar{d}\right) \approx n^{-1}\left[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right] \tag{2.124}$$

The $k^{th}$ autocovariance of $d_t$ is $\gamma_k$. The test statistic in Diebold and Mariano (2002) is

$$DM = \left[\hat{V}\left(\bar{d}\right)\right]^{-1/2}\bar{d} \tag{2.125}$$

The distribution of DM approximates the asymptotic standard normal characterisation (Kang et al., 2009).

## 2.13 Trading Rules and Trading Systems

In Lukac, Brorsen, and Irwin (1988) an attempt was made to simulate profits in 12 agricultural commodities using trading systems. Short-run disequilibrium over-and-above transaction costs and risk aversion was found. Trading systems in agricultural futures markets were also used in Irwin, Zulauf, Gerlow, and Tinker (1997) and Hamm and Wade (2000), the latter study involving wheat futures. Computer trading systems were generally found not profitable. Further, simulations of returns for wheat in Kastens and Schroeder (1996) were found not consistently profitable. Futures returns seasonality is sometimes viewed as a barometer for the efficiency of a market (Lucey & Tully, 2006). In efficient markets, a buy-and-hold strategy is not consistently beaten by a trading rule exploiting market anomalies (Lucey, 2002; Lucey & Pardo, 2005; Lucey & Tully, 2006). Malkiel (2003) and many scholars in the above literature conclude that there exists long-run efficiency in futures markets punctuated by short-term inefficiencies that emerge from time to time.

## 2.14 Risk, Margins and Extreme Value Analysis

Extreme value theory (EVT) is very reliable in the calculation of extreme risk, value at risk (VaR) and expected shortfall (ES) (Singh, Allen, & Robert, 2013). Principal models used as

part of multi-stage processes include the GARCH jointly with the block maxima model (BMM) and the peak over threshold (POT) approach. Singh et al. (2013) postulates that the broad distribution used for extreme value analysis is the generalized extreme value distribution (GEV), which is made up of the Gumbell, Fretchet and Weibull distributions. When it comes to the study of exceedances over some given threshold levels, the generalized pareto distribution (GPD) is applied (Singh et al., 2013). Value-at-Risk (VaR), is a leading measure of potential loss to an investment. VaR has been defined as a measure of maximum potential loss at a given probability level associated with a market position (Cotter, 2005). In Cotter (2005), we have the relation

$$VaR_p = r_{m,n}\left(m/np\right)^{\gamma} \tag{2.126}$$

Where $\gamma$ is the Hill estimator, *m* is the tail value level, *n* is the total number of random variables in the full set. Reboredo and Ugando (2014) define VaR at *t* with *(1-p)* confidence level for return $r_t$ as

$$\Pr\left(r_t \le VaR_t \middle| \psi_{t-1}\right) = p \tag{2.127}$$

Given *u* and probability *p*, VaR is defined as

$$VaR(p) = u + \frac{\beta}{\xi}\left[\frac{n}{N_{(u)}}\left(1-p\right)^{-\xi} - 1\right] \tag{2.128}$$

Where *u* is the threshold, *n* is the number of observations and $N_{(u)}$ is the number of observations above the threshold. Computation of VaR from the EGARCH follows the relation

$$VaR_t(p) = \mu_t - t_{\upsilon}^{-1}(p)\sqrt{h_t} \tag{2.129}$$

Conditional mean of asset returns are captured in $\mu_t$ while $\sqrt{h_t}$ is the standard deviation of asset returns. $t_{\upsilon}^{-1}$ is the *(1-p)* quantile of student-*t* distribution with $\upsilon$ degrees of freedom.

Expected shortfall in Reboredo and Ugando (2014) takes the form

$$ES = E\left[r_t \middle| r_t < VaR_t(p)\right] = \frac{\int_{-\infty}^{VaR_t(p)} rf(r)dr}{\int_{-\infty}^{VaR_t(p)} f(r)dr} \tag{2.130}$$

When given *u* and probability *p*, expected shortfall is defined as

$$ES = \frac{VaR(p)}{1-\xi} + \frac{\beta - \xi u}{1-\xi} \tag{2.131}$$

Derived from the EGARCH model, the expected shortfall in Reboredo and Ugando (2014) has the relation

$$ES_t = \mu_t + \sqrt{h_t}\left(\frac{g_v\left(t_\upsilon^{-1}(p)\right)}{p}\right)\left(\frac{\upsilon + t_\upsilon^{-1}(p)^2}{\upsilon - 1}\right) \tag{2.132}$$

In the above *g* is the standardized *t*-density function. The student-*t* distribution is captured in *t*.[10]

## 2.15 Model Specification

Commodity return and its variability are the key dependent variables in the econometric modelling under this project. A broad model in the case of the spill-over investigation is specified as follows:

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-2} + \alpha_3 \sigma_{lt-1} + \alpha_4 \sigma_{lt-2} + \alpha_5 \sigma_{ft-1} + \alpha_6 \sigma_{ft-2} + \alpha_7 \Delta x_t + \varepsilon_{1t} \tag{2.133}$$

$$\sigma_{lt} = \beta_0 + \beta_1 \sigma_{lt-1} + \beta_2 \sigma_{lt-2} + \beta_3 r_{t-1} + \beta_4 r_{t-2} + \beta_5 \sigma_{ft-1} + \beta_6 \sigma_{ft-2} + \beta_7 \Delta x_t + \varepsilon_{2t} \tag{2.134}$$

$$\sigma_{ft} = \lambda_0 + \lambda_1 \sigma_{ft-1} + \lambda_2 \sigma_{ft-2} + \lambda_3 r_{t-1} + \lambda_4 r_{t-2} + \lambda_5 \sigma_{lt-1} + \lambda_6 \sigma_{lt-2} + \lambda_7 \Delta x_t + \varepsilon_{3t} \tag{2.135}$$

The term $r_t$ represents return, $\alpha_0,.....\alpha_6$, $\beta_0,....\beta_6$ and $\lambda_0,.....\lambda_6$ are constants, $\sigma_{lt}$ stands for local volatility, $\sigma_{ft}$ is foreign volatility, $\Delta x_t$ are changes in economic variables of interest while $\varepsilon_{1t}, \varepsilon_{2t}$ and $\varepsilon_{3t}$ are error terms. The lags of return and volatility are given in the terms $r_{t-1}, \sigma_{lt-1}$ or $\sigma_{ft-1}$. At least two lags are considered for each term. Essentially, the project is

[10] Programming code in MATLAB and R is provided on the website of Gilli (2006).

testing the extent to which each of the variables on the right-hand side explains the dependent variable on the left-hand side. To determine causality, the system considers the lags of each of the explanatory variables. The above system of equations can be resolved by the multivariate GARCH system, Granger causality analysis or VAR models. The rule of thumb in considering Granger causality is to see if the effect happens after the cause (Doornik, 2006).

In this project, key commodity classes include:

- Agricultural commodities
- Energy commodities, especially crude oil
- Precious metals, to include, platinum and gold

Co-movement tests are carried out using the error correction method[11] similar to Cooke (2009). The error correction model is represented as

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \gamma x_{t-1}) + u_t \quad (2.136)$$

In the brackets is the error correction term. The residual terms $u_t$ are $I(0)$ when the variables $y_t$ and $x_t$ are cointegrated. The augmented Dickey Fuller test is performed on

$$\Delta \hat{u}_t = \psi \hat{u}_{t-1} + v_t \quad (2.137)$$

The error term $v_t$ is identically and independently distributed (Brooks, 2014). The hypothesis is $H_0 : \hat{u}_t \sim I(1)$ while the alternative is $H_1 : \hat{u}_t \sim I(0)$. Long run relationships exist in the case of the alternative hypothesis. OLS is conducted and the residuals are saved for testing if they are $I(0)$. The vector error correction method (VECM) is an extension of the error correction method and involves several variables that require testing (Minot, 2010). The following steps are used in Minot (2010) as preparation to run the VECM model i) stationarity testing for the

[11] Tse (1995) and C. Brooks et al. (2001) demonstrated the use of this approach

various series under study ii) use of Johansen test to determine cointegration iii) estimation of the VECM if the Johansen test confirms cointegration. Where cointegration is not confirmed, information flows or spill-overs are estimated using VAR or multiple regression approaches.

## 2.16 Time Series Analysis

Much of this section points out some of the pitfalls in running time series models and the measures to be taken in this project to develop sound econometric methodologies. It is imperative to avoid so-called spurious regressions[12] (see Granger & Newbold, 1974). Such regressions are associated with misspecifications that emanate from the autocorrelation structure of the errors in the variables. In spurious regressions, $R^2$ is typically larger than the Durbin Watson statistic (Granger & Newbold, 1974). The time series data first and second moments comprise the mean and the variance respectively. Third and fourth moments include the skewness and the kurtosis. White noise entails data that has constant mean and variance as well as zero autocovariances (Brooks, 2014). The Jarque-Bera test for normality is employed for the time series datasets and for regression residuals. Where significant outliers are observed, dummies could be used to identify these observations. This takes out the effect of such outliers from the process completely. Another important test acknowledged in Sariannidis (2011) is the test for heteroskedasticity. This can be conducted with the autocorrelation function (ACF) and partial autocorrelation function and the Ljung-Box statistics (Sariannidis, 2011).

A stationary series entails that the roots of an autoregressive data series fall outside the unit circle (Granger & Newbold, 1974). In general, stationarity is associated with constant mean,

[12] Spurious regressions have been referred to as nonsense regressions due to their lack of accuracy and underlying theoretical foundation or explanation (Granger & Newbold, 1974).

variance and autocovariance at each lag of a time series process. Spurious regressions emanate from data that is not stationary (Brooks, 2014). More broadly, in large samples, as a result of spurious regression, two non-stationary series may appear significantly linked, yet there would be no theoretical basis for such association (Minot, 2010). Tests for unit root are conducted using the Augmented Dickey Fuller test, Kwiatkowski test, the Phillips Schmidt and Sheen test (KPSS) (Busse et al., 2010). If $y_t$ is integrated to the order of $d$, this means that

$$\Delta^d y_t \sim I(0) \tag{2.138}$$

In the case where there is evidence of unit root, differences are taken (Brooks, 2014). It has been known to be advantageous to transform financial time series using the logarithmic transformation (Moholwa, 2005). The benefits include the stabilization of time series variability, doing away with negative values and making it easier to identify cointegration (Moholwa, 2005). Cointegration occurs when two distinct non-stationary series are regressed and the residuals of the one variable fitted on the other are stationary. This means the variables in the two series have a linear combination. The series have to be integrated to the same order if cointegration exists between them. Cointegration tests are performed using the Johansen Trace test or the Saikkonen-Lütkepohl (2000) test. Seasonality is determined by generating a plot of the AR process and testing the lag analysis using various criteria approaches. Another approach for testing seasonality in Auret and Schmitt (2008) is to use the Census X12 seasonal test.

## 2.17 Data

Before the above models are used, summary statistics and time series plots of the data are presented in the empirical analysis section of the thesis. This gives a visual impression of the quality of the data before time series analysis tests to be carried out. Daily, weekly and

monthly commodity prices are collected from DataStream International and Bloomberg. Local data is sourced from the JSE and SAFEX as well as from Agri-SA. This data includes commodity price statistics as well as index prices for respective financial markets falling under the JSE. SAFEX also provides the time series for the South African Volatility Index (SAVI). Commodity returns are calculated as the logarithmic daily price differences. Commodity price series for futures markets in this thesis are obtained from the JSE, KCBT, ZCE and Euronext/Liffe. Data on macro-variables are collected from StatsSA and the South African Reserve Bank (SARB). IMF indices for agricultural, beverages, metals and energy commodities are sourced from the IMF international financial statistics database. Information on financial markets indices for various regions in the world is available from the Financial Times World Index All countries Africa (Bhar & Nikolova, 2009). This data is essential for the co-movement analysis described above.

The FAO has extensive data on agricultural commodities. The Committee for World Food Security (CFS), which is the United Nations' forum for world food security issues, have a food price volatility portal on the FAO website.

## 2.18 Robustness Checks

Checks are conducted for every regression to ensure there is robustness. One popular method used by Wang–Iftekhar and Xie (2013) is to carry out median regression which helps control for outliers. Additional control variables can also be used to see if this significantly changes the effect of a particular variable under study. Wang–Iftekhar and Xie (2013) also suggest truncation of the outliers at the first and the $99^{th}$ percentiles. Most studies also typically split the sample into say a "pre-crisis period" then a "post-crisis period". Any major event can be used to determine suitable split positions. There is need to determine if the results will be similar for the different periods and for the combined sample (Wang–Iftekhar &

Xie, 2013). It is also possible to run econometric models using weekly data comparing results with estimation for the daily or monthly series depending on the length of the mean reversion cycles (Wang–Iftekhar & Xie, 2013).

# 3 A STUDY OF SEASONALITY ON THE SAFEX WHEAT MARKET

## 3.1 Introduction

An examination of futures market return and volatility is imperative for decision-making involving investment, asset valuation, risk management as well as monetary policy-making (Brooks, 1998; Poon & Granger, 2003). A significant number of studies on agricultural commodities return and volatility have focussed on derivatives markets within the BRICS countries, but only a few have analysed derivatives markets in South Africa.[13] South Africa is an emerging market within the BRICS and SAFEX is the most advanced, fully-functional commodity futures market on the African continent. Although SAFEX was created in 1996, little is known about the behaviour of its prices.

Agricultural markets in South Africa only became fully liberalized after the promulgation of the Marketing of Agricultural Products Act of 1996 (Adelegan, 2009; Vink & Kirsten, 2002). Deregulation of agricultural markets resulted in the removal of control boards that had previously maintained single-channel marketing systems (Viljoen, 2004). The opening up of the food commodity markets gave way to international competition in the wheat markets. In fact, Phukubje and Moholwa (2006) suggest that the disbanding of the commodity boards and changes in trade policies made wheat trade integration with the world easier.

Liberalization opened up the South African grain markets to global investors. Deregulation and enactment of the Marketing of Agricultural Products Act of 1996 laid the ground for the setting up of SAFEX. Marketing boards, which used to impose floor and ceiling prices, were removed allowing interaction of market forces to influence price discovery. Opening up to

[13] BRICS is the acronym for the economic grouping involving Brazil, Russia, India, China and South Africa.

free international trade and the resulting international competition culminated in local prices settling within a band between import and export parity prices. In the current trading dispensation, JSE (2013) finds grain prices increasing towards import parity in times of shortages and towards export parity during surplus periods. However, Arshad, Rizvi, and Ibrahim (2014) posit liberalized markets are prone to contagion as goods, services and capital flow through the borders. In this thesis, the idea put forward by way of hypothesis is deregulation is likely to improve price discovery. However, as prices are influenced by global markets through information transmission, liberalization would not necessarily guarantee market efficiency. On the basis of the above arguments, it was anticipated market efficiency would be time-varying and market anomalies on SAFEX were likely to persist for some time in the future.

Specifically, this section of the thesis examines seasonality in the SAFEX wheat contract returns and volatilities from the beginning of 1999 to September 2013 in order to identify market inefficiencies that can be exploited for financial gain. Although South Africa produces the highest volumes of wheat within the Southern Africa Development Community (SADC), wheat has not been studied in detail in South Africa hence limited knowledge of the contract return and volatility behaviour is available. Another reason for looking at the SAFEX wheat contract is that the underlying asset is highly comparable to commodities traded in the most important global futures exchanges and this allows analysis of international links across diverse markets. Furthermore, it is important noting that there has yet to be a paper on the SAFEX wheat contract that utilizes both non-parametric and parametric approaches to determine seasonal effects.

The chapter is organized as follows. Section 3.2 reviews literature on seasonality in futures return and volatility with special focus on wheat. Section 3.3 presents the methodology for

this study. Section 3.4 describes the SAFEX wheat data. Section 3.5 provides the preliminary results while the volatility models are estimated in section 3.6. Section 3.7 describes the robustness checks carried out using alternative GARCH models. Section 3.8 explains the results of the Monte Carlo simulation comparing a buy-and-hold approach and the trading rule developed in the study. Section 3.9 concludes the paper.

## 3.2 Literature Review

The efficient market hypothesis postulates that public information is already incorporated into prices and is hence is already discounted (Dawson, 2011; Fama, 1970). As such, it is unlikely that speculative trading gains can be achieved from using public information (Fama, 1970). In Fung, Tse, Yau, and Zhao (2013), information efficiency entails it is not possible to predict returns using historical information. Markets are typically distinguished as weak-form, semi-strong form and strong-form efficient (Fama, 1970). Weak-form efficiency is primarily about the link between past and subsequent asset prices. In Hansen and Hodrick (1980) semi-strong efficiency is defined as asset prices that embody all public information. In Phukubje and Moholwa (2006) strong-form efficiency suggests asset prices have taken account of both publicly available and private or “insider” information. If unexpected news is received today, it becomes pivotal in driving prices. Dawson (2011) describes long-range dependence in prices as characterised by information at long lags that influences current prices. Efficient markets typically have asset returns with the pattern of white noise (Dawson, 2011).

Phukubje and Moholwa (2006) investigated weak-form efficiency in the wheat and sunflower seed markets on SAFEX. They found that futures prices for the two commodities could be partially predicted using past prices. In a study of 36 single-stock futures on SAFEX Smith and Rogers (2006) found four of them consistent with the random walk hypothesis. When

this hypothesis is true, historical price patterns are not useful in predicting future prices (Sharpe, 1966). Chen and Lin (2014) concluded the random walk phenomenon was not met in the case of prices of crude oil, coal and natural gas in the USA. Non-stationarity was tested using the augmented Dickey-Fuller test (ADF) that incorporates a regime switching framework (Chen & Lin, 2014). Studies on market efficiencies by Piesse and Hearn (2005) identified a number of factors considered when benchmarking futures market performance. The factors include market liquidity, concentration, price volatility levels, returns volatility and asset pricing efficiency (Piesse & Hearn, 2005).

Garcia and Leuthold (2004) have reviewed literature on market efficiency with a primary focus on agricultural futures contracts. When futures prices are reflecting all available information, then the market is efficient (Fama, 1970, 1991, 1998). In efficient markets, achieving returns consistently greater than zero by buying and selling assets using a trading rule strategy is not possible (Garcia & Leuthold, 2004). Beja and Goldman (1980) postulate that under the disequilibrium theory, there is slow adjustment of prices to information arriving on the market, as the marketplace is not a perfect system. Costs associated with securing and disseminating information also slow down information flows (Grossman & Stiglitz, 1980). Kolb (1992) examined 29 commodities including wheat using data from the 1950s to 1988. Wheat futures were found efficient. Kastens and Schroeder (1996) found the KCBT wheat July futures contract increasing in efficiency in the 50 years prior to their study. Wheat futures on the KCBT were analysed in the study using data from 1947 through 1995. Aulton, Ennew, and Rayner (1997) used cointegration and error correction models to find long-run wheat futures market efficiency in the UK. Long-run inefficiencies could not be confirmed by this study.

Chaos in commodity futures was examined in Neftci (1991), Clyde and Osler (1997), Yang and Brorsen (1993), Chatrath, Adrangi, and Dhanda (2002) and Adrangi and Chatrath (2003). In a chaos scenario, measurement errors increase exponentially rendering profitable systems unsustainable. Chaos was found in the maize market by Yang and Brorsen (1993) as opposed to Chatrath et al. (2002) who did not find chaos in maize, soybeans, sugar, coffee and cocoa prices. Wheat exhibited persistent price non-linearity that was over-and-above ARCH effects (Adrangi & Chatrath, 2003; Chatrath et al., 2002).

When market anomalies exist, a futures market does not follow the efficient market hypothesis (Chowdhury, 1991; French, 1980). The dummy-variable approach is common in academics when estimating market anomalies (Lucey & Pardo, 2005). Futures markets studies examining statistical anomalies include Kastens and Schroeder (1996), Kolb (1992), Kolb and Gay (1983), Dorfman (1993) and Koontz, Hudson, and Hughes (1992). Seasonality in five agricultural commodities and three metal futures was confirmed in Milonas (1986a) with data covering the period 1972 to 1983. Market anomalies included seasonality at the monthly and annual levels. Gay and Kim (1987) examined seasonality in commodities comprising the Commodity Research Bureau (CRB) index. The index is calculated as a geometric average of 27 futures contracts. Seasonality effects found included daily and monthly effects, low Monday returns, high Friday returns, high January and low December returns. In the study by Malick and Ward (1987), frozen concentrated orange juice was examined with the basis found dependent on seasonality of monthly stock levels. In Milonas (1991), five agricultural commodities including wheat are investigated for monthly, yearly and half-monthly effects. These effects are confirmed with the yearly effect found stronger than the monthly effect.

Literature including Agrawal and Tandon (1994), Lucey and Pardo (2005) and Frieder and Subrahmanyam (2001) acknowledged the occurrence of diverse market anomalies. Financial market anomalies have been categorised broadly in terms of the size effect, the value effect, the weekend effect, the dividend yield effect, holiday effect, momentum effect, turn-of-the-month effect, weather effect and the holy day effect, among others (Agrawal & Tandon, 1994; Lucey & Pardo, 2005). The year-effect is known to be linked to random disruption of demand and supply and the influence of public policy (Khoury & Yourougou, 1993.

Seasonality in returns of wheat futures markets has been studied in many papers. Milonas (1986b) and Milonas (1991) examined five USA agricultural futures contracts. By using non-parametric procedures, wheat futures in the study were found to have monthly, yearly and half-monthly effects. Khoury and Yourougou (1989) studied the Canadian wheat futures contracts over the period 1980 to 1987 and found maturity effects with prices adjusting more strongly to new information as contract maturity approached. In an extension of this study, Khoury and Yourougou (1993) found that wheat futures contracts had very small yearly seasonality. Fabozzi, Ma and Briley (1994) confirmed the existence of pre-holiday effects in commodity futures traded in both the USA and the world futures markets. The study included wheat traded on the Chicago Board of Trade (CBOT) and the KCBT and used the dummy-augmented linear regression approach. Lee, Hsu and Ke (2013) examined returns seasonality for maize, wheat, soybeans and soymeal on the CBOT with data from 1979 through 2012. In the case of wheat, returns in August were found to be significantly higher than for the other months. Musunuru (2013) looked at monthly seasonality in 14 agricultural commodities on the CBOT. Ordinary least squares regression and GARCH models with dummy-augmentation were used to find significant and positive wheat futures returns in the month of July for the period 1992 to 2012.

In the case of futures volatility seasonality, Anderson (1985) looked at the volatility of wheat on both the CBOT and the KCBT. Volatility was found to be at its lowest around February and at its highest in June and July. Seasonality in the volatility of USA maize, wheat and soybeans was also confirmed in Kenyon, Kling, Jordan, Seale and McCabe (1987) using monthly and annualized variances of daily prices. Volatility of the July wheat contract was found to increase in the months before contract maturity. Yang and Brorsen (1993), using the GARCH approach, examined 15 commodity futures markets and found daily seasonality in 13 out of 15 contracts. Futures contracts examined included wheat on the CBOT and KCBT, and seasonality in wheat volatility on both CBOT and KCBT was found significant on Mondays. Bester (1999) investigated volatility seasonality in several commodities inclusive of wheat on the CBOT using the P-GARCH approach. Wheat volatility monthly effects were confirmed with March, June, September and December being robustly significant across the econometric models compared.

Xin, Chen and Firth (2005) used several measures of price variability to investigate seasonality in several contracts in China's commodity futures markets. Volatility in prices was derived from daily high, low and open-to-close futures prices. Wheat volatility was found significant on Mondays. In addition, volatility in the wheat contract had significant year effects in 2000. In Karali and Thurman (2010), volatility in maize, soybeans, wheat and oats is examined for seasonality including time-to-delivery effects, calendar effects, and volatility persistence. CBOT futures contracts with data from 1986 to 2007 were analysed. A generalized least squares approach was used with volatility measures generated using high-low ranges and daily close-to-close prices. Volatility in maize, soybeans, wheat and oats was found to have monthly as well as maturity effects. Monthly volatility peaks were found in June and July. Finally, Dawson (2014) estimates the volatility of daily wheat futures prices on

the Euronext/LIFFE market and observes a structural break in June 2007 and an increase in the level of volatility after that time.

Unlike the high number of papers that have focused mainly on the USA futures markets, the existence of seasonality in returns and volatilities in the wheat futures contract on SAFEX has scarcely been studied, and findings are mixed. Viljoen (2004) used non-parametric analysis to examine SAFEX white maize, yellow maize and wheat. Daily seasonality was confirmed for white and yellow maize on SAFEX but not for wheat. In the case of wheat returns, only turn-of-the-month effects were observed. Phukubje and Moholwa (2006) found SAFEX wheat futures prices from 2000 to 2003 partially predictable from past prices suggesting the market was not an efficient one. In Mashamaite and Moholwa (2005), wheat prices on SAFEX from 1997 to 2003 were found to be asymmetric with volatility responding more significantly to declining prices than increasing prices. These results are in contrast with those obtained by Jordaan, Grove, Jooste and Alemu (2007) with data from 1997 through 2006. Their findings were that SAFEX wheat price volatility was constant over time. This led the authors to conclude that it was plausible to use the ARIMA process to model wheat volatility.

This study has a number of fundamental differences with Viljoen (2004) giving it the scope and depth to make a unique and incremental contribution to literature. Firstly, a more comprehensive dataset capturing both the pre-crisis and post-crisis periods up to 2014 is used to study seasonality behaviour.[14] Secondly, the current study uses two econometric approaches, parametric and non-parametric. The current study went further effecting necessary standardization for parametric analysis to be valid. Parametric research can

[14] Viljoen (2004) only looks at about 5 years around the time of inception of SAFEX when the market was still building liquidity and momentum.

typically be richer, allowing in this case the use of diverse GARCH extensions and other multiple regression-based models. In this study, three dummy-augmented GARCH models are used in addition to multiple regressions, besides non-parametric analysis.

Thirdly, the current study incorporates regime-switching with the main dataset split into two separate samples. The height of the global financial crisis is the point of separation for the two samples. It is worth noticing that the behaviour of the two samples is found markedly different. Fourthly, this study develops a trading rule based on market anomalies in the wheat contract. This is important as it shows how the results of the study could be utilized by the investing community to accomplish their trading objectives. Fifthly, this study validates the unique trading rule it develops using an out-of-sample period by way of Monte Carlo simulation. Results of the simulation are exciting in that it is demonstrated the trading rule can consistently be exploited for financial gain after accounting for transaction costs.

We summarize our views on existing literature allowing the specification of our ex-ante expectations on the SAFEX wheat market. Studies finding wheat futures markets inefficient based on contract anomalies include Milonas (1986, 1991), Young and Brorsen (1993), Agrawal and Tandon (1994), Phukubje and Moholwa (2006), Rojers (2006), Karali and Thurman (2010), Lee, Hsu and Ke (2013) and Musunuru (2013). On the other hand, literature finding no evidence of daily seasonality in the wheat contract includes Kolb (1992), Aulton, Ennew and Rayner (1997) and Viljoen (2004). It is quite clear that the majority of the studies have found daily seasonality in commodity futures, including in the wheat contract. It is felt that as major markets like KCBT are exhibiting seasonality, most other markets could be influenced to have this market inefficiency. In terms of ex-ante view therefore, this study had the expectation of finding wheat contract inefficiencies on SAFEX, given that more than 50 % of locally consumed wheat is imported into the country. A key observation in reviewing

existing studies is that market inefficiencies in young and developing markets like SAFEX have not been exhaustively examined in literature.

## 3.3 Methodology

The approach used to arrive at the appropriate model specification starts with considering the plausibility of an ARMA(*p,q*) for the data set. Values of *p* and *q* are varied between 0 and 4 while observing criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The ARCH-test is carried out as suggested in Engle (1982). This allows for application of ARCH/GARCH approaches. The simple AR(*m*)-GARCH(*p,q*) before augmentation with dummies has the following mean equation:

$$R_t = \alpha + \sum_{i=1}^{m} \beta_i R_{t-i} + \varepsilon_t \tag{3.1}$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t)$$

$R_t$ is the wheat return and $R_{t-i}$ is the lag of the wheat return for *i=1,…..,m*. $\varepsilon_t$ is conditional on past information $\psi_{t-1}$ following the normal distribution. Representation of the GARCH(*p,q*) variance is:

$$h_t = \delta + \sum_{k=1}^{p} \xi_k \varepsilon_{t-k}^2 + \sum_{l=1}^{q} \eta_l h_{t-l} \tag{3.2}$$

$\varepsilon_{t-k}^2$, for *k=1,…,p,* are lagged squared residuals and $h_{t-l}$, for *l=1,……q,* are lagged conditional variance terms. The lag length in *m,p,q* is typically determined before the inclusion of the dummies in the above model (Auer, 2014; Bollerslev, 1988; Choudhry, 2000, among others). A good starting point suggested in literature is to initially set *m* to zero and *p=q=1*. The maximum likelihood procedures are then used similar to Auer (2014). Ljung and Box (1978) provide the procedures for testing serial correlation which necessitates moving to higher order lags as is necessary.

The GARCH has been dummy-augmented and alternative ARCH/GARCH approaches are used in the robustness analysis. The AR(*m*)-GARCH(*p,q*) which allows for testing "day-of-the-week", holiday and the structural break effects (linked to the mid-2008 structural break) is given as

$$R_t = \alpha + \sum_{i=1}^{m} \beta_i R_{t-i} + \sum_{j=1}^{4} \lambda_j D_{j,t} + \zeta S_t + \kappa H_t + \varepsilon_t \quad (3.3)$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t)$$

The augmented variance equation is

$$h_t = \delta + \sum_{k=1}^{p} \xi_k \varepsilon_{t-k}^2 + \sum_{l=1}^{q} \eta_l h_{t-l} + \sum_{j=1}^{4} \theta_j D_{j,t} + \tau S_t + \pi H_t \quad (3.4)$$

The $D_{j,t}$ terms are dummies, where $j=1,\ldots..,4$ representing respectively the weekdays from Tuesday to Friday. If $D_{j,t}=0, \ \forall j$ , this will give a Monday. $S_t$ is the dummy for the regimes used to generate two subsamples from the full returns set. $S_t$ takes the value 1 from 8 July 2008 onwards and zero otherwise. The holiday dummy is $H_t$ and takes the value 1 during a holiday and zero otherwise.

Non-linear GARCH methodologies have been found more consistent and accurate in return and volatility forecasting (Andersen & Bollerslev, 1997; Ding, Granger, & Engle, 1993; Nelson, 1991). In this analysis, non-linear GARCH models have been applied in the robustness checks. Specifically, the asymmetric power ARCH (APARCH) and the threshold GARCH of Glosten, Jagannathan and Runkle (1993) (GJR GARCH) have been estimated. These models are able to capture persistence in volatility and the asymmetric features or leverage effects of data (Ding et al., 1993; Glosten et al., 1993b). The APARCH model, developed in Ding et al. (1993), has the same mean equation as the dummy-augmented GARCH. The following variance equation represents the APARCH

$$\sigma_t^{\kappa} = \delta + \sum_{i=1}^{q} \xi_i \left( |\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i} \right)^{\kappa} + \sum_{j=1}^{p} \eta_j \sigma_{t-j}^{\kappa} + \sum_{n=1}^{4} \theta_n D_{n,t} + \tau S_t + \pi H_t \quad (3.5)$$

Volatility in the APARCH is captured in $\sigma_t^{\kappa}$. The parameter $\kappa$ has the restriction $\kappa > 0$ and a special case of $\kappa = 2$ and $\gamma_i = 0$, for all *i,* gives the structure similar to the GARCH*(p,q)* (Bollerslev, 2008; Ding et al., 1993). In the APARCH approach, the size effect is captured in $\xi_i$ and the asymmetry effect in $\gamma_i$. A positive coefficient in $\gamma_i$ suggests negative information is more influential on volatility than positive information. In the above equation, $\delta$ is a constant and the daily, regime and holiday dummies have functions as already described above.

The specification of the GJR GARCH model maintains the same mean relation as equation (3). The variance equation for the dummy-augmented GJR GARCH is

$$\sigma_t^2 = \delta + \sum_{i=1}^{p} \xi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \eta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^{-} + \sum_{n=1}^{4} \theta_n D_{n,t} + \tau S_t + \pi H_t \quad (3.6)$$

In the GJR GARCH, $I_t$=1 when $\varepsilon_t < 0$, and 0 otherwise. The effect of good news is captured in $\xi_i$ and bad news has the effect $\xi_i + \gamma_i$. There is asymmetric news effect when $\gamma_i \neq 0$ and, specifically, bad news increases volatility when $\gamma_i > 0$. Persistence of variance is captured in the parameter $\eta_i$. The daily, regime and holiday dummies have been described above already.

## 3.4 Data

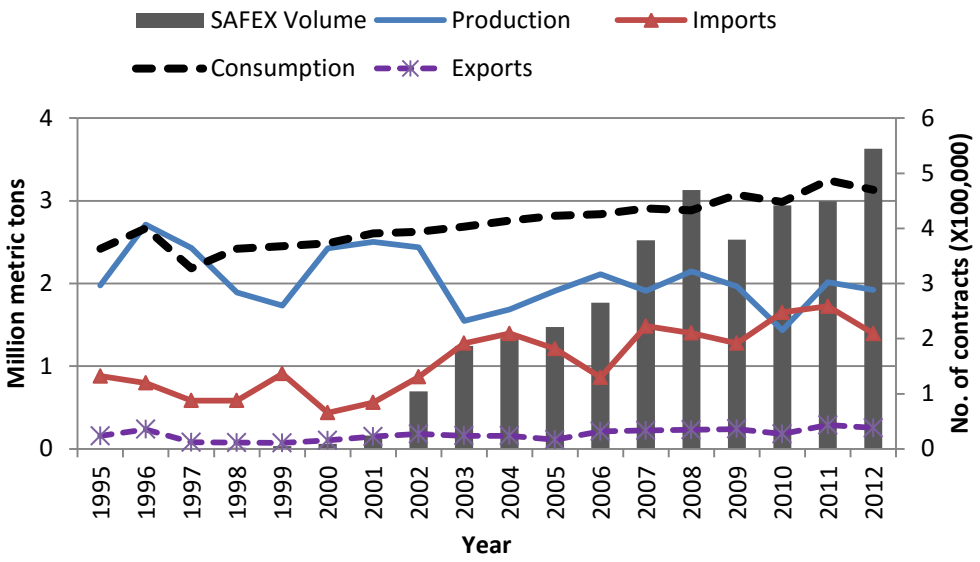
Wheat is among the most important food commodities in South Africa. South Africa is the highest producer of wheat among the 14 countries within the Southern Africa Development Community (DAFF, 2012). Wheat is produced in South Africa from around May to October under both irrigation and winter rainfall, the latter occurring in the southern-most provinces of the country. The split between winter rainfall and dry-land wheat production (usually using

irrigation) is respectively 80% to 20% (DAFF, 2012). It is worth noting that about 75% of the wheat marketed in South Africa is hard wheat (DAFF, 2012).

The trends for wheat supply and demand in South Africa from 1995 to 2012 are presented in Figure 3.1. SAFEX wheat trade volumes are also included in the graph. Consumption of wheat has been increasing steadily since liberalization in 1996, while production has been declining. The consumption gap was matched by increasing imports over the years while exports remained fairly steady over time. Finally, Figure 3.1 shows that, after the wheat futures contract was listed in 1997, consistent and sizable wheat trade volumes were traded through SAFEX from 1999.

The study is motivated by the need to identify wheat market patterns and inefficiencies that may be profitably exploited. Such wheat market anomalies have not been extensively analysed on the SAFEX market. In addition to possible economic gain through a trading rule, seasonality at the daily level may be used by market participants for aligning and timing of already planned purchases and sales.

**Figure 3.1: Wheat demand, supply (million metric tons) and SAFEX volume**




Wheat supply and demand is presented in the graph to include South African wheat production, imports, consumption and exports from 1995 to 2012. Trends for wheat futures volume are also depicted over the same period. Source: The Department of Agriculture, Forestry and Fisheries of South Africa (DAFF), SAFEX, and own elaboration.

Wheat futures close-to-close prices on SAFEX have been used for this study. Daily data was collected through Thompson Reuters for the period from 1 January 1999 to 23 September 2014. Prices are expressed in Rands (the South African currency) per tonne, and returns are expressed in percentage terms.

SAFEX wheat contracts have maturities in the months of March, May, July, September and December. A single time series representing wheat futures prices has been generated. The last day criterion was used in order to rollover the series. According to this criterion, the last price with which the first maturity series contributes to the continuous series is the delivery price. This implies that on the expiry date, the series uses the close price of the first maturity and on the following day, the close price of the second maturity is used. In the construction of the return series, the wheat return on the day after the rollover date was calculated as the

quotient between the closing price of the following contract and the previous closing price of such a contract.

Figure 3.2 presents the evolution of the continuous price series of the wheat futures contract traded on SAFEX during the period 1 January 1999 to 23 September 2014.

**Figure 3.2: SAFEX wheat price series**




SAFEX wheat contract prices expressed in Rands per tonne from 1 January 1999 to 23 September 2014 are presented in the table. The price data used are daily SAFEX wheat closing prices obtained from the next-to-maturity futures contract.

An exponential price rise was observed in the SAFEX wheat contract between 2004 and mid-2008. In the run-up to the crisis, commodity prices experienced substantial increases alongside prices in other financial asset classes such as equities. The highest point in the wheat price series occurred mid-way through 2008 at the height of the global financial crisis. Figure 3.2 shows that prices started falling substantially after July 2008. From then on, the lowest wheat price recorded was about R2,100.00 per tonne around mid-2010. Wheat prices have been on an oscillating but gradually rising path after this.

Annual wheat price peaks and troughs appear to be guided by wheat planting and marketing cycles. Wheat planting occurs around May and June while harvesting commences from the

end of September into October. Typically, prices rise to their highest just before the onset of the harvest. Taking into account that seasonality could be impacted by market direction or the occurrence of financial crisis, following Auer (2014), the wheat return series was split into two samples. The division of the samples is based on peak prices reached during the global crisis and 7 July 2008 is the demarcation point. The first sample has prices that are increasing exponentially just before July 2008. The second sample has an exponential decay in prices followed by a gradual price increase.

Finally, wheat daily returns are generated using the relation

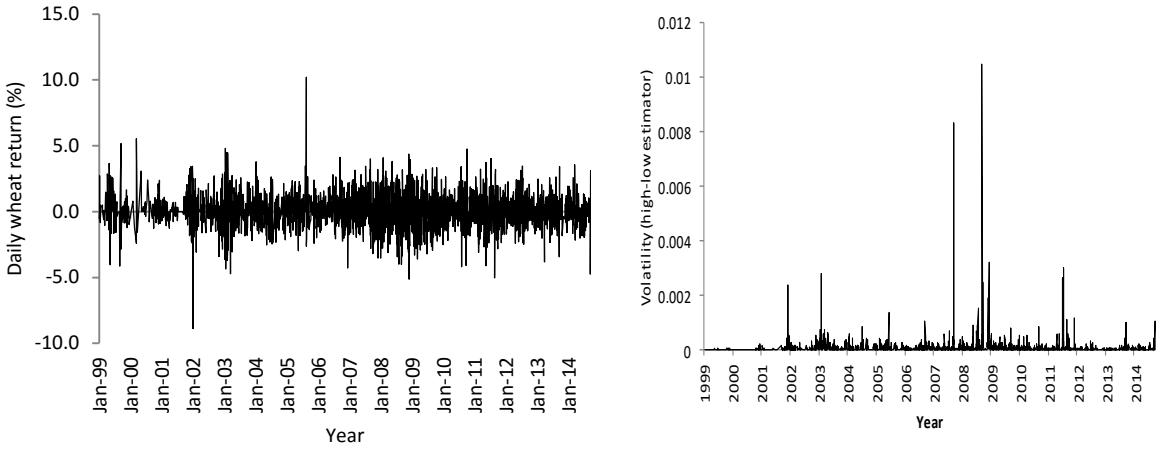
$$R_t = 100 * \ln\left(P_t / P_{t-1}\right)$$

where $R_t$ is the daily wheat return and the price and lagged price series are respectively given in $P_t$ and $P_{t-1}$. A volatility series incorporating wheat daily high-low prices is generated going by Parkinson (1980). Figure 3.3 presents graphs of both wheat return and volatility which suggest there may be annual peaks in returns and volatility as well as jumps in prices associated with financial crises.

The returns pattern indicates the existence of volatility clustering and spikes in volatility are visible around 2007/2008 and 2008/2009. The two mentioned spikes coincided with the global financial crisis during which commodities experienced high levels of volatility. The approach was to introduce the sample dummy around the peak of the global economic downturn.[15]

[15] The lowest daily return of -8.8831% was recorded on January 8, 2002 while the highest daily return of 10.2075% was registered on 23 August 2005. The study has run the model presented in Table 3.4 (GARCH with daily augmentation) without these two extreme returns. As the results in Table 3.4 were not significantly altered after removing the extreme points, the rest of the analysis was carried out with the two returns included.

**Figure 3.3: SAFEX daily wheat return and volatility**




Daily wheat returns are presented in the graph on the left while a proxy for volatility is depicted on the right. Returns are calculated using the equation: $R_t = 100*ln(P_t/P_{t-1})$. The proxy of volatility is the estimate generated using daily high and low prices similar to Parkinson (1980). Sample period goes from 1 January 1999 to 23 September 2014.

## 3.5 Preliminary results

The full wheat returns set used for the preliminary analysis runs from 1 January 1999 to 23 September 2013. The first sample covers the period 1 January 1999 to 7 July 2008 while the second sample starts from 8 July 2008 to 23 September 2013. Wheat data for the one-year period from 24 September 2013 to 23 September 2014 was set aside for out-of-sample simulation analysis and validation of the trading rules developed with data up to 23 September 2013.

### *3.5.1. Daily Seasonality*

Table 3.1 shows daily summary returns statistics in Panels A, B and C, for the full sample, the first and the second samples, respectively. Evidence of non-normality of the data is confirmed using Jacque-Berra tests. Non-parametric methods are typically suitable in the case of non-normal data. However, in the case of the parametric GARCH extensions, the research used robust standard errors consistent with Bollerslev and Wooldridge (1992) to

guarantee validity of the findings. As such both parametric and non-parametric approaches could be used in this study.

**Table 3.1: Summary statistics for weekdays**

| | Min | Max | Mean | Median | St. dev. | JB Test | KW Test | Levene's Test |
|---|---|---|---|---|---|---|---|---|
| *Panel A: All returns* | | | | | | | | |
| All days | -8.8831 | 10.208 | 0.0774 | 0.0000 | 1.2396 | 1508.9*** | 13.185** | 1.3192 |
| Monday | -3.1104 | 4.7520 | 0.1999 | 0.1192 | 1.2536 | [0.0000] | [0.0104] | [0.2603] |
| Tuesday | -8.8831 | 10.208 | -0.0685 | 0.0000 | 1.3391 | | | |
| Wednesday | -4.0822 | 4.7989 | 0.0487 | 0.0000 | 1.2036 | | | |
| Thursday | -4.7147 | 4.4913 | 0.1054 | 0.0722 | 1.2291 | | | |
| Friday | -5.1293 | 5.5350 | 0.1134 | 0.0000 | 1.1507 | | | |
| *Panel B: First sample* | | | | | | | | |
| All days | -8.8831 | 10.208 | 0.1151 | 0.0000 | 1.2233 | 2045.7*** | 2.9628 | 0.8110 |
| Monday | -3.1104 | 4.4687 | 0.1585 | 0.0000 | 1.2126 | [0.0000] | [0.5641] | [0.5180] |
| Tuesday | -8.8831 | 10.208 | 0.0091 | 0.0000 | 1.3894 | | | |
| Wednesday | -3.1307 | 4.7989 | 0.1378 | 0.0561 | 1.2107 | | | |
| Thursday | -4.7147 | 4.4913 | 0.1232 | 0.0738 | 1.1753 | | | |
| Friday | -4.3485 | 5.5350 | 0.1533 | 0.0000 | 1.1036 | | | |
| *Panel C: Second sample* | | | | | | | | |
| All days | -5.1293 | 4.7520 | 0.0218 | 0.0000 | 1.2617 | 66.446*** | 18.020*** | 1.2012 |
| Monday | -2.8261 | 4.7520 | 0.2583 | 0.3041 | 1.3099 | [0.0000] | [0.0012] | [0.3085] |
| Tuesday | -5.0294 | 4.0426 | -0.1852 | -0.0879 | 1.2533 | | | |
| Wednesday | -4.0822 | 3.5021 | -0.0835 | -0.1813 | 1.1831 | | | |
| Thursday | -3.5887 | 3.7458 | 0.0780 | 0.0299 | 1.3091 | | | |
| Friday | -5.1293 | 3.3594 | 0.0552 | 0.0647 | 1.2163 | | | |

Descriptive statistics for weekday SAFEX wheat returns are expressed in percentages. Panel A includes all the returns for the entire dataset from January 1999 to September 2013. Panel B is for the first sample from the start of the series up to 7 July 2008 and Panel C is for the rest of the wheat returns dataset up to September 2013. JB Test is the Jacque Berra test of normality Kruskal-Wallis test (KW test) compares the equality of medians of the daily wheat returns. Levene's test compares the variances by weekday within each panel. Significance levels at 1%, 5% and 10% are represented by ***, ** and *, respectively.

In the case of the full sample (Panel A), the mean for the wheat series for all the days combined is 0.0774%. Out of all the weekdays, Mondays have the highest mean wheat returns (0.1999%). In Schwert (2003) and Rubinstein (2001), higher returns on Monday have been attributable to Monday returns actually spanning three days (Saturday, Sunday and Monday). There are also greater risks associated with these three days compared to any one of the ordinary weekdays. The higher Monday returns therefore allow compensation for

the higher risks and opportunity costs of the three days that are all closed off together on a Monday.

Every other weekday except Tuesday has positive mean returns. Panels B and C present a similar pattern with highest mean returns on Mondays and lowest mean returns detected on Tuesdays. These results are in contrast with those obtained by Viljoen (2004), who used data for the period 1997 to 2002, finding all mean daily wheat returns positive with Thursdays being the weekdays with the highest wheat mean returns and Friday the day with the lowest mean returns. In this study, variance of returns is highest on Tuesday, the day with the lowest or negative returns. It should be noted that the differences in findings may be due to the different periods sampled by the two studies given the apparent change in returns and volatility behaviour over time. Evidence of regime dissimilarities is demonstrated by the differences between Sample A and Sample B. For example, in Sample A, there is evidence of equality of daily median returns while with Sample B, the KW test suggests different trading days have different median returns. By using the regime dummy in the parametric analysis, the study finds evidence of time-varying and potentially dynamic market efficiencies in the SAFEX wheat contract. Changes over time explain why an earlier study (Viljoen, 2004) would have different results.

The Kruskal and Wallis (1952) (*KW test*) which involves a non-parametric procedure is used to ascertain the equality of medians of daily returns. The KW test is carried out on returns for the five days from Monday to Friday for each panel (A to C). A rank statistic is generated that follows a $\chi^2$ distribution with the number of observations similar to the degrees of freedom. The KW statistic is significant only in Panels A (full sample) and C (second sample). This entails “day-of-the-week” seasonality in the respective wheat returns and highlights the influence of the second sample on the full sample. The test of equality of variances is carried

out with the Browne-Forsythe Modified statistic or Levene's statistic. The inferential Levene's test has the null hypothesis that population variances in two or more groups or samples are homogeneous or equal (Levene, 1960). There is no evidence of differences in wheat variances among weekdays in any of the panels. This result is in line with findings in Viljoen (2004). It is important to note the magnitude of maximum and minimum daily prices in the analysed samples and that it ranges respectively from 10.208% (first sample) to -8.883% (first sample).

### *3.5.2. Holiday effects*

The effects of another daily anomaly documented in the commodity financial literature, that is, the "holiday effect", were also tested. The South African calendar was used to identify all the days that were public holidays since 1999 up to September 2013. A dummy column, where a one was used to signify a holiday, was constructed, a zero representing a day that was not a holiday, in that same column. Another dummy column for pre-holidays, that is, one day before a holiday, was also constructed in the same way as for holidays. In that column, non pre-holidays were represented by a zero. One day after a holiday was our definition of a post-holiday, and a dummy for such days was created similar to the case of holidays above. Non post-holidays had a zero in the column for post-holidays. These dummies were then incorporated into the econometric model as shown in the methodology section.

Fabozzi et al. (1994) examined pre-holiday effects on prices of selected commodity futures contracts (including wheat) in the USA as well as 12 contracts from the global markets. Pre-holiday returns were found to be higher than non-holiday returns. In the case of post-holidays in the USA, Fabozzi et al. (1994) did not find any effects if the futures market was not operating (exchange-closed holiday) during the holiday.[16] Evidence was found of significantly positive returns on post-holidays where the exchange was open over the

[16] Of the 20 USA holidays analyzed by Fabozzi et al. (1994), futures markets were closed on 9 holidays while open on the other 11 holidays.

holidays.[17] In this chapter, SAFEX wheat returns were decomposed into pre-holiday returns, post-holiday returns and the rest of the returns. All the holidays between 1 January 1999 and 23 September 2013 were taken into account.

**Table 3.2: SAFEX Pre and Post-holiday Analysis**

| | | Mean | Median | St. dev. | KW Test | | Levene's Test | |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Non-parametric approach* | | | | | | | | |
| *Full return series* | | | | | | | | |
| | Pre-holidays | 0.1549 | 0.0000 | 1.2804 | | | | |
| | Non pre-holidays | 0.0748 | 0.0000 | 1.2383 | 0.1936 | [0.6599] | 0.0395 | [0.8426] |
| | Post-holidays | 0.1117 | 0.0652 | 1.3919 | | | | |
| | Non post-holidays | 0.0762 | 0.0000 | 1.2338 | 0.4686 | [0.4936] | 1.2582 | [0.2621] |
| *First sample* | | | | | | | | |
| | Pre-holidays | 0.0001 | 0.0000 | 1.1904 | | | | |
| | Non pre-holidays | 0.1189 | 0.0000 | 1.2245 | 0.1680 | [0.6819] | 0.2797 | [0.5970] |
| | Post-holidays | 0.1271 | 0.0625 | 1.0076 | | | | |
| | Non post-holidays | 0.1146 | 0.0000 | 1.2306 | 0.0658 | [0.7975] | 2.0474 | [0.1526] |
| *Second sample* | | | | | | | | |
| | Pre-holidays | 0.3702 | 0.1590 | 1.3820 | | | | |
| | Non pre-holidays | 0.0094 | 0.0000 | 1.2561 | 1.4008 | [0.2366] | 0.6391 | [0.4242] |
| | Post-holidays | 0.0904 | 0.0885 | 1.8078 | | | | |
| | Non post-holidays | 0.0192 | 0.0000 | 1.2370 | 0.5769 | [0.4475] | 12.307*** | [0.0005] |

| *Panel B: Parametric approach* | | |
|---|---|---|
| $\alpha$ | 0.0978*** | [0.0012] |
| $\beta_{1h}$ | 0.0958*** | [0.0000] |
| $\beta_{2h}$ | 0.0209 | [0.2570] |
| $\gamma_1$ | 0.0981 | [0.4392] |
| $\gamma_2$ | 0.0362 | [0.7676] |
| $\zeta$ | -0.0833* | [0.0722] |
| $R^2$-adjusted. | 0.0098 | |

SAFEX pre and post-holiday returns are analyzed using non-parametric and parametric approaches. We take into account the full wheat return series (1/1/1999 to 23/9/2013), the first sample (1/1/1999 to 7/7/2008) and the second sample (8/7/2008 to 23/9/2013). Panel A shows the KW test (the Levene's test) that compares the equality of the medians (the variances) among returns on pre-holidays against non pre-holidays and post-holidays against non-post holidays. Panel B presents the estimation of the equation

$$R_t = \alpha + \beta_{1h}R_{t-1} + \beta_{2h}R_{t-2} + \gamma_1 D_{pre} + \gamma_2 D_{post} + \zeta S_t + \varepsilon_t$$

In the parametric test, comparison of differences between the first and the second sample is done by way of the dummy $S_t$, where $S_t$ takes the value 1 in the second sample, and zero elsewhere. P-values are presented in parenthesis. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

[17] The higher returns after exchange-open holidays (post-holidays) were justified on the positive sentiments attributable to the holidays.

Panel A of Table 3.2 reports means and variances for pre-holidays compared to non pre-holidays and post-holidays against non post-holidays. The full return series and the second sample present similar results with respective wheat mean returns on pre-holidays being higher than returns on non pre-holidays, post-holidays and non post-holidays. However, there is no evidence of difference in median returns on pre-holidays as opposed to non pre-holidays or post-holidays compared to non post-holidays. In the second sample, there is evidence at the 1% significance level of differences in the variances of returns between post-holidays compared to days that are not post-holidays. Additionally, the KW test (the Levene's test) was used to determine if there was equality in medians (variances) of wheat returns on pre-holidays compared to post-holidays. The results, which are not presented in the table, do not provide evidence of significant differences between medians (variances) of wheat returns on pre compared to post-holidays on SAFEX.

In order to determine wheat mean return differences amongst pre, post and non-holidays using parametric approaches, a dummy-augmented regression model was estimated. To do this, pre-holiday and post-holiday wheat returns were examined using dummies in a mean return equation. The relation used is presented below:

$$R_t = \alpha + \beta_{1h} R_{t-1} + \beta_{2h} R_{t-2} + \gamma_1 D_{pre} + \gamma_2 D_{post} + \zeta S_t + \varepsilon_t \qquad (3.7)$$

The parameters to be estimated are $\beta_{1h}, \beta_{2h}, \gamma_1, \gamma_2$. The pre and post-holiday dummies for the SAFEX market are respectively $D_{pre}$ and $D_{post}$. $S_t$ is the dummy for the two samples separated on 7 July 2008 and assumes the value 1 in the second sample and zero otherwise, as before. The results of this regression are presented in Panel B of Table 3.2 for ease of comparison with the non-parametric results in Panel A. The wheat returns autocorrelation tests (not reported in the paper), show autocorrelation significant at the first and second lags and justify the inclusion of two lags in the mean equation. The coefficients of the dummies for pre-holidays and post-holidays are not significantly different from zero,

indicating that pre-holidays and post-holidays mean returns are not significantly different from non-holidays on SAFEX. This finding is consistent with our non-parametric approach and with that of Viljoen (2004) who found that South African holidays do not have an impact on maize and wheat returns. Furthermore, the dummy for the regimes ($S_t$) is negative and significant at the 10% level, suggesting it was prudent to split the samples.

Next, the effect on SAFEX wheat returns of holidays on Euronext/Liffe and the KCBT futures market was investigated. The reason is that Euronext/Liffe and KCBT are trading hard wheat with highly comparable features to SAFEX-traded wheat. Hard red wheat is used for bread production and has high protein content comparable to South African produced wheat. Euronext/Liffe is the largest commodities market in the European Union area while KCBT is a subsidiary of the Chicago Mercantile Exchange (CME) that trades the highest volumes of hard red wheat in the USA. The results are presented in Table 3.3 and both non-parametric and parametric analysis has been carried out.

A regression is carried out to take into account the effects of Euronext and KCBT holidays on SAFEX wheat returns. The results are presented in Panel B of Table 3.3. The regression is presented as follows:

$$R_t = \alpha + \beta_{1g} R_{t-1} + \beta_{2g} R_{t-2} + \lambda_1 D_{eu} + \lambda_2 D_{kcbt} + \tau S_t + \varepsilon_t \qquad (3.8)$$

Euronext/Liffe and KCBT have the dummies $D_{eu}$ and $D_{kcbt}$, respectively. Parameters estimated are $\beta_{1g}, \beta_{2g}, \lambda_1, \lambda_2$. $S_t$ is the dummy for the samples or regimes already described.

Panel A of Table 3.3 reports means and variances of SAFEX wheat returns on Euronext/Liffe and KCBT holidays for the full returns set, the first sample, and the second sample. Evidence is found that SAFEX wheat returns are abnormally high on KCBT holidays at the 5% level in the full return series and in the second sample. In the case of Euronext holidays,

SAFEX returns are abnormally high only in the second sample at the 10% level. The Levene's test does not detect any differences in variances in the case of returns on both KCBT and Euronext holidays.

**Table 3.3: Influence on SAFEX of Euronext/Liffe and KCBT holidays**

| | | Mean | Median | St. dev. | KW Test | | Levene's Test | |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Non-parametric approach* | | | | | | | | |
| *Full return series* | | | | | | | | |
| | Euronext holiday returns | 0.1493 | 0.0000 | 1.0604 | 0.0562 | [0.8127] | 1.5149 | [0.2185] |
| | Non-Euronext returns | 0.0743 | 0.0000 | 1.2317 | | | | |
| | KCBT holiday returns | 0.3284 | 0.3314 | 1.2815 | 4.8958** | [0.0269] | 0.1033 | [0.7479] |
| | Non-KCBT returns | 0.0685 | 0.0000 | 1.2373 | | | | |
| *First sample* | | | | | | | | |
| | Euronext holiday returns | -0.1109 | 0.0000 | 0.9066 | 1.3843 | [0.2394] | 2.5632 | [0.1096] |
| | Non-Euronext returns | 0.1186 | 0.0000 | 1.2311 | | | | |
| | KCBT holiday returns | 0.2659 | 0.0846 | 1.2841 | 0.6247 | [0.4293] | 0.5321 | [0.4658] |
| | Non-KCBT returns | 0.1096 | 0.0000 | 1.2211 | | | | |
| *Second sample* | | | | | | | | |
| | Euronext holiday returns | 0.5567 | 0.3483 | 1.1716 | 3.2149* | [0.0730] | 0.0024 | [0.9613] |
| | Non-Euronext returns | 0.0084 | 0.0000 | 1.2302 | | | | |
| | KCBT holiday returns | 0.4253 | 0.4362 | 1.2877 | 5.6672** | [0.0173] | 0.4350 | [0.5097] |
| | Non-KCBT returns | 0.0078 | 0.0000 | 1.2590 | | | | |
| *Panel B: Parametric approach* | | | | | | | | |
| $\alpha$ | 0.0922*** [0.0021] | | | | | | | |
| $\beta_{1g}$ | 0.0955*** [0.0000] | | | | | | | |
| $\beta_{2g}$ | 0.0217 [0.2386] | | | | | | | |
| $\lambda_1$ | 0.0396 [0.8080] | | | | | | | |
| $\lambda_2$ | 0.2611** [0.0366] | | | | | | | |
| $\tau$ | -0.0825* [0.0748] | | | | | | | |
| $R^2$-adjusted | 0.0111 | | | | | | | |

The influence of Euronext/Liffe and KCBT holidays is analyzed using non-parametric and parametric approaches. We also take into account the full return series (1/1/1999 to 23/9/2013), the first sample (1/1/1999 to 7/7/2008) and the second sample (8/7/2008 to 23/9/2013). Panel A shows the KW test (the Levene's test) that compares the equality of the medians (the variances) among wheat returns during Euronext and KCBT holidays as opposed to trading days that are not these respective holidays. Panel B presents an estimation of the equation

$$R_t = \alpha + \beta_{1g} R_{t-1} + \beta_{2g} R_{t-2} + \lambda_1 D_{eu} + \lambda_2 D_{kcbt} + \tau S_t + \varepsilon_t$$

In the parametric test, comparison of differences between the first and the second sample is done by way of the dummy $S_t$, where $S_t$ takes the value 1 in the second sample, and zero elsewhere. P-values are presented in parenthesis. Significance at 1%, 5% and 10% are indicated by ***, ** and *, respectively.

As shown in Panel B of Table 3.3, SAFEX wheat returns on KCBT holidays are positive and significant at the 5% level. Therefore, SAFEX wheat returns increase by 0.2611% on those days on which KCBT is closed due to a holiday. This confirms an association between KCBT holidays and the pattern of SAFEX wheat returns. Note that the sample dummy $S_t$ is also negative and significant at 10%, justifying again the need for splitting the original sample.

## 3.6 Volatility Models

In this section, GARCH models with dummies are introduced allowing comparison of returns and volatility across weekdays while enabling statistical significance of seasonality to be determined. Table 3.4 presents the results for the GARCH before and after augmentation with daily and regime dummies.

The most appropriate values of the GARCH(*p,q*) are *p=1* and *q=1*.[18] The table thus presents the parameters of the simple GARCH(1,1) model for the wheat returns data as well as the parameters for equations (3.1) and (3.2) above. The coefficients of GARCH(*p,q*) are significant and a test is carried out to evaluate the extent of persistence of shocks in the GARCH-related coefficients. This test involves evaluating the sum of $\xi + \eta$ (GARCH coefficients) as suggested in Bollerslev (1986). Where the sum of these GARCH coefficients is close to 1, high levels of volatility persistence exist (Bollerslev, 1988). This is the case with the simple GARCH (first column in Table 3.4), as opposed to the dummy-augmented GARCH (second column in Table 3.4), which has a much lower sum of GARCH coefficients. Persistence in volatility suggests shocks to returns have a longer-lasting effect.

[18] Different values of *p* and *q* were tested for the most appropriate specification. The search commenced with the values *p=4* and *q=4* before reducing these values iteratively. The model with the minimum AIC but the maximum log likelihood was preferred. Fitted models are checked to ensure there were no remaining ARCH effects. To provide for autocorrelation in the mean equation of the GARCH extensions, autoregressive lags were iteratively included from 1 to 4. In all the extensions, lags 3 and 4 were found not significant. Lags 1 and 2 are therefore reported in the autoregressive structure of the mean relations of the results.

The augmented GARCH has better explanatory power of conditional variance while being less susceptible to the persistence in volatility. Following Bollerslev and Wooldridge (1992), in the derivation of standard errors, the consistent covariance estimation of heteroskedasticity is specified as the residuals were not fully conditionally normally distributed.

**Table 3.4: GARCH model with daily augmentation**

| GARCH Model | | | Dummy Augmented GARCH Model | | |
|---|---|---|---|---|---|
| | | | *Mean equation* | | |
| $\alpha$ | 0.0762*** | [0.0001] | $\alpha$ | 0.2042*** | [0.0002] |
| $\beta_1$ | 0.1103*** | [0.0000] | $\beta_1$ | 0.1091*** | [0.0000] |
| $\beta_2$ | 0.0230 | [0.2666] | $\beta_2$ | 0.0194 | [0.3848] |
| | | | $\lambda_1$ | -0.2380*** | [0.0012] |
| | | | $\lambda_2$ | -0.1321* | [0.0564] |
| | | | $\lambda_3$ | -0.0670 | [0.3503] |
| | | | $\lambda_4$ | -0.0678 | [0.3005] |
| | | | $\varsigma$ | -0.0859** | [0.0432] |
| | | | $\kappa$ | 0.1554*** | [0.0028] |
| | | | *Variance equation* | | |
| $\Delta$ | 0.0657*** | [0.0000] | $\delta$ | 1.3156*** | [0.0000] |
| $\xi$ | 0.1377*** | [0.0000] | $\xi$ | 0.1114*** | [0.0000] |
| $\eta$ | 0.8264*** | [0.0000] | $\eta$ | 0.5503*** | [0.0000] |
| | | | $\theta_1$ | -0.3859 | [0.1537] |
| | | | $\theta_2$ | -0.8018*** | [0.0000] |
| | | | $\theta_3$ | -0.6057*** | [0.0004] |
| | | | $\theta_4$ | -0.7646*** | [0.0000] |
| | | | $\tau$ | -0.2123*** | [0.0005] |
| | | | $\pi$ | -0.8656*** | [0.0000] |
| | | | *Diagnostics* | | |
| LL | -4604.9 | | LL | -4759.3 | |
| $\xi+\eta$ | 0.9641 | | $\xi+\eta$ | 0.6617 | |
| Q(5) for $\varepsilon_t / h_t^{0.5}$ | 2.8595 | | Q(5) for $\varepsilon_t / h_t^{0.5}$ | 3.3382 | |
| Q(5) for $\varepsilon_t^2 / h_t$ | 1.3013 | | Q(5) for $\varepsilon_t^2 / h_t$ | 46.275 | |

Maximum likelihood estimation of the GARCH with and without daily dummies is presented in this table. The p-values are shown in parenthesis. LL gives the log-likelihood value and $Q(\cdot)$ is the $Q$ statistic for serial correlation. Significance levels at 1%, 5% and 10% are depicted by ***, ** and *, respectively. The GARCH model of the first column has been estimated using equations (3.1) and (3.2). The dummy-augmented GARCH model of the second column has used equations (3.3) and (3.4).

The first column of Table 3.4 presents the results for the GARCH model. All the parameters of the model are significant at the 1% level. For the dummy-augmented GARCH model, equations (3) and (4) were estimated. The second column of the table presents the results. It

is noted in Table 3.4 that all the typical GARCH parameters of the dummy-augmented model are significant suggesting the data supports the specification. Although the persistence in volatility is lower, the parameters of the non-augmented model are not quantitatively affected by the inclusion of the dummy variables. Mean returns tend to be the highest on Mondays and lowest on Tuesdays. In the variance equation, all the dummy coefficients for Wednesdays, Thursdays and Fridays are negative at the 1% level, implying less volatility than on Mondays and Tuesdays.

The sample dummy, $S_t$ is significant in both the mean and variance equations at the 5% and 1% levels, respectively, indicating a decrease in wheat returns and volatility after the crisis. In general, the second sample was associated with lower wheat return levels when compared to the first sample. It should be noted that prices of both commodities and equities on most financial markets started increasing consistently from around 2003 right up to the peak of the global financial crisis. In the case of wheat, 7 July 2008 marked the peak of the "bull run" and prices started then either declining or fluctuating moderately thereafter. This decreasing trend in both returns and fluctuations is what explains the negative sample dummy for the second sample. Findings in Table 3.4 confirm SAFEX trading on days coinciding with KCBT holidays has a positive and additional return of 0.1554% and less volatility than the rest of the days. In the variance relation of the augmented GARCH, KCBT holidays are significantly negative at the 1 % level.

## 3.7 Robustness checks

To check the consistency of the analysis, some robustness checks were conducted. To do so, alternative GARCH models have been estimated. In particular, the daily dummy-augmented APARCH model has been estimated with equations (3.3) and (3.5), while the GJR GARCH solution is generated from equations (3.3) and (3.6). Furthermore, in order to

identify the potential of seasonal effects through the year, combined daily and monthly seasonality analysis is performed using GARCH, APARCH and GJR GARCH models.

### *3.7.1. Alternative GARCH Models*

The results of estimations of daily dummy-augmented APARCH and GJR GARCH models are shown in Table 3.5. Key parameters of the two alternative GARCH models are all significant suggesting the specifications are supported by the data.

**Table 3.5: Results for the APARCH and GJR GARCH models**

| | APARCH Model | | GJR GARCH Model | |
|---|---|---|---|---|
| *Mean Equation* | | | | |
| $\alpha$ | 0.2059*** | [0.0001] | 0.2076*** | [0.0001] |
| $\beta_1$ | 0.1043*** | [0.0000] | 0.1044*** | [0.0000] |
| $\beta_2$ | 0.0237 | [0.2838] | 0.0224 | [0.3157] |
| $\lambda_1$ | -0.2503*** | [0.0005] | -0.2461*** | [0.0008] |
| $\lambda_2$ | -0.1239* | [0.0679] | -0.1248* | [0.0723] |
| $\lambda_3$ | -0.0728 | [0.3003] | -0.0704 | [0.3287] |
| $\lambda_4$ | -0.0651 | [0.3143] | -0.0645 | [0.3282] |
| $\varsigma$ | -0.0857** | [0.0419] | -0.0850** | [0.0470] |
| $\kappa$ | 0.1587*** | [0.0032] | 0.1610*** | [0.0042] |
| *Variance Equation* | | | | |
| $\Delta$ | 1.3196*** | [0.0001] | 1.3127*** | [0.0000] |
| $\xi$ | 0.1162*** | [0.0000] | 0.1137*** | [0.0011] |
| $\eta$ | 0.5537*** | [0.0000] | 0.5496*** | [0.0000] |
| $\gamma$ | -0.0071 | [0.9404] | -0.0229 | [0.6445] |
| $\theta_1$ | -0.3612 | [0.2664] | -0.3877 | [0.1552] |
| $\theta_2$ | -0.7973*** | [0.0003] | -0.8102*** | [0.0000] |
| $\theta_3$ | -0.5924** | [0.0101] | -0.6067*** | [0.0005] |
| $\theta_4$ | -0.7641*** | [0.0006] | -0.7727*** | [0.0000] |
| $\tau$ | -0.2105** | [0.0192] | -0.2082*** | [0.0009] |
| $\pi$ | -0.8897*** | [0.0000] | -0.8511*** | [0.0000] |

Parameters for alternative models are presented here. The two models presented have augmentation with daily dummies. The p-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and *, respectively. The dummy-augmented APARCH and GJR GARCH models in this table have used the mean relation in equation (3). Variance equations for the APARCH and GJR GARCH are given in equations (5) and (6), respectively.

The asymmetry effect captured by the sign of the parameter $\gamma$ is not significant for both the APARCH and GJR GARCH estimations. Thus, a drop in prices in respect of the wheat contract on SAFEX does not have a different impact compared to an increase in prices. This

result disagrees with Mashamaite and Moholwa (2005) who found evidence of asymmetry in SAFEX wheat contracts from 1997 to 2003. On the other hand, coefficients for returns on Mondays are significantly positive in the APARCH and GJR GARCH, and wheat returns on Tuesdays remain consistently significantly negative in both models. The sample dummy is negative and significant at the 5% level in the mean equations of both the GJR GARCH and APARCH models; the implication is there are lower wheat returns in the second sample compared to the first. Wheat returns on KCBT holidays are significant at the 1% level in both the GJR GARCH and APARCH estimations.

Regarding the variance equations, both the APARCH and GJR GARCH models suggest less volatility in the second sample and less volatility on Wednesdays, Thursdays and Fridays. These two models also confirm that volatility on KCBT holidays is lower than volatility on the rest of the days.

### *3.7.2. Daily and Monthly Seasonality Analysis*

Combined daily and monthly seasonality analysis was estimated using the GARCH, APARCH and GJR GARCH relations. The mean equation for the GARCH extensions which allows for testing daily, monthly, holiday and the structural break effects (linked to the global economic crisis) is given as

$$R_t = \alpha + \sum_{i=1}^{m} \beta_i R_{t-i} + \sum_{j=1}^{4} \lambda_j D_{j,t} + \sum_{k=1}^{11} \phi_l M_{k,t} + \zeta S_t + \kappa H_t + \varepsilon_t \qquad (3.9)$$

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t)$$

$M_{k,t}$ is the monthly dummy which takes the value 1 for the months February to December and zero otherwise. $D_{j,t}$, $S_t$ and $H_t$ are the daily, regime and holiday dummies respectively taking the values 1 as defined above and zero elsewhere. All the dummies are also included in the variance equations of the GARCH, APARCH and GJR GARCH models as follows:

$$h_t = \delta + \sum_{i=1}^{p} \xi_i \varepsilon_{t-i}^2 + \sum_{l=1}^{q} \eta_l h_{t-l} + \sum_{j=1}^{4} \theta_j D_{j,t} + \sum_{k=1}^{11} \varphi_k M_{k,t} + \tau S_t + \pi H_t \quad (3.10)$$

$$\sigma_t^{\kappa} = \delta + \sum_{i=1}^{q} \xi_i \left( \left| \varepsilon_{t-i} \right| - \gamma_i \varepsilon_{t-i} \right)^{\kappa} + \sum_{j=1}^{p} \eta_j \sigma_{t-j}^{\kappa} + \sum_{n=1}^{4} \theta_n D_{n,t} + \sum_{m=1}^{11} \varphi_m M_{m,t} + \tau S_t + \pi H_t \quad (3.11)$$

$$\sigma_t^2 = \delta + \sum_{i=1}^{p} \xi_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \eta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- + \sum_{n=1}^{4} \theta_n D_{n,t} + \sum_{m=1}^{11} \varphi_m M_{m,t} + \tau S_t + \pi H_t \quad (3.12)$$

Equations (3.10), (3.11) and (3.12) enable volatility estimation that accounts for daily plus monthly seasonality. Table 3.6 gives the results of the mean equations for the three GARCH extensions. Mean equation estimations in Table 3.6 provide evidence that Mondays are significant and positive while Tuesdays are negative and significant.

**Table 3.6: Results for daily plus monthly seasonality**

| | GARCH Model | | APARCH Model | | GJR GARCH Model | |
|---|---|---|---|---|---|---|
| *Mean Equation* | | | | | | |
| $\alpha$ | 0.2393** | [0.0487] | 0.2395** | [0.0387] | 0.2403** | [0.0478] |
| $\beta_1$ | 0.1018*** | [0.0000] | 0.0993*** | [0.0000] | 0.1002*** | [0.0000] |
| $\beta_2$ | 0.0121 | [0.5479] | 0.0152 | [0.4718] | 0.0140 | [0.4950] |
| $\lambda_1$ | -0.2407*** | [0.0051] | -0.2465*** | [0.0038] | -0.2429*** | [0.0054] |
| $\lambda_2$ | -0.1194 | [0.1468] | -0.1159 | [0.1601] | -0.1182 | [0.1599] |
| $\lambda_3$ | -0.0682 | [0.3759] | -0.0703 | [0.3619] | -0.0688 | [0.3812] |
| $\lambda_4$ | -0.0584 | [0.4702] | -0.0567 | [0.4850] | -0.0558 | [0.4991] |
| $\phi_1$ | -0.1269 | [0.3185] | -0.1281 | [0.3050] | -0.1288 | [0.3167] |
| $\phi_2$ | 0.0270 | [0.8397] | 0.0277 | [0.8310] | 0.0281 | [0.8346] |
| $\phi_3$ | -0.0959 | [0.4494] | -0.0973 | [0.4384] | -0.0970 | [0.4492] |
| $\phi_4$ | 0.1518 | [0.2394] | 0.1518 | [0.2337] | 0.1529 | [0.2419] |
| $\phi_5$ | -0.0584 | [0.6489] | -0.0697 | [0.5788] | -0.0674 | [0.6009] |
| $\phi_6$ | 0.1316 | [0.3041] | 0.1298 | [0.2989] | 0.1298 | [0.3138] |
| $\phi_7$ | -0.0027 | [0.9857] | -0.0080 | [0.9569] | 0.0098 | [0.9496] |
| $\phi_8$ | -0.1195 | [0.3831] | -0.1172 | [0.3776] | -0.1197 | [0.3836] |
| $\phi_9$ | -0.0240 | [0.8567] | -0.0395 | [0.7660] | -0.0354 | [0.7944] |
| $\phi_{10}$ | -0.1877 | [0.1377] | -0.1977 | [0.1050] | -0.1968 | [0.1167] |
| $\phi_{11}$ | -0.0676 | [0.6104] | -0.0575 | [0.6565] | -0.0619 | [0.6380] |
| $\varsigma$ | -0.0929** | [0.0499] | -0.0941* | [0.0527] | -0.0939* | [0.0531] |
| $\kappa$ | 0.1794* | [0.0666] | 0.1822* | [0.0759] | 0.1840* | [0.0610] |

Parameters in the mean equation for GARCH extensions capturing daily plus monthly seasonality are presented here. The p-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively. The dummy-augmented GARCH, APARCH and GJR GARCH models in this table have used the mean relation in equation (9). Variance equations for the GARCH, APARCH and GJR GARCH are provided respectively by equations (10), (11) and (12).

Coefficients for wheat returns on Mondays and KCBT holidays are significantly positive at 5% and 10% levels, respectively. On the other hand, Tuesdays are significant and negative

in the mean equation at 1% level. None of the monthly dummies are significant in the mean equation. The sample dummy $S_t$ is negative and significant at 5 % in the GARCH's mean equation while significant and negative at 10% level in both mean equations of the APARCH and GJR GARCH.

Volatility estimations for equations (3.10), (3.11) and (3.12) are presented in Table 3.7.

**Table 3.7: Results for daily plus monthly seasonality (Continued)**

| | GARCH Model | APARCH Model | GJR GARCH Model |
|---|---|---|---|
| *Variance Equation* | | | |
| $\delta$ | 1.3294*** [0.0000] | 1.3338*** [0.0001] | 1.3287*** [0.0000] |
| $\xi$ | 0.1234*** [0.0000] | 0.1227*** [0.0000] | 0.1217*** [0.0000] |
| $\eta$ | 0.5559*** [0.0000] | 0.5595*** [0.0000] | 0.5560*** [0.0000] |
| $\gamma$ | | 0.0093 [0.8538] | -0.0060 [0.8306] |
| $\theta_1$ | -0.3677*** [0.0044] | -0.3415* [0.0639] | -0.3661*** [0.0059] |
| $\theta_2$ | -0.6806*** [0.0000] | -0.6744*** [0.0014] | -0.6805*** [0.0000] |
| $\theta_3$ | -0.4949*** [0.0000] | -0.4892*** [0.0047] | -0.4944*** [0.0001] |
| $\theta_4$ | -0.6667*** [0.0000] | -0.6629*** [0.0006] | -0.6684*** [0.0000] |
| $\varphi_1$ | -0.3179*** [0.0040] | -0.2984 [0.1078] | -0.2884** [0.0103] |
| $\varphi_2$ | -0.2335** [0.0199] | -0.2052 [0.1944] | -0.2096** [0.0397] |
| $\varphi_3$ | -0.3862*** [0.0005] | -0.3685* [0.0578] | -0.3649*** [0.0012] |
| $\varphi_4$ | -0.2818*** [0.0052] | -0.2556 [0.1426] | -0.2551** [0.0121] |
| $\varphi_5$ | -0.3342*** [0.0022] | -0.3267* [0.0734] | -0.3200*** [0.0038] |
| $\varphi_6$ | -0.2683** [0.0110] | -0.2490 [0.1548] | -0.2492** [0.0193] |
| $\varphi_7$ | -0.0416 [0.6569] | -0.0060 [0.9616] | -0.0180 [0.8480] |
| $\varphi_8$ | -0.1664* [0.0971] | -0.1501 [0.3339] | -0.1523 [0.1345] |
| $\varphi_9$ | -0.3681*** [0.0005] | -0.3365* [0.0797] | -0.3253*** [0.0024] |
| $\varphi_{10}$ | -0.2830** [0.0062] | -0.3044* [0.0910] | -0.2916*** [0.0050] |
| $\varphi_{11}$ | -0.2615** [0.0140] | -0.2537 [0.1054] | -0.2628** [0.0136] |
| $\tau$ | -0.1628*** [0.0000] | -0.1664*** [0.0038] | -0.1611*** [0.0000] |
| $\pi$ | -0.6707*** [0.0000] | -0.6992*** [0.0000] | -0.6677*** [0.0000] |

Parameters in the variance equations capturing daily and monthly seasonality are presented here for three GARCH extensions. The p-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively. The dummy-augmented GARCH, APARCH and GJR GARCH models in this table have used the mean relation in equation (9). Variance equations for the GARCH, APARCH and GJR GARCH are provided respectively by equations (10), (11) and (12).

In the variance equations of the three GARCH models, coefficients from Tuesdays to Fridays are negative and significant at the 1% level, suggesting declining conditional volatility through the week. Coefficients for volatility are significant and negative for all the other months except August in the GARCH, February, March, May, July, August and September in

the APARCH, and August and September in the GJR GARCH model. It is noted that the dummies $S_t$ (sample effect) and $H_t$ (KCBT holiday effect) are significant at 1% in the variance relations of all three GARCH extensions. Finally, the sum of $\xi + \eta$ in Table 3.7 is not very close to one for the three GARCH models suggesting limited persistence in volatility.

In summary, although none of the monthly dummies are significant in the mean equations, the monthly analysis gives robustness to the previous empirical findings. Our results indicate that KCBT-linked returns are robust across the non-parametric analysis, simple linear regression, the GARCH, APARCH and GJR GARCH estimations. Furthermore, returns for Mondays and Tuesdays remain significantly robust across the return equations in the GARCH, APARCH and GJR GARCH and may, together with KCBT holiday returns, therefore be considered for inclusion in potential trading rule strategies based on seasonality. Market anomalies in the wheat contract could be explained as emanating from investor psychology, settlement procedures and bid-ask spread biases.

## 3.8 Trading Rule Analysis

In this section, simulation analysis is performed to study the significance of seasonal effects detected in the previous analysis. Since monthly seasonality did not prove to be robust in the mean return equations, there was no need for a monthly-based trading rule. Trading strategies suggested by empirical findings above point to abnormal returns on Mondays, Tuesdays and KCBT holidays.

For example, in the case of Mondays, the trading strategy consists of opening a long position at the end of trading on Friday which is closed at the end of trading on Monday by taking a short position. This therefore means that investors would hold the position throughout the

weekend only to offset at the end of Monday.[19] The total outcome from the Monday trading strategy is the sum of the Monday profits (557 observations). Following Johnson (2001), this total outcome is compared with the benchmark. In the case of Mondays, the benchmark is established by taking 10,000 sets of possible combinations of 557 randomly selected days among the total sample (2,959 observations). Note that each set in the benchmark represents the profit from trading over 557 days. The Mondays' combined profit is then compared to the benchmark. If the profit from the trading strategy is in the upper tail (Z>+1.96 or return higher than 95th percentile), it is considered significantly better than that which could be earned by chance. While the trading for KCBT holidays also implies opening long positions in the wheat contract, the strategy for Tuesdays is based on taking short positions. In this case, the profit from the strategy on Tuesdays would need to be in the lower tail (Z<-1.96 or return lower than 5th percentile) to be considered significantly better than could be achieved by chance.

Table 3.8 presents the results of the Monte Carlo simulation or repeated resampling technique.

**Table 3.8: Trading Rule Monte Carlo Simulation**

| Parameters | Monday | Tuesday | KCBT Holidays |
|---|---|---|---|
| # observations | 557 | 606 | 102 |
| # observations /Total | 18.82% | 20.48% | 3.45% |
| Trading rule (TR) | 111.34% | -41.49% | 33.50% |
| TR/BHR | 48.60% | -18.11% | 14.62% |
| MTR | 0.200% | -0.068% | 0.328% |
| $P_{i\%}$ | 0.193% | -0.013% | 0.273% |

The *# observations* indicates the number of daily observations in each component of the trading rule strategy and *Total* is the total number of observations, which is 2,959. *TR* is the summation of all the daily returns occurring under each respective strategy, that is, Mondays, Tuesdays and KCBT holidays and *BHR* is the summation of all the daily returns in the full sample and calculates to 229.11% from 1/1/1999 to 23/9/2013. *MTR* is the mean return of the trading rule. $P_{i\%}$ denotes the 95$^{th}$ percentile of the generated series both for the mean return in the strategy (Mondays, KCBT holidays) and the 5$^{th}$ percentile for the Tuesdays component of the strategy.

[19] Empirical evidence confirms only Tuesdays and Mondays have significant movements in returns.

Firstly, it is important to note that a substantial amount of cumulative wheat returns earned during fourteen years is accruing on Mondays (48.60%) and Tuesdays (41.49%) which respectively account for 18.82% and 20.48% of the trading days in the sample. In the case of KCBT holidays, 102 SAFEX trading days coincide with the holidays of the most important wheat futures market in the world. These days only account for 3.45% of all trading days in the sample, but represent 33.50% of the total buy-and-hold return.

Secondly, the analysis compares the daily mean return of each trading rule (MTR) with a proxy for the risk-free rate. In the South African context, this proxy could be the R186 government bond which has about 15 years to maturity (PwC, 2012). This rate averaged 10.25% between 1997 and 2014, calculated to a daily risk-free rate of approximately 0.0004 or 0.04%. In all cases, the daily mean return of any of the three strategies is remarkably higher than the risk-free rate implying the trading rule is financially profitable.

Thirdly, the last row in Table 3.8 presents the outcomes of benchmarking the trading strategies. The daily mean return (MTR) on Mondays, Tuesdays and KCBT holidays are significantly different from returns achieved from trading on a set of randomly selected days. Furthermore, to find out if profitable transactions are achievable with the three trading rules, transaction costs incurred by an investor have been taken into account. Specifically, the bid-ask spread has been accounted for using sampled nearest-to-maturity wheat futures contracts. This has been combined with fees payable for SAFEX clearing and those for the broker. The sum of all the round-trip costs is estimated at 0.148%. Therefore, the Monday,

Tuesday and KCBT holidays trading strategies achieve positive returns both before and after total transaction costs.[20]

Finally, as a robustness test, the same procedure has been repeated in an out of sample period that goes from 24/9/2013 to 23/9/2014, taking into account 203 trading days. These results are provided in Table 3.9. The mean returns for the trading rule are respectively 0.307%, 0.174% and 0.324% for Mondays, Tuesdays and KCBT holidays. These results indicate that the chosen seasonal strategies are profitable after accounting for transaction costs. Furthermore, the last row shows that the profit from Mondays and KCBT holidays are in the upper tail of the distribution of the benchmark while the strategy for Tuesdays, based on taking short positions, is in the lower tail.

**Table 3.9: Out of Sample Trading Rule Monte Carlo Simulation**

| Parameters | Monday | Tuesday | KCBT Holidays |
|---|---|---|---|
| # observations | 40 | 44 | 7 |
| # observations /Total | 19.70% | 21.67% | 3.45% |
| Trading rule (TR) | 12.29% | -7.65% | 2.27% |
| TR/BHR | 159.36% | -99.22% | 29.43% |
| MTR | 0.307% | -0.174% | 0.324% |
| $P_{i\%}$ | 0.067% | -0.055% | 0.155% |

The *# observations* indicates the number of daily observations in each component of the trading rule strategy and *Total* is the total number of observations for the out-of-sample period which are 203. *TR* is the summation of all the daily returns occurring under each respective strategy, that is, Mondays, Tuesdays and KCBT holidays and *BHR* is the total buy-and-hold return of the sample which adds up to 7.71% from 24/9/2013 to 23/9/2014. *MTR* is the mean return of the trading rule. $P_{i\%}$ denotes the 95$^{th}$ percentile of the generated series both for the mean return in the strategy (Mondays, KCBT holidays) and the 5$^{th}$ percentile for the Tuesdays component of the strategy.

Therefore, the three strategies can be considered significantly better than any strategy achieved by chance. Thus, after controlling for round-trip trading costs, the trading rule still

[20] The average bid-ask spread was derived using the nearest-to-maturity contracts of sampled SAFEX wheat prices for random days in years 2009 to 2014. The average spread was R2.17 per ton while the average wheat price in the sample used was R2,810.50 per ton. The spread calculated to 0.077%. Industry experts have put total transaction fees at between R0.50 and R1.00 per ton. We have considered the highest fees, R1.00 for buying (selling) and R1.00 for selling (buying), a total of R2.00 per ton. Using the wheat price of R2,810.50 per ton gives total transaction fees for buying and selling of 0.071%. Total transaction costs are therefore 0.148% (0.077% plus 0.071%).

proves financially profitable. The no-arbitrage conditions are also violated and the SAFEX wheat market does not obey the efficient market hypothesis. Having done all the diagnostics and robustness checks and controlling for bid-ask-spread, these results can be used for policy formulation and trading strategy execution.

## 3.9 Concluding Remarks

In this chapter, the existence of daily and holiday-related seasonality in the SAFEX wheat contract returns and volatility are examined in order to seek market inefficiencies that can be exploited for financial gain. By applying both non-parametric and parametric-based techniques, significant seasonality in the wheat returns and wheat volatility is found on SAFEX. Wheat returns are significantly positive on Mondays and significantly negative on Tuesdays. The pre-holiday and post-holiday effect is not significant in influencing daily wheat returns on SAFEX. However, the holidays on the KCBT are significant and have an abnormally positive effect on SAFEX wheat returns.

Regarding volatility, findings from the study show that Mondays and Tuesdays have higher (positive) volatilities than the rest of the days. It has also been observed that a drop in prices does not have a different impact on SAFEX wheat volatility compared to an increase in prices. Furthermore, all the estimated models indicate a significant decrease in the level of volatility after the economic crisis.

Finally, based on these findings, some trading rules have been developed involving going long on Mondays, short on Tuesdays and long on KCBT holidays. The rules have been compared to the performance of buy-and-hold strategies by way of the Monte Carlo simulation. After taking into account trading costs, the rules achieve better outcomes than trading based on chance. Therefore, these results are of special interest not only for academics but also for SAFEX traders.

# 4 INFORMATION FLOWS ACROSS WHEAT FUTURES MARKETS

## 4.1 Introduction

In international food trade, wheat is the most important commodity. Some figures indicate the prominent role of wheat at the international level: out of the total wheat produced globally, 18% goes into export markets (Taylor & Koo, 2012); around 70% of global wheat output goes directly to human consumption (FAO, 2011); and wheat provides about 20% of total human calorific supply (Atchison, Head, & Gates, 2010). Major global wheat producing regions include the EU (21%), China (17%), India (12%), USA (9%), Russia (4%) and Australia (4%) (CME, 2014). However, when all the countries are taken into account individually, China produces and consumes more wheat than any other country (Zhang, 2008).

The three key wheat categories are *triticum aestivum*, *triticum durum* and *triticum compactum* (Lukow et al., 2006). *Triticum aestivum* is typically known as bread wheat or, sometimes, common wheat (Angus, Bonjean, & Van Ginkel, 2011). *Triticum durum* is identified as durum wheat used in pasta production while *triticum compactum* is a minor wheat category, produced in the Pacific North West of the USA, that includes club wheats known to have low protein content (Bettge, 2009). Bushuk (1997) estimates that 95% of global wheat supplies are *triticum aestivum,* while about 5% are the durum type. *Triticum compactum* comprises less than 1% of total global wheat supplies.[21]

This chapter examines information flows among wheat futures markets located in different continents taking into account their relative market trading times. Specifically, we look at

[21] A table on the classification and identification of wheat is presented in Appendix 4.1

wheat futures information transmission among Zhengzhou Commodity Exchange (ZCE), South African Futures Exchange (SAFEX), Euronext/Liffe and Kansas City Board of Trade (KCBT). We focus on comparable bread wheat futures contracts traded on the four markets. Ordinary bread is derived from high protein wheat while confectionaries and cookies are produced from low protein, soft wheat as shown in Appendix 4.1 (Bushuk, 1997; Lukow et al., 2006).

Three main econometric approaches have been applied to study information flows among the markets: cointegration techniques, vector autoregression analysis, and a multiple regression model proposed by Peiró, Quesada, and Uriel (1998). This model, unlike the previous ones, allows analysis of the ability of one market to impact another and, at the same time, enables measurement of the sensitivity of each influenced market. Our model structuring takes into account the non-synchronous trading across the four markets of interest. As far as we know, there is yet to be a paper linking simultaneously comparable wheat futures markets in four different continents: China, Africa, Europe and America. The chapter is organised as follows. Section 4.2 summarises literature on wheat futures transmission and international wheat market linkages. Section 4.3 describes the data used in the study and carries out preliminary analysis. Section 4.4 describes the methodology and presents the empirical analysis. Section 4.5 concludes.

## 4.2 Literature Review

Information transmission and cross-market linkages involving futures and spot markets have been investigated in several academic studies. Furthermore, a high number of empirical studies have provided evidence of the dominant role of futures markets in the price discovery process between spot and futures markets (see Antonakakis, Floros, & Kizys, 2015). Surprisingly, as Hua and Chen (2007) indicate, only a few studies have sought to understand

the relationship between futures prices of the same underlying asset in different markets. Within these studies, we have the paper by Geoffrey, Brockman, and Tse (1998) that analysed the information flows between US and Canadian wheat futures from 1980 through 1994 and found that futures prices on Winnipeg Commodities Exchange (WCE) and CBOT are cointegrated. Balcombe, Bailey, and Brooks (2007) studied the relationship among maize, wheat, and soybeans markets in Brazil, USA and Argentina from 1988 through 2001. It was found that information causality for wheat and soybeans flowed from Argentina and USA to Brazil. Sendhil and Ramasundaram (2014) analysed wheat information flows between CBOT and the National Commodities and Derivatives Exchange (NCDEX), then the largest wheat futures market in India. Following the commencement of wheat futures trading in India in June 2005, trading in the contract was banned between 2007 and May 2009. In their study, Sendhil and Ramasundaram (2014) investigated information flows before and after the banning and no evidence of wheat price cointegration between CBOT and NCDEX could be confirmed.

Some literature has also focused on agricultural commodity price transmission involving European Union-based futures markets. Bessler, Yang, and Wongcharupan (2002) analysed information flows in five wheat markets using the error correction method and directed acylic graphs. Wheat data from 1981 through 1999 was collected from the Canadian, Australian, European Union, Argentinian and USA markets. Using monthly free on board export price quotations for each market, USA wheat prices were found cointegrated with those of the European Union and Argentina.

Lence, Ott, and Hart (2013) examined long-run linkages between wheat contracts on Chicago Mercantile Exchange (CME) and Euronext/Liffe. They observed that the CME wheat futures curve reverts to the mean in the long-term, as opposed to the Euronext curve which

seems not to. Lence et al. (2013) attribute this difference to the fact that CME is much more liquid than Euronext/Liffe as far as the wheat contracts are concerned. Yang, Zhang, and Leatham (2003) examined cross-market linkages of wheat futures in the European Union, USA and Canada. Data for the study covered 1996 through 2002 and was collected from LIFFE, CBOT, and WCE. EU prices were found independent of US prices as opposed to the opposite causal direction where EU prices significantly influenced US prices in the long-run. Canada prices were found influential to US wheat prices while the reverse relationship was rejected.

The development of Chinese commodity markets has seen increased research focused on futures contracts behaviour. Du (2004) examined the ZCE wheat market and the CBOT market using data from 1999 to 2003 and found ZCE and CBOT wheat prices were not cointegrated. Similar results were obtained for the same markets by Hua and Chen (2007) using data from 1998 to 2002. Li and Lu (2012) analysed cross-correlation between USA and Chinese agricultural futures contracts. For small fluctuations, cross-correlations for maize and wheat were persistent in the short-run. However, cross-correlations for large fluctuations were found not persistent in the long-run. Finally, Fung, Tse, Yau, & Zhao (2013) examined 16 futures contracts in China and compared them with foreign contracts.[22] Foreign markets included were Japan, Malaysia, USA and UK and wheat data was from 2003 to 2011 comprising contracts listed on ZCE. Although no evidence of cointegrating

[22] Underlying assets examined were aluminium, copper, zinc, gold, natural rubber, long-grain rice, white sugar, hard white wheat, strong gluten wheat, cotton, soybeans, soybean meal, crude soybean oil, corn and palm oil. These futures contracts are traded on the Shanghai Futures Exchange (SHFE), the Zhengzhou Commodity Exchange (CZCE) and the Dalian Commodity Exchange (DCE).

relationships involving wheat was found, short-run relations in prices for strong gluten wheat from USA markets to ZCE were confirmed.

Compared to the other markets described above, financial literature involving SAFEX futures contracts is very scarce. Minot (2010) looks at linkages between agricultural prices in 11 Sub-Saharan African markets compared to US Gulf prices, used as a proxy for world prices. VECM techniques are used for the analysis of data running from 1994 through 2006 to detect a long-run relationship between South African and US Gulf maize and wheat prices.

By way of summary, cointegration across different wheat markets has been confirmed in Geoffrey, Brockman and Tse (1998) (WCE and CBOT), in Bessler Yang and Wongcharupan (2002) (USA and European Union) and in Minot (2010) (South African and US Gulf spot markets). Evidence of no cointegration among wheat markets is found in Sendhil and Ramasundaram (2014) (CBOT and NCDEX), Lence, Ott and Hart (2013) (CME and Euronext/Liffe), Du (2004) (ZCE and CBOT) and Fung, Tse, Yau and Zhao (2013) (Japan, Malaysia, USA and UK). A pattern seems to be emerging where major global wheat markets have long-run relationships, while emerging and established markets have no evidence of cointegration between them. Significant participation by governments particularly in food markets appears to be resulting in disconnection of such markets from the global system, sometimes resulting in inefficient price discovery. This study expected SAFEX to be significantly linked to the global commodities markets following liberalization after 1996.

## 4.3 Markets and Data

The focus is on four commodity exchanges, each the largest hard wheat futures market within the continents examined. Hard wheat, the underlying commodity in this study, is suitable for producing bread and is typically traded as hard white wheat or hard red wheat.

Firstly, the commodity of interest in the USA, hard red wheat, is predominantly traded on KCBT. Secondly, ZCE, the Chinese futures market trading the largest wheat volumes domestically, has listed hard white wheat, also known as common wheat (Fung et al., 2013). Thirdly, Euronext/Liffe, the largest commodity derivatives market in the European Union area, lists its bread wheat, as milling wheat. Euronext/Liffe consolidates futures businesses located in Amsterdam, Brussels, Lisbon, London and Paris. Fourthly, the main wheat contract on SAFEX, locally referred to as bread milling wheat, trades virtually all South African produced wheat.

It is important to point out that domestically produced South African wheat meets only about half of national consumption requirements (see DAFF, 2012; Phukubje & Moholwa, 2006; Van Wyk, 2012). As such, it remains an interesting question if South African wheat imports potentially explain some information spill-overs with the global system. This research anticipated dependence on imports influences information transmission consistent with the observation in JSE (2013) that SAFEX prices ordinarily hover within the band between import and export parity price levels. It is worth pointing out that the KCBT-based hard red wheat contract has also been listed on SAFEX for trading in Rands. Meyer and Kirsten (2005) indicate that KCBT hard red winter wheat No. 2 is the USA wheat type comparable to wheat traded in South Africa. Wheat contract specifications for the four markets are provided in Appendix 4.2. [23]

Wheat contracts on the four markets are traded in Rands/ton (SAFEX), US$/ton (KCBT), Euro/ton (Euronext/Liffe) and Yuan/ton (ZCE). However, as we have mentioned, underlying

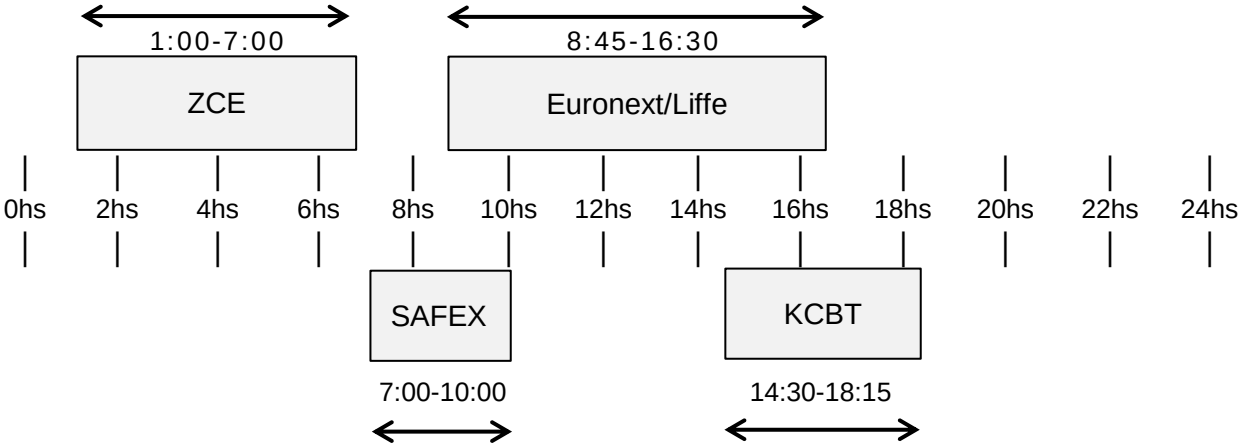
[23] The Indian wheat futures market was another possible candidate to represent the wheat futures price in Asia. However, the first Indian futures market began to trade in 2005 and, as we have mentioned, trading in wheat futures market was banned between 2007 and 2009 (see Ghosh (2010) for further details). Therefore, the election of Indian wheat market would have shortened the whole sample considerably.

wheat contracts traded on the four futures markets present similar features that make them comparable. Appendix 4.2 shows that hard red wheat traded on KCBT has protein content between 9.5% and 13.5% and is comparable to the hard wheat traded on SAFEX, the milling wheat on Euronext/Liffe (originating from the EU region) and the hard white or common wheat traded on the ZCE. Wheat impurities amount to about 2.0% for each of the four markets. Foreign matter ranges between 0.7% and 1.0% across the four markets. Maximum moisture content permissible ranges between 13.0% and 15.0%.

Firstly, we present diagrammatically the trading times for the four markets under study. Figure 4.I shows relative market operating times using the coordinated universal time (UCT). The UCT standardises global timeframes to a uniform 24-hr day. The first market to open amongst the four is ZCE (at 1:00 am in UCT terms). ZCE closes at 7:00 am UCT time. At this same time, SAFEX opens. Euronext opens at 8:45 am UCT time. SAFEX and Euronext close at 10:00 am UCT and 4:30 pm UCT, respectively. The overall order of market closing is therefore, ZCE, SAFEX, Euronext, and KCBT. Each market is potentially impacted by the markets closing ahead of it, such that the order of closing determines how the markets relate to each other.

Daily wheat futures data were collected through Thompson Reuters and include daily settlement prices of the nearest-to-maturity futures contract traded on ZCE, SAFEX, Euronext/Liffe, and KCBT. Price data is collected in local currencies for each market. Daily average foreign exchange rates for ZCE, SAFEX and Euronext/Liffe were sourced from databases of central banks in China and South Africa as well as from the European Central Bank (ECB).

**Figure 4.1: Diagrammatic comparative trading times for the 4 markets**




Universal coordinated times (UCT) for operations on ZCE, SAFEX, Euronext/Liffe and KCBT are given above. UCT provides a 24-hr standardised global clock. The order of opening and closing times is comparable using the UCT system.

The analysis on information flows across the four markets is carried out in US dollars. Prices in local currency and in US dollar terms have been used for the preliminary analysis. However, similar to many comparable studies, all prices are converted to US dollars when conducting the analysis on market linkages (Francis & Leachman, 1998; Fung, Leung, & Xu, 2003; Hauser, Tanchuma, & Yaari, 1998; Xu & Fung, 2005, among others).

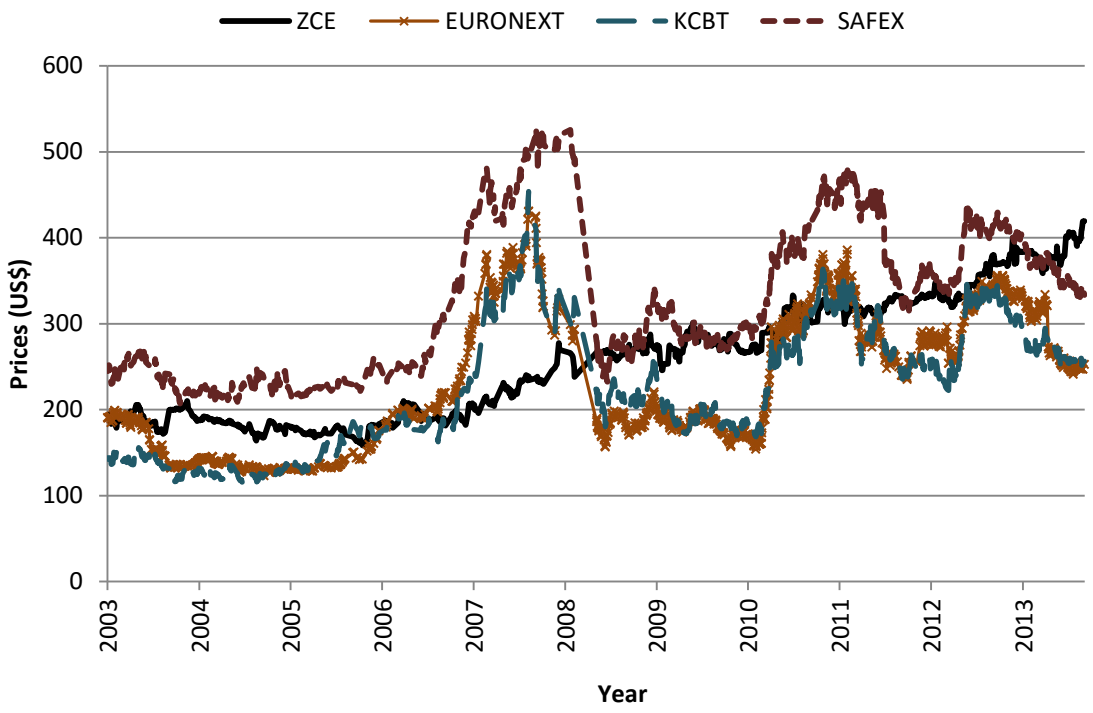
Our sample covers the period December 2003 through September 2013. The one year period between September 2013 and September 2014 is used for out-of-sample forecasting purposes. It is important to highlight that notable events happened over the period under study such as the world food price crisis, the global financial crisis and the European sovereign debt crisis.

Secondly, based on the last day criterion, we have generated a single time series representing wheat futures prices for each market (see Carchano & Pardo, 2009). Daily wheat prices for the four markets are plotted in Figure 4.2. KCBT and Euronext wheat prices appear to be closely tracking each other. SAFEX wheat prices also follow this joint pattern

but with generally higher prices than for KCBT and Euronext. The difference between the KCBT or Euronext wheat prices with SAFEX prices is probably a reflection of approximate logistics costs of moving wheat from the US or Europe to South Africa.

It is observed that wheat prices on ZCE appear to be out of sync with the other three markets. ZCE wheat prices have been on a gradually increasing path and appear not to have been affected by the global commodity price shocks around 2007/2008 or 2010/2011.

**Figure 4.2: Comparative daily prices for the four markets**

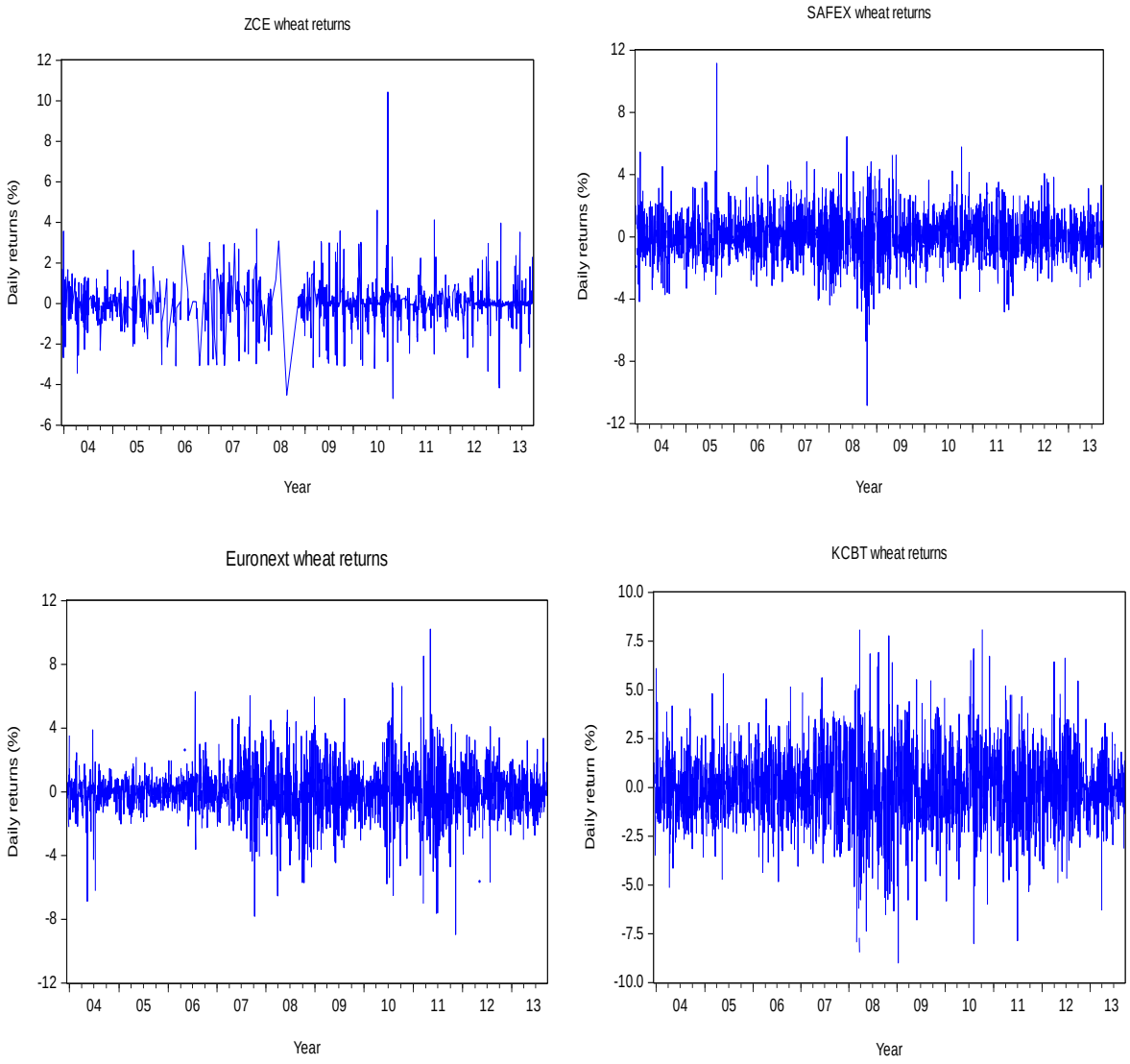



The daily wheat price series for ZCE, SAFEX, Euronext/Liffe and KCBT are presented. All prices are converted to US$ for ease of comparison. Prices shown cover the period 2003 to September 2013.

Fang (2010) contends there is significant government participation in agricultural markets in China. Support for production of maize, rice and wheat culminated in surplus output for the three crops leading up to 2008. Intervention by the Chinese government includes farm support subsidies, export restrictions through withholding VAT rebates on grain exports,

bans on grain export licenses and temporary taxes on grain exports. Furthermore, a floor price system that guarantees high producer prices is managed by SinoGrain, a state enterprise responsible for managing the national strategic grain reserves. Therefore, it appears there was no scope for arbitraging across the Chinese and other markets given rigid controls governing the movement of wheat into and out of China.

**Figure 4.3: Wheat returns for ZCE, SAFEX, Euronext/Liffe and KCBT**




Daily wheat returns for ZCE, SAFEX, Euronext/Liffe and KCBT are presented. All prices for the price series are first converted to US$ for ease of comparison. Returns are in percentage terms and cover the period 2003 to September 2013.

Thirdly, we calculate wheat returns using the relation

$$R_t = 100 * \ln\left(P_t / P_{t-1}\right) \quad (4.1)$$

where $R_t$ are the wheat returns for each of the four markets and $P_t$ and $P_{t-1}$ are the price and lagged price series, respectively. Figure 4.3 is a joint plot of the returns (calculated using US Dollar prices) for the four price series, presented in percentage terms.

In the plots of the return series, volatility clustering and major price shocks are observable around 2004, 2008, 2010 and 2011. For SAFEX, Euronext and KCBT, wheat prices reached their peak in 2008. Except for the ZCE, return volatility had been increasing exponentially leading up to around mid-2008. The absence of a peak in prices in China in 2008 is explained in Fang (2010) as resulting from government participation through setting floor prices, providing subsidies and export restrictions.

Finally, we next look at the summary statistics for the returns series. Table 4.1 presents summary statistics from 2003 to September 2013. Mean wheat returns are expressed in percentage terms. The highest wheat daily mean returns were experienced on SAFEX (0.0356%) while the lowest are observed on ZCE (-0.0378%). Regarding volatility, KCBT appears as the most volatile futures market while ZCE is the least. SAFEX daily returns present the highest difference between the maximum and the minimum, which indicates the high spread of SAFEX data. Measures of skewness and kurtosis indicate that series are far from being normally distributed.

**Table 4.1: Wheat returns daily summary statistics**

| Summary Statistics | $ZCE_t$ | $SAF_t$ | $EU_t$ | $KCB_t$ |
|---|---|---|---|---|
| Mean | -0.0378 | 0.0356 | 0.0295 | 0.0138 |
| Median | -0.0015 | -0.0170 | 0.0279 | 0.0000 |
| Maximum | 10.434 | 11.151 | 10.222 | 8.0977 |
| Minimum | -4.6863 | -10.842 | -8.9500 | -8.9948 |
| Std. deviation | 0.9760 | 1.4821 | 1.5817 | 1.9724 |
| Skewness | 0.6628 | 0.1259 | -0.1044 | -0.0605 |
| Kurtosis | 15.582 | 6.3526 | 6.9041 | 4.5124 |
| Jarque-Bera | 9,703.2 | 1,076.6 | 1,484.0 | 214.09 |
| Observations | 1,455 | 2,286 | 2,567 | 2,232 |

The returns series for wheat on ZCE, SAFEX, Euronext/Liffe and KCBT are represented as $ZCE_t$, $SAF_t$, $EU_t$, and $KCB_t$, respectively. The returns are calculated after first converting prices in local currencies for China (Yuan), South Africa (Rands) and the Eurozone (Euros) to US dollars. Returns are expressed in percentage terms. For each market, the sample covers the period December 2003 through September 2013.

Wheat daily returns contemporaneous and non-contemporaneous cross-correlations for the four markets are presented in Table 4.2.

**Table 4.2: Wheat returns daily cross-correlations**

| | $ZCE_t$ | $SAF_t$ | $EU_t$ | $KCB_t$ | $ZCE_{t-1}$ | $SAF_{t-1}$ | $EU_{t-1}$ | $KCB_{t-1}$ |
|---|---|---|---|---|---|---|---|---|
| $ZCE_t$ | 1.0000 | | | | | | | |
| $SAF_t$ | 0.0419 | 1.0000 | | | | | | |
| $EU_t$ | -0.0024 | 0.1544* | 1.0000 | | | | | |
| $KCB_t$ | -0.0098 | 0.1069* | 0.5744* | 1.0000 | | | | |
| $ZCE_{t-1}$ | -0.0255 | -0.0374 | -0.0059 | 0.0291 | 1.0000 | | | |
| $SAF_{t-1}$ | 0.0070 | -0.0001 | -0.0069 | -0.0295 | 0.0826 | 1.0000 | | |
| $EU_{t-1}$ | 0.0443 | 0.3234* | 0.0465 | 0.0293 | 0.0080 | 0.1913* | 1.0000 | |
| $KCB_{t-1}$ | 0.0394 | 0.3643* | 0.1457* | 0.0193 | 0.0059 | 0.1315* | 0.5468* | 1.0000 |

Correlations in wheat daily returns cover the period December 2003 to September 2013. The wheat returns on the four markets are denoted as $ZCE_t$, $SAF_t$, $EU_t$ and $KCB_t$ corresponding to ZCE, SAFEX, Euronext/Liffe and KCBT futures markets, respectively. The * indicates correlation coefficient significantly different from zero at 1% level.

As was expected, all cross-correlation coefficients that are significant are also positive. SAFEX, Euronext and KCBT have significant cross-relationships among them. Cross-

correlations between Euronext and KCBT, both contemporary (57.44%) and lagged (54.68%), are the highest. This is not surprising given that both markets are overlapped during two hours of their respective trading sessions. Furthermore, SAFEX is significantly correlated with Euronext/Liffe and KCBT. Finally, no correlation is detected between ZCE and the rest of the markets.

## 4.4 Methodology and Empirical Analysis

Our methodological approach firstly looks at cointegration following a handful of studies on commodity transmission that used cointegration and the VECM (see Du & Wang, 2004; W. Du, 2004; Minot, 2010; Rosa & Vasciaveo, 2012 among others). Following from this, we use the vector autoregressive (VAR) approach as applied in Balcombe et al. (2007). In Engle, Ito, and Lin (1991) and Ito, Engle, and Lin (1992), a financial market may disseminate information influencing the next open markets. Finally, given that the wheat markets under study are non-synchronous, we have applied the model by Peiró et al. (1998). The system of seemingly unrelated equations they proposed, originally used with stock markets data, fits in well with the context of our study.

Vector autoregression class of models were proposed by Sims (1980). VAR's have been used extensively in macroeconomics. VAR's are also able to predict the responsiveness of one variable when a shock has been experienced by a related variable (Swanson & Granger, 1997). Brooks (2014) explains that VARS are an amalgamation of univariate series models and simultaneous equations. The simplest VAR is given in Brooks (2014) as

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \ldots + \beta_{1k} y_{1t-k} + \alpha_{11} y_{2t-1} + \ldots + \alpha_{1k} y_{2t-k} + u_{1t} \quad (4.1)$$

$$y_{2t} = \beta_{20} + \beta_{21} y_{2t-1} + \ldots + \beta_{2k} y_{2t-k} + \alpha_{22} y_{1t-1} + \ldots + \alpha_{2k} y_{1t-k} + u_{2t} \quad (4.2)$$

The two series are represented by $y_{1t}$ and $y_{2t}$ with lags of both series featured on the right-hand side of the two equations. The $\beta's$ and $\alpha's$ are constants and $u_{1t}$ and $u_{2t}$ are error terms (Brooks, 2014). Application of the marginal approach to modelling involves beginning with a set of variables that might have theoretical linkages then including an additional variable consecutively.

In reduced form VARS, every one of the variables under study can be expressed in terms of its own lags, past values of other explanatory variables and an error term (Stock & Watson, 2001). The OLS approach can then be used to generate the coefficients for each explanatory term (Stock & Watson, 2001).

The key requirement for recursive VARs is that each error term for each of the equations in the system is uncorrelated to any of the other error terms (Stock & Watson, 2001). This is achieved by ensuring each equation contains one more or one less variable than the previous or preceding equation respectively (Stock & Watson, 2001). The typical way to do this is to increase the explanatory variables successively, thus including a different current value of a variable in respective equations (Stock & Watson, 2001).

In structural VARS, economic theory is utilized to arrive at a system structure (Stock & Watson, 2001). This requires some identifying assumptions to be defined. Stock and Watson (2001) further explain this process using the example of Taylor's Rule in economics to generate a plausible form of the VAR. This enables instrumental variables to be incorporated to lay out the causal links (Stock & Watson, 2001).

The three important stages in using VARS encompass causality testing, generating impulse responses and carrying out forecast error variance decompositions (Stock & Watson, 2001). The key advantages of the VAR system are flexibility in specifying the relationships and no

need of specifying the endogenous and exogenous variables (Brooks, 2014). VARS also capture a good deal of the features of the data allowing reasonably accurate forecasts (Brooks, 2014). The other benefit of a VAR system is its ability to depict the response of other variables to a one-time shock to the system (Kilian, 2011). This enables some hypothetical scenarios to be used to forecast possible impacts on some variables of interest (Kilian, 2011).

The major challenge however is that VAR's fall into the a-theoretical model class and thus there is constant need to watch out for spurious regressions (Brooks, 2014). Misleading results can be obtained when one or more variables in VARs are very persistent (Stock & Watson, 2001). Instability of the system can be experienced when too few variables are included with poor forecasting being experienced (Stock & Watson, 2001). On the other hand, too many variables make VARs unstable with the many unknown parameters (Stock & Watson, 2001). Relationships may not be identified where there are non-linear series trends, conditional heteroskedasticity or drifts and breaks in parameters (Stock & Watson, 2001). The determination of the ideal lag lengths is not easy and a pre-requisite for using VAR's is to ensure stationarity of the data series (Brooks, 2014). Stock and Watson (2001) point to the difficulty faced in determining causation with VARs in the absence of some underlying economic rational. Arriving at the precise lag length can be guided by observing some cross-equation restrictions. The use of various information criterion is also advisable. A rule of thumb for calculating the number of regressors for $p$ equations and $k$ lags is to use

$$p^2k + p \tag{4.3}$$

Impulse responses indicate the sign of the relationship between variables and the duration for one variable influencing the other (Brooks, 2014). Variance decompositions attempt to attribute the total variance in a dependent variable to effects of the explanatory variable (Brooks, 2014). Granger causality occurs in the above structure when the lags of $y_1$ are

significant in the relation where $y_2$ is the dependent variable. The case of $y_1$ being influenced by lags of $y_2$ gives the other direction of causality.

The structural vector autoregression (SVAR) has been used to decompose the influence of several variables on a dependent variable (McPhail, Du, & Muhammad, 2012). In their study, (McPhail et al., 2012) analysed the price volatility of maize prices. The aim was to find out the contribution of demand for maize, energy and speculation to change in prices. It was found that speculation was only important in the short-run while energy price changes were the most important of the variables considered (McPhail et al., 2012). The SVAR has also been used to simulate the effect of certain monetary variable changes on key areas of the economy in Bernanke, Gertler, Watson, Sims, and Friedman (1997). Their studies were able to show that increases in oil prices Granger-cause economic downturns. The SVAR structure constructed by Bernanke et al. (1997) included oil prices on the one side with the other side of the relation capturing real GDP growth levels, short-term interest rates, long-term interest rates and commodity prices. Some notable advantages of using SVARS include their flexibility in conducting modelling and their appropriateness for determining transmission mechanisms. The SVAR model is deemed suitable when the inclusion of many variables simultaneously is investigated. Lags are incorporated enabling visualization of the effects in the case of slow and drawn-out adjustments. Besides, the SVAR allows for causal inference to be conducted in the same manner as Granger causality tests (Auffhammer et al., 2012). However, identifying restrictions incorporated based on timing are usually unrealistic and not plausible (Stock & Watson, 2001). SVAR is a dominant tool in empirical analysis in the USA and to some extent in Europe (Demiralp & Hoover, 2003).

The methodology and empirical analysis for each of the three approaches is presented below.

### *4.4.1. Analysis of long-run relationships*

Following Engle and Granger (1987), if the price series in two or more markets were cointegrated, a model expressed in first differences would not be well-specified. Hence, firstly, we look at the possible cointegration among the wheat markets in order to determine if there are any long-term price relationships. Our approach is to carry out unit root tests for the price series, both in levels and in first differences, and determine if the price series for each market is integrated of the same order. Where the price series for each market is, say *I*(1), the Johansen cointegration test may be used to determine the number of cointegrating relationships. If it is confirmed that there are cointegrating relationships, we can proceed with the vector error correction method. Following from Engle and Granger (1987), cointegration in the vector error correction approach is represented as

$$\Delta P_t = \alpha * \beta^{'} P_{t-1} + \sum_{i=1}^{q-1} A_i \Delta P_{t-i} + \zeta_t \tag{4.4}$$

$P_t$, the vector of prices for the four markets is given as follows

$$P_t = \left(P_t^{ZCE}, P_t^{SAF}, P_t^{EU}, P_t^{KCB}\right) \tag{4.5}$$

The cointegration rank for the system of prices is *r (≤k).* In the VECM(q), $\alpha$ and *β* are *k x r* matrices. $A_i$ is a *k x k* matrix of parameters for *i=1,…..,q-1*. The above prices represent trade close prices on ZCE, SAFEX, Euronext/Liffe and KCBT, respectively. An error correction coefficient is captured in $\alpha = \left(\alpha_{ZCE}, \alpha_{SAF}, \alpha_{EU}, \alpha_{KCB}\right)^{'}$ corresponding to the four markets and *β* is the cointegrating vector. Random error terms are explained by

$$\zeta_{it} = \left(\zeta_{ZCE,t}, \zeta_{SAF,t}, \zeta_{EU,t}, \zeta_{KCB,t}\right) \tag{4.6}$$

$$\zeta_{it} \sim N\left(0, \sigma_i\right) \tag{4.7}$$

Cointegration analysis in this study follows Engle and Granger (1987). Unit root tests for the prices of wheat in the four markets are presented in Table 4.3. The table shows unit root results before and after differencing.

Non-stationary series, when combined together, may turn out stationary. If this is the case, then the series have cointegration. All the logged price series are not stationary as shown in Table 4.3. However, after taking the first order differences, the entire set of differenced series becomes stationary. Where the series compared are both *I*(1), but *I*(0) after differencing, cointegration may be suitable for further analysis (Engle & Granger, 1987).

**Table 4.3: Unit root tests**

| | *ZCE* | *SAFEX* | *Euronext* | *KCBT* |
|---|---|---|---|---|
| Level series | 0.8333 [0.9946] | -0.8796 [0.7951] | 0.0276 [0.9599] | -1.7106 [0.4258] |
| First order differences | -37.84*** [0.0000] | -46.54*** [0.0001] | -44.62*** [0.0001] | -45.20*** [0.0001] |

Augmented Dickey-Fuller tests are carried out to determine the stationarity of the wheat price series for ZCE, SAFEX, Euronext/Liffe and KCBT. The log of the price series for wheat on ZCE, SAFEX, Euronext/Liffe and KCBT are used for unit root tests for the level series. First order differences are the series of returns for each market, whose unit root tests are presented in the second row. Parentheses present the p-values. For each market, the sample covers the period December 2003 through September 2013. Significance at 1%, 5% or 10% is shown as ***, ** or *, respectively.

The cointegration framework we use is outlined in Johansen (1991) and Johansen (1995) and in practice starts off with an estimated VAR object incorporating the variables of interest. If cointegration is confirmed, the VECM can be used for estimating the cointegration equation. The critical values for the cointegration tests are given in MacKinnon, Haug, and Michelis (1998). Johansen's contegration test results for the system of prices for the four markets are presented in Table 4.4.

The test for cointegration has two parts, the trace test and the maximum eigenvalue test. These results are presented in Panel A and Panel B of Table 4.4. As shown in Table 4.4, we find no cointegrating relationships amongst wheat prices on ZCE, SAFEX, Euronext and KCBT. This means that there are no long term relationships in the wheat prices of the four markets. Therefore, our results are in line with those obtained by Hua and Chen (2007) and by Fung et al. (2013) who found no evidence of cointegration between US and Chinese wheat futures. However, our findings are in contrast with those obtained by Bessler et al. (2002) who found cointegration between EU and USA wheat futures, using a different sample period.

**Table 4.4: Cointegration test results**

| | Hypothesized cointegrating equations | | | |
|---|---|---|---|---|
| | None | At most 1 | At most 2 | At most 3 |
| *Panel A: Trace Test* | | | | |
| Eigenvalues | 0.0101 | 0.0060 | 0.0020 | 0.0003 |
| Trace statistic | 13.677 | 6.1761 | 1.7201 | 0.2173 |
| Critical value (0.05) | 47.856 | 29.797 | 15.495 | 3.8415 |
| Prob. | 1.0000 | 0.9998 | 0.9978 | 0.6411 |
| *Panel B: Maximum Eigenvalue* | | | | |
| Max-eigen statistic | 7.5009 | 4.4560 | 1.5027 | 0.2173 |
| Critical value (0.05) | 27.584 | 21.132 | 14.265 | 3.8415 |
| Prob. | 0.9994 | 0.9984 | 0.9980 | 0.6411 |

Both trace test and maximum eigenvalue tests confirm no cointegration of the log wheat price series on ZCE, SAFEX, Euronext and KCBT. For each market, the sample covers the period December 2003 through September 2013. MacKinnon et al. (1998) *p*-values are reported in the row "Prob." allowing representation of significance at 1%, 5% or 10% using ***, ** or *, respectively.

### *4.4.2. Dynamic Analysis using VAR*

The absence of long-term relationships has no effect on possibilities for short-term market linkages. Therefore, dynamic analysis is next considered using the VAR approach that enables determination of short-term causality as explained in Granger (1969). The returns

for the four markets are the endogenous variables in our VAR system and the variance decomposition analysis allows disentangling the effects and relative importance of a given market on the other three wheat markets. Variance decomposition results for wheat returns on ZCE, SAFEX, Euronext and KCBT are shown in Table 4.5 and the ordering has been established based on the chronology of the closing hours of the four wheat markets. It is important to point out that variance decomposition results may be influenced by the different time zones of the four markets.

We focus on the decomposition of variance by market at the 5 and 10-day prediction horizons.[24]

**Table 4.5: Variance decomposition by wheat market**

| Market | Horizon | Changes in | | | | |
|---|---|---|---|---|---|---|
| | (days) | ZCE | SAFEX | Euronext | KCBT | Rest |
| ZCE | 5 | 0.0000 | 0.3851 | 69.4077 | 30.2071 | 99.9999 |
| | 10 | 0.0000 | 0.3852 | 69.4074 | 30.2074 | 100.000 |
| SAFEX | 5 | 0.0000 | 81.9190 | 12.2864 | 5.7947 | 18.0810 |
| | 10 | 0.0000 | 81.9187 | 12.2865 | 5.7948 | 18.0813 |
| Euronext | 5 | 0.0000 | 0.1695 | 96.4257 | 3.4048 | 3.5743 |
| | 10 | 0.0000 | 0.1695 | 96.4256 | 3.4049 | 3.5744 |
| KCBT | 5 | 0.0000 | 0.3983 | 34.1541 | 65.4476 | 34.5524 |
| | 10 | 0.0000 | 0.3985 | 34.1539 | 65.4476 | 34.5524 |

Each cell represents the variance decomposition of the return of the market in the first column as it is explained by the market displayed above each cell. In the "Rest" column, the cell gives the variance attributable to the rest of the markets other than the market in the first column. The sample for each market covers the period December 2003 through September 2013.

This analysis points to the most exogenous market as the wheat market with the highest percentage of forecast error variance accounted for by its own disturbances, while the most

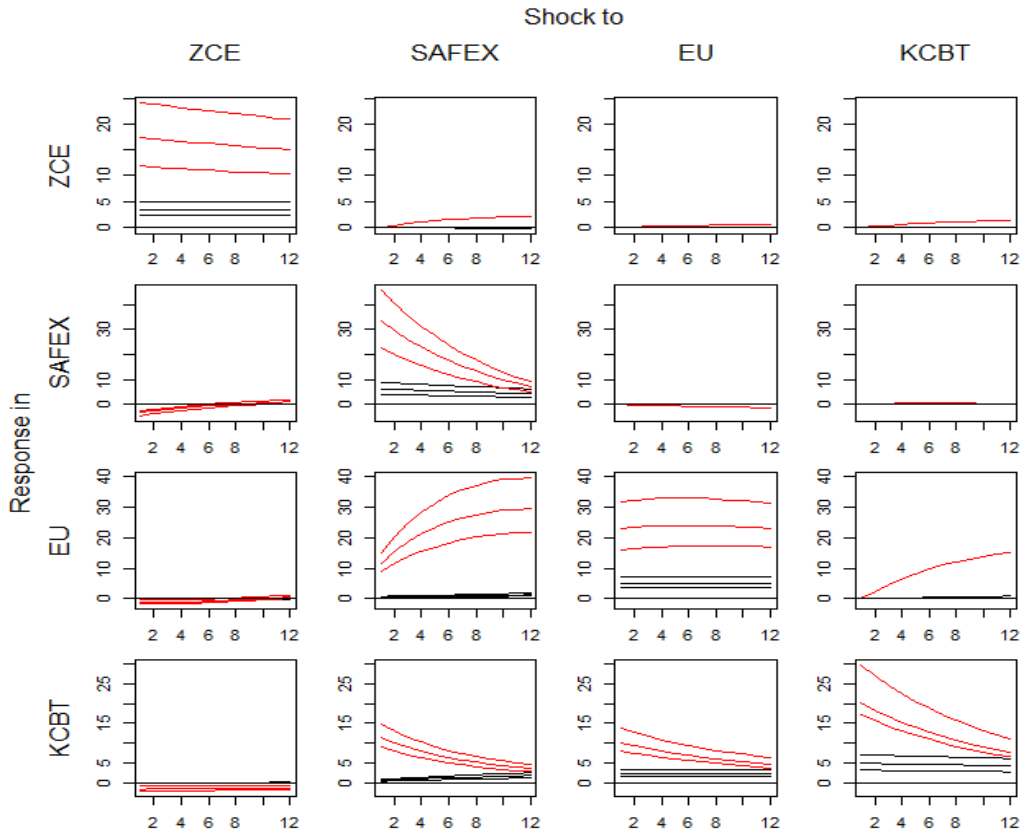
[24] The SAFEX settlement period is about 5 working days. The 10-day horizon captures lagged shock effects attributable to each of the other three markets while accounting for non-synchronous trading times given settlement cycles for the markets are not matched.

endogenous is the market that presents the highest percentage explained by other wheat futures markets. On one hand, Euronext/Liffe is the most exogenous market with the bulk of its forecast error variance embodied in its own innovations (around 96%). Besides, in terms of largest impact on the other markets, Euronext/Liffe and KCBT show this largest influence in relative terms. On the other hand, the market appearing to be controlled by the largest number of other markets is ZCE and hence is the most endogenous. The next question would be whether there is a high degree of international linkages in the major wheat futures markets across the four continents covered in the study. At the 5 and 10-day prediction horizons, the influence of the rest of the markets on a given market ranges from 3.5744 % to 100 %. This indicates that there are high levels of international linkages in wheat returns among the markets under study.

We also took into account the possibility of time-based regimes in the relationships taking into account the varying volatility patterns in Figure 4.3. Going by Sims, Waggoner, and Zha (2008), we have constructed impulse response plots accounting for switching of regimes using the Markov-switching Bayesian VAR (MSBVAR) approach. Figure 4.4 shows these plots with variables to the extreme left as dependent variables. At the top of the plot, under the heading “Shock to” are the explanatory variables within the MSBVAR system. Two regimes have been used similar to Droumaguet (2012) with the four-variable MSBVAR system which successfully ran all the way to convergence. Findings are that ZCE has virtually no influence on the other three markets. However, the other three markets can to a small extent potentially influence ZCE. The substantial linkages among SAFEX, Eutonext/Liffe and KCBT are futher confirmed in Figure 4.4. For example, a shock to Euronext/Liffe significantly generates a response in the KCBT wheat market taking at least 12 trading days to die down. A shock to KCBT will still be impacting Euronext/Liffe well beyond this 12-day trading horizon, confirming the more pronounced influencing ability of

KCBT. A shock to SAFEX impacting KCBT takes roughly two weeks to whittle down to zero. This confirms the sensitivity of the KCBT wheat market, regardless of KCBT being influential itself .

**Figure 4.4: Markov Switching Bayesian Impulse Response**




Impulse response functions plots for the four markets estimated with Markov-switching Bayesian VAR (MSBVAR) are presented. Variables to the extreme left are dependent variables. At the top of the plots, with the heading “Shock to”, are the explanatory variables within the MSBVAR system.

### *4.4.3. Multiple regression analysis*

Finally, we look at the model in Peiró et al. (1998) that postulates that the correlations of any two markets depend on the overlapping time periods running concurrently from the market-close on *t-1* to the close on time *t*. This suggests that a given market tends to have higher correlation to the market which most recently closed operations in the last 24 hours. The approach proposed by Peiró et al. (1998) is particularly suited for our analysis because (i)

wheat markets considered are non-synchronous, and (ii) the model enables separating the influence of a specific market on the other three, as well as the influence received from other wheat markets. Therefore, firstly, the regression equations below are resolved by ordinary least squares (OLS):

$$ZCE_t = \gamma_{10} + \gamma_{11} SAF_{t-1} + \gamma_{12} EU_{t-1} + \gamma_{13} KCB_{t-1} + u_{1t} \quad (4.8)$$

$$SAF_t = \gamma_{20} + \gamma_{21} ZCE_t + \gamma_{22} EU_{t-1} + \gamma_{23} KCB_{t-1} + u_{2t} \quad (4.9)$$

$$EU_t = \gamma_{30} + \gamma_{31} ZCE_t + \gamma_{32} SAF_t + \gamma_{33} KCB_{t-1} + u_{3t} \quad (4.10)$$

$$KCB_t = \gamma_{40} + \gamma_{41} ZCE_t + \gamma_{42} SAF_t + \gamma_{43} EU_t + u_{4t} \quad (4.11)$$

Returns for ZCE, SAFEX, Euronext/Liffe and the KCBT are represented by $ZCE_t$, $SAF_t$, $EU_t$ and $KCB_t$, respectively. Lags for these returns are defined by $SAF_{t-1}$, $EU_{t-1}$ and $KCB_{t-1}$. The parameters to be estimated are $\gamma_{10,\ldots\ldots\ldots}\gamma_{43}$ and the error terms are $u_{1t}, \ldots\ldots u_{4t}$. Table 4.6 presents the results of running the initial regressions in equations (4.8) to (4.11). The results show ZCE wheat returns are generally not dependent on the wheat returns of the other three markets. SAFEX wheat returns are significantly influenced by Euronext and KCBT wheat returns at the 1% level and Euronext wheat returns have significant relationships at 1% level with SAFEX and KCBT returns. It is noted that KCBT wheat returns are highly influenced only by Euronext wheat returns.

In Peiró et al. (1998), it was found that removing the regressor of the most-recently closed stock market substantially increased the significance and magnitude of the influence of the remaining variables. Following a similar approach, regression equations were solved after excluding the wheat market with the most recent closing with respect to endogenous variables in (4.8) to (4.11). The most recently closed market is expected to have a more significant regressor compared to a market closing earlier. Excluding most-recently closed regressors gives:

$$ZCE_t = \phi_{10} + \phi_{11} SAF_{t-1} + \phi_{12} EU_{t-1} + \varepsilon_{1t} \quad (4.12)$$

$$SAF_t = \phi_{20} + \phi_{21} EU_{t-1} + \phi_{22} KCB_{t-1} + \varepsilon_{2t} \quad (4.13)$$

$$EU_t = \phi_{30} + \phi_{31} ZCE_t + \phi_{32} KCB_{t-1} + \varepsilon_{3t} \quad (4.14)$$

$$KCB_t = \phi_{40} + \phi_{41} ZCE_t + \phi_{42} SAF_t + \varepsilon_{4t} \quad (4.15)$$

Wheat returns for ZCE, SAFEX, Euronext/Liffe and the KCBT in equations (4.12) to (4.15) are respectively $ZCE_t$, $SAF_t$, $EU_t$ and $KCB_t$. Parameters to be estimated in the above regressions are $\phi_{10,.....,}\phi_{42}$ and the error terms are $\varepsilon_{1t}$, $\varepsilon_{2t}$, $\varepsilon_{3t}$ and $\varepsilon_{4t}$.

Of interest is to compare the initial regressions with the set that excludes the market most-recently closed, which usually has the most significant coefficient. Doing this allows the element of collinearity to be taken out of the explanatory variables while focus is placed on positions occupied by respective markets in the trading sequences.

Results for equations (4.12) to (4.15) are also given in Table 4.6. These results fall under the columns labelled “4.12 to 4.15”. The dependent variable for each column is included as a column heading. In each column, results either fall within the set of equations in “4.8 to 4.11” or the set in “4.12 to 4.15”. This makes it easier to check changes in the coefficients across the two sets of models.

In Table 4.6, ZCE did not have any relationship with any of the markets at the first regression stage (equations (4.8) to (4.11)). After removal of KCBT from the ZCE wheat return equation, still no significant influence on ZCE can be discerned from the other markets. When ZCE wheat return is removed from the SAFEX relation (equation (4.9)), the magnitude of the coefficient of the lagged Euronext return increases while that of the lagged KCBT wheat

return decreases slightly. For Euronext, the removal of SAFEX wheat returns from equation (4.10) increases the significance and influence of KCBT wheat returns.

**Table 4.6: Regressions: wheat returns for equations (4.8) to (4.11) and (4.12) to (4.15)**

| Independent Variables | | Dependent variables | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $ZCE_t$ | | $SAF_t$ | | $EU_t$ | | $KCB_t$ | |
| | | (4.8)-(4.11) | (4.12)-(4.15) | (4.8)-(4.11) | (4.12)-(4.15) | (4.8)-(4.11) | (4.12)-(4.15) | (4.8)-(4.11) | (4.12)-(4.15) |
| Const. | | -0.0606** | -0.0455 | 0.0316 | 0.0334 | 0.0126 | 0.0313 | -0.0144 | -0.0030 |
| | | [0.0357] | [0.1060] | [0.4216] | [0.2913] | [0.7805] | [0.4726] | [0.7549] | [0.9555] |
| $\gamma_{11}$, $\phi_{11}$ | $SAF_{t-1}$ | 0.0127 | 0.0118 | | | | | | |
| | | [0.5373] | [0.5594] | | | | | | |
| $\gamma_{12}$, $\phi_{12}$ | $EU_{t-1}$ | 0.0149 | 0.0298 | | | | | | |
| | | [0.5143] | [0.1056] | | | | | | |
| $\gamma_{13}$ | $KCB_{t-1}$ | 0.0145 | | | | | | | |
| | | [0.4224] | | | | | | | |
| $\gamma_{21}$ | $ZCE_t$ | | | 0.0455 | | | | | |
| | | | | [0.2589] | | | | | |
| $\gamma_{22}$, $\phi_{21}$ | $EU_{t-1}$ | | | 0.1585*** | 0.1872*** | | | | |
| | | | | [0.0000] | [0.0000] | | | | |
| $\gamma_{23}$, $\phi_{22}$ | $KCB_{t-1}$ | | | 0.1944*** | 0.1718*** | | | | |
| | | | | [0.0000] | [0.0000] | | | | |
| $\gamma_{31}$, $\phi_{31}$ | $ZCE_t$ | | | | | -0.0285 | -0.0154 | | |
| | | | | | | [0.5403] | [0.7339] | | |
| $\gamma_{32}$ | $SAF_t$ | | | | | 0.1225*** | | | |
| | | | | | | [0.0003] | | | |
| $\gamma_{33}$, $\phi_{32}$ | $KCB_{t-1}$ | | | | | 0.0846*** | 0.1147*** | | |
| | | | | | | [0.0009] | [0.0000] | | |
| $\gamma_{41}$, $\phi_{41}$ | $ZCE_t$ | | | | | | | -0.0126 | -0.0441 |
| | | | | | | | | [0.7930] | [0.4298] |
| $\gamma_{42}$, $\phi_{42}$ | $SAF_t$ | | | | | | | 0.0311 | 0.1562*** |
| | | | | | | | | [0.3458] | [0.0000] |
| $\gamma_{43}$ | $EU_t$ | | | | | | | 0.6639*** | |
| | | | | | | | | [0.0000] | |
| $R^2$ | | 0.0020 | 0.0027 | 0.1440 | 0.1381 | 0.0320 | 0.0199 | 0.2998 | 0.0141 |

Regression solutions for wheat daily returns in equations (4.8) to (4.11) are compared to equations (4.12) to (4.15). The second set of equations excludes the market that had most recently closed. The sample for each market covers the period December 2003 through September 2013. The parentheses give respective p-values. Significance is given by ***, ** and * for 1%, 5% and 10% levels respectively.

In the KCBT wheat returns situation, excluding Euronext as a regressor substantially increases the relationship between the former and SAFEX wheat returns. In fact, the effect of SAFEX on KCBT changes from insignificant to significant at 1%. The above findings would suggest that trading times play an important part in the relationships between the various wheat markets.

Finally, the main model used for the empirical analysis is presented below and is similar to the one used in Peiró et al. (1998) for the analysis of stock markets.

$$ZCE_t = \alpha_{ZCE} + \beta_{SAF}\lambda_{ZCE}SAF_{t-1} + \beta_{EU}\lambda_{ZCE}EU_{t-1} + \beta_{KCB}\lambda_{ZCE}KCB_{t-1} + u_{ZCE,t} \quad (4.16)$$

$$SAF_t = \alpha_{SAF} + \beta_{ZCE}\lambda_{SAF}ZCE_t + \beta_{EU}\lambda_{SAF}EU_{t-1} + \beta_{KCB}\lambda_{SAF}KCB_{t-1} + u_{SAF,t} \quad (4.17)$$

$$EU_t = \alpha_{EU} + \beta_{ZCE}\lambda_{EU}ZCE_t + \beta_{SAF}\lambda_{EU}SAF_t + \beta_{KCB}\lambda_{EU}KCB_{t-1} + u_{EU,t} \quad (4.18)$$

$$KCB_t = \alpha_{KCB} + \beta_{ZCE}\lambda_{KCB}ZCE_t + \beta_{SAF}\lambda_{KCB}SAF_t + \beta_{EU}\lambda_{KCB}EU_t + u_{KCB,t} \quad (4.19)$$

The wheat price return series for ZCE, SAFEX, Euronext/Liffe and KCBT are denoted by $ZCE_t$, $SAF_t$, $EU_t$ and $KCB_t$, respectively. $SAF_{t-1}$, $EU_{t-1}$ and $KCB_{t-1}$ are lags for wheat returns on SAFEX, Euronext and KCBT, respectively. The size of $\beta$ determines the level of influence that one market has on the other markets. In the system of equations (4.16) to (4.19), $\lambda_{ZCE}$, $\lambda_{SAF}$, $\lambda_{EU}$, and $\lambda_{KCB}$ are measures of the sensitivity of each wheat market to global factors. Constant terms for each equation are $\alpha_{ZCE}$, $\alpha_{SAF}$, $\alpha_{EU}$ and $\alpha_{KCB}$. The error terms are $u_{ZCE,t}$, $u_{SAF,t}$, $u_{EU,t}$ and $u_{KCB,t}$. The order of the equations and variables allows for the current return of one market to be linked to latest available returns from the other three markets.

Specifically, this model takes into account the non-synchronous trading amongst the wheat futures markets with the closing prices of each market potentially influenced by the other three markets. For example, SAFEX can potentially be influenced by ZCE on the same day. No time overlap occurs between these markets. A time overlap of 1 hour and 15 minutes,

however occurs between SAFEX and Euronext/Liffe. This means that the closing price for Euronext/Liffe can be influenced by the SAFEX closing price of the same day, while the KCBT closing price can be influenced by the closing prices of Euronext/Liffe and SAFEX of the same day. Euronext/Liffe and KCBT overlap in trading time for about 2 hours.

For resolution of the system in (4.16) to (4.19), a non-linear least squares modelling approach is applied making use of the Gauss-Newton method. Furthermore, as the above system of equations is not identified, there is need to incorporate some restrictions to enable a solution to be found. Following from Peiró et al. (1998), the value of $\lambda_{EU}$ is set to 1. Joint estimation of the parameters is carried out to derive the required coefficients. Essentially, we seek to isolate the information transmitting effect of a given market regardless of the order of timeframes involved between the markets. The equations are resolved simultaneously as a joint system using the seemingly unrelated regression approach. Joint estimation results for system of equations (4.16) to (4.19) are given in Table 4.7.

As shown in Table 4.7, KCBT is the most influential market and, at the same time, the most sensitive market. We further explain why this result on KCBT is not contradictory. Findings on KCBT's influencing ability and at the same time ability to be influenced suggest KCBT has the largest amount of linkages with all the other markets, perhaps partly due to the extra-ordinary openness of its marketing environment. That KCBT is the most sensitive market means it responds the most and the fastest to shocks from other markets owing to its connectedness with each of SAFEX, Euronext/Liffe and ZCE. This connectedness could be attributable to global trade activities, global business linkages and availability and ease of access of important global information. While KCBT responds to information from other markets, this does not hinder these three markets from being influenced by market shocks

originating from KCBT. That influencing ability is consistent with KCBT's size within the global futures markets.

**Table 4.7: Joint estimation of models (4.16) to (4.19)**

| Market | $\hat{\beta}$ | | $\hat{\lambda}$ | |
|---|---|---|---|---|
| ZCE | -0.0009 | [0.8936] | 0.1420 | [0.1231] |
| SAFEX | 0.0042 | [0.4106] | 1.6607*** | [0.0000] |
| Euronext/Liffe | 0.0981*** | [0.0028] | 1.0000 | [ - ] |
| KCBT | 0.1166*** | [0.0000] | 6.6286*** | [0.0030] |

Estimation of models (4.16) to (4.19) is presented in this table. Joint estimation is carried out using non-linear least squares or seemingly unrelated regression with data covering the period December 2003 to September 2014. As a restriction $\lambda_{EU}$ is fixed as 1. The sample for each market covers the period December 2003 through September 2013. Parentheses present the p-values. Significance at 1%, 5% or 10% is shown as ***, ** or *, respectively.

SAFEX is more sensitive to receiving market information than Euronext, but is only a receiver of information while not influencing other markets. This finding is consistent with SAFEX's relatively small size and with the fact that South Africa is a net importer of wheat, securing approximately half of its wheat requirements from the international system (DAFF, 2012). Finally, ZCE appears as the least influential and least sensitive of the four markets.

### *4.4.4. Out of Sample Estimations*

Finally, it is imperative to find out which relations (4.8) to (4.11) or (4.16) to (4.19) would be more useful and appropriate for econometric use. It may therefore be prudent to test the out-of-sample predictive potential of the two sets of equations. Comparison of equations (4.8) to (4.11) with equations (4.16) to (4.19) is provided in Table 4.8. Forecasts are generated by these set of equations to find out if the latter adds value to the former. Root mean squared errors are used as the measure of evaluating the forecasts of corresponding equations in the two groups.

**Table 4.8: Out-of-sample forecasts and root mean squared errors**

| Market | Models (4.8) to (4.11) | Models (4.16) to (4.19) |
|---|---|---|
| $ZCE_t$ | 0.9994 | 0.8199 |
| $SAF_t$ | 0.8206 | 0.6215 |
| $EU_t$ | 1.0186 | 0.8206 |
| $KCB_t$ | 1.1980 | 0.9286 |

Root mean squared errors evaluate out-of-sample forecasts for models (4.8) to (4.11) compared to models (4.16) to (4.19). The forecast period is the one year commencing on 9/24/2013 to 9/23/2014.

Table 4.8 shows that out-of-sample forecasts were generated for the one-year period 9/24/2013 to 9/23/2014. Root mean squared errors calculated using models (4.16) to (4.19) are less than those for models (4.8) to (4.11).

Modest improvements in the predictive power in respect of all the endogenous variables are registered. In addition to securing information on the levels of sensitivity and influence of each market, models (4.16) to (4.19) also enable us to secure more accurate forecasts. This finding is in agreement with Peiró et al. (1998) who also got better forecasts by using the joint system rather than the individual simple regression equations implying the former has more useful results than the latter.

## 4.5 Concluding Remarks

We investigate information flows among wheat futures markets located in different geographical regions. The wheat contracts examined are on the ZCE (China), SAFEX (South Africa), the Euronext/Liffe (Europe) and KCBT (USA). Cross-correlation analysis of the markets shows close linkages between Euronext/Liffe and KCBT and between these two markets and SAFEX. However, no cointegration relationships are found within the four

markets. We then carry out variance decomposition to establish the influence of the markets on each other. The Euronext/Liffe wheat futures market is the most exogenous and also contributes the most to the prediction of the variance of the other three markets while ZCE has the least amount of linkages with the other markets, and, as a consequence, can be considered as a net receiver of information.

To better understand the nature of information flows across the markets, we use the Peiró et al. (1998) approach which seeks to separate the influencing ability and the sensitivity or openness of a market to receiving information from other markets. We find the KCBT futures market is the most influential market of the four wheat markets examined. It may be obvious that KCBT prices drive most of the other markets; however, we have also found that KCBT is, at the same time, the most sensitive of the four futures markets. This fact does not occur with the Euronext/Liffe market, which appears as an influential market with low sensitivity to news coming from other markets. Regarding the ZCE market, it seems that market participation by state-owned entities in the Chinese food markets has eliminated wheat market linkages with the global system.

Findings of this study are in agreement with the views in Fang (2010) who found the Chinese government has imposed both controls and support mechanisms in the wheat market in China. This intervention is such that wheat price movements in China are substantially disconnected with international wheat price movements.

Our findings highlight the leading role of the USA futures markets in the global system and their importance in world commodities and financial systems. We have also seen that the relative openness of the SAFEX wheat market supports information flows and linkages with the KCBT and Euronext/Liffe. However, more supportive policies to incentivise higher wheat

production in South Africa are required to mitigate the impact of price shocks emanating from the global wheat markets.

## Appendices

### Appendix 4.1: Wheat classification and identification

| Class | Category | Sub-class | Protein content | Products | Properties |
|---|---|---|---|---|---|
| Hard red spring | Hard | i. Dark northern spring | 12-15% | Bread | 75% or more hard, vitreous kernels |
| | Hard | ii. Northern spring | 12-15% | Bread | 25-75% hard, dark, vitreous kernels |
| | Hard | iii. Red spring | 12-15% | Bread | <25% hard, dark, vitreous kernels |
| Hard white | Hard | None | 10-15.0% | Bread | |
| Hard red winter | Medium hard | None | 9.5-13.5% | Bread | Medium to hard kernels |
| Durum | Extra hard | i. Hard amber durum | 11-15% | Pasta | 75% or more hard, vitreous kernels |
| | Extra hard | ii. Amber durum | 11-15% | Pasta | 60-75% hard and vitreous kernels |
| | Extra hard | iii. Durum | 11-15% | Pasta | <60% hard and vitreous kernels |
| Soft red winter | Very soft | | 8.0-11.0% | Cookies | |
| Soft white | Very soft | i. Soft white | 8.0-11.0% | Cookies | Soft, <10% white club wheat |
| | | ii. White club | 8.0-11.0% | Cookies | Soft, <10% other soft white |
| | | iii. Western white | 8.0-11.0% | Cookies | <10% white club, ≥10% other soft |
| Unclassed | Unclassed | | - | | Not classified, includes other colors |
| Mixed | Mixed | | - | | <90% one class, ≥10% other class |

Appendix 4.1 has been included to assist with classification and harmonisation of wheat grading. Bread is made using hard wheat while confectionaries are made using soft wheat. This table is classifying USA wheat and has been used as a guide for making comparisons with other global markets. Triticum compactum falls under the soft wheats which include the club wheats shown in the table. Wheat classification in China has two major categories, strong gluten wheat and weak gluten wheat. Strong gluten wheat has crude protein content of at least 14.0% and test weight of 770 grams/Litre. Weak gluten wheat has crude protein content of at least 11.5% and test weight greater than 750 grams/Litre. Zhang (2008) contends that bread is produced using strong gluten wheat while cookies and confectionaries are produced using weak gluten wheat. Milling wheat is the name used on Euronext/Liffe to refer to wheat with bread making characteristics comparable to the hard wheat in the table. Sources: Own elaboration based on tables from Bushuk (1997) and Lukow et al. (2006).

**Appendix 4.2: Wheat futures contract specifications for four markets**

| Futures Exchange | SAFEX | KCBT | NYSE Euronext Liffe | ZCE |
|---|---|---|---|---|
| Region | South Africa | USA | European Union | China |
| Reference point | Randfontein | Kansas | Rouen | Zhengzhou |
| Impurities (%) | 2.0 % | 2.0 % | 2.0 % | 2.0% |
| Specific weight | 76 kg/hl | 78 kg/hl | 76 kg/hl | 76 kg/hl |
| Contract size | 50 tons | 50 tons | 50 tons | 50 tons |
| Trading hours | 9:00am to 12.00pm | 9:30am to 1:15pm | 10:45am to 6:30pm | 9:00 am to 3:00 pm |
| Maturity months | Mar, May, July, Sept, Dec | July, Sept, Dec, Mar, May | Nov, Jan, Mar, May, Sept | Jan, Mar, May, July, Sept., Nov. |
| Foreign material | 1.0 % | 0.7 % | 1.0 % | 1.0 % |
| Broken grains | 5 % | 5% | 4 % | 8.0 % |
| Protein content | 11.0 % | 9.5-13.5 % | 11.0 % | 14-15.0 % |
| Moisture | 13.0 % | 13.5 % | 15.0 % Max. | 13.5 % |
| ISIN Codes | WEA | KW | BL2 | CPM & CWT |
| Quotation | Rands/ton | US Dollars/ton | Euro/ton | Yuan/ton |
| Data Source | www.jse.co.za | www.cmegroup.com | www.nyx.com/liffe | http://www.czce.com.cn |
| Wheat product | RSA bread milling wheat | No. 2 hard red winter | Milling wheat | Hard white and common wheat |

SAFEX stands for the South African Futures Exchange, KCBT is the Kansas City Board of Trade, ZCE is China's Zhengzhou Commodity Exchange.

# 5 MATURITY EFFECTS IN FUTURES CONTRACTS ON THE SAFEX MARKET

## 5.1 Introduction

The chapter looks at the hypothesis that volatility in three asset classes on the futures market in South Africa tends to increase nearer to maturity. The focus is on agricultural, metals and energy contracts. When futures volatility and sensitivity to new information rises as contract maturity nears, the Samuelson effect is said to hold (Galloway & Kolb, 1996; Samuelson, 1965). Understanding futures volatility behaviour is important in determining initial margins, margin adequacy, hedging positions, futures risk and option prices. Maturity effects in SAFEX agricultural futures contracts are investigated for white maize, yellow maize and wheat in Viljoen (2004) using non-parametric approaches. In that study, the Samuelson hypothesis was confirmed in white maize, but not in yellow maize and wheat. In this paper, maturity effects are examined using parametric approaches. Besides revisiting Samuelson effects in agricultural futures, it is believed that this paper is the first study to look at maturity effects in energy or metal contracts on SAFEX. Furthermore, this chapter examines maturity effects taking into account traded volume, open interest and spread in SAFEX contracts.

Findings from the study will be useful to brokers, market operators, risk managers and other market participants in optimising hedging, speculation, margin computations and option pricing (Brooks, 2012). Margins derived using accurate estimates of volatility enable balancing the twin objectives of prudentiality and opportunity cost minimisation sustaining the integrity of a futures exchange (Booth, Broussard, Martikainen, & Puttonen, 1997; Brooks, 2012). When the Samuelson effect holds, margin levels should be increased as the contract nears maturity. Knowledge of volatility behaviour is pivotal in forecasting and developing risk-mitigation strategies on the futures market (Chevallier, 2012). The usefulness of the results

to market participants derives in providing the answer to whether volatility increases as the contract delivery date nears (Samuelson, 1965). Traders are concerned about high volatility as risk premiums increase proportionately with higher price fluctuations (Chevallier, 2012). Hedgers would need to proportionately adjust hedge ratios as price fluctuations vary. As speculators trade volatility, characterising price change behaviour enables capturing arbitrage opportunities (Chevallier, 2012).

The results in this chapter are that only wheat on SAFEX supports the Samuelson effect going by the various tests in literature or using extensions to previously used analysis. The chapter is organized as follows. Section 5.2 provides literature and findings by selected authors on maturity effects. Section 5.3 presents the methodology and data for this study. In Section 5.4, research findings are presented. Section 5.5 describes the robustness analysis carried out to further validate key findings. Section 5.6 concludes the paper.

## 5.2 Literature Review

Tests for maturity effects in literature have generated mixed outcomes (Liu, 2014). Segall (1956) and Telser (1956) first formally acknowledged the tendency for increased financial asset volatility as maturity nears, while Samuelson (1965) put forward the hypothesis to this effect. Samuelson (1965) posited that as a contract gets nearer to maturity, variability in prices rises. In this section, we critically review a number of papers that investigated the Samuelson hypothesis. Galloway and Kolb (1996) suggest sensitivity to new information increases nearer maturity as spot and futures prices converge, hence the occurrence of maturity effects. A phenomenon called “negative covariance” hypothesis has also been identified as promoting maturity effects (Bessembinder, Coughenour, Seguin, & Smoller, 1996; Duong & Kalev, 2008). In Bessembinder et al. (1996) the negative covariance effect suggests a negative relation between spot prices and changes in the net carry costs for a

given futures contract. Several scholars have also supported the negative covariance hypothesis (Allen & Cruickshank, 2002; Galloway & Kolb, 1996; Khoury & Yourougou, 1993). One of the key implications as pointed out in Milonas (1986a) is that margins used as deposit for taking futures positions ought to be lower in distant months compared to nearer-to-maturity months. Duong and Kalev (2008) posit that hedging is impacted by maturity effects as volatility is a key consideration. Option pricing is dependent on volatility and should therefore take into account the Samuelson hypothesis (Duong & Kalev, 2008).

In Castelino and Francis (1982), maturity effects are accepted for CBOT soybean and wheat futures for data from 1960 through 1971. In Anderson (1985), data from 1966 through 1980 on 8 commodities is used in maturity-effect estimations. CBOT, KCBT, CME and COMEX futures contracts were examined finding five commodities with Samuelson effects including wheat, oats, soybeans, live cattle and cocoa. Maturity effects in agricultural, financial and metal futures are investigated in Milonas (1986) and Milonas (1991). The studies examine 5 agricultural, 3 financial and 3 metal futures contracts. Out of the 11 futures contracts, 10 supported the Samuelson hypothesis (4 agricultural, 3 financial and 3 metals contracts). Evidence was also provided that far-from-maturity futures contracts were reacting less strongly to information than nearer-maturity contracts.

Serletis (1992) finds support for the Samuelson hypothesis in NYMEX energy contracts in data from 1987 through 1990. Khoury and Yourougou (1993) examined 6 agricultural futures on the Winnipeg Commodity Exchange (WCE) with data from 1980 to 1989. Price data used includes WCE daily high, low, open, and close levels for canola, rye, feed barley, feed wheat, flaxseed and oats. All futures contracts supported calendar seasonality effects as well as maturity effects using OLS regression estimation. Goodwin and Schnepf (2000) confirm the Samuelson hypothesis in maize but not wheat in US futures markets using weekly data.

GARCH estimations and the VAR approaches used find seasonality, crop growing conditions and the maturity effect as key determinants of price volatility. In Chatrath et al. (2002) there is support for the Samuelson effect for maize but not wheat. The analysis uses augmented GARCH extensions with control for seasonality and maturity effects. Daal, Farhat and Wei (2003) find support for maturity effects by agricultural and energy contracts listed in London, Sydney, Tokyo, Winnipeg and the US over the period 1960 through 2000.

In a study involving 20 futures contracts from four categories (agricultural, energy, metals, financial), Duong and Kalev (2008) confirmed the Samuelson effect for agricultural futures, but not for metals, energy and financial futures. Data in the study was from 1996 to 2003. A different study by Kalev and Duong (2008) investigated the Samuelson effect in 14 futures using data from 1996 through 2003. Agricultural contracts supporting the Samuelson hypothesis included maize, soybean, soybean oil, soybean meal and wheat. The maturity effect was not supported by energy, metal and financial futures. Maturity effects were examined in Karali and Thurman (2010). Futures contracts studied were maize, soybeans, wheat and oats, all on the North American grain futures markets. Strong evidence of the Samuelson effect in contracts studied is confirmed. Kenourgios and Katevatis (2011) examined two leading Greek indices on the Athens Derivatives Exchange (ADEX) finding support for the Samuelson hypothesis in both of them. OLS and GARCH approaches were used with data from 1999 through 2007. It has also been suggested in a number of studies the maturity effect is not common in financial futures (Allen & Cruickshank, 2000; Duong & Kalev, 2008; Galloway & Kolb, 1996).

Finally, Kenourgios and Katevatis (2011) have incorporated market liquidity and seasonality-related variables into maturity effect estimations. Their idea was to find out if these variables were more important in explaining volatility than time-to-maturity. A positive link between

volatility and traded volume and a negative link between volatility and open interest were confirmed. For the two financial indices examined, inclusion of volume and open interest in the maturity effect relation diminished the significance of the coefficient for time-to-maturity. This paper has looked at this literature and gone further to consider the bid-ask spread, another key liquidity variable in financial markets.

In this study, more contracts have been added to the analysis extending from Viljoen (2004) who looked at white and yellow maize as well as wheat, but did not look at maturity effects in the energy and metals classes on SAFEX. It should be noted that literature has obtained different results for commodities in different asset classes (see Daal et al., 2003; Duong & Kalev, 2008; Galloway & Kolb, 1996; Kalev & Duong, 2008; Milonas, 1986b; Milonas, 1991; Serletis, 1992). It was felt important to the analysis to know whether there could be specific patterns on SAFEX leading to support for maturity effects, or lack thereof, across commodity classes, within a specific asset class, or depending on the market of primary listing of a given contract.

Literature also generally agrees, including in Castelino and Francis (1982), Milonas (1986a) and Kolb (1997), that futures and spot prices converge at contract maturity leading to higher sensitivity to new information just before contract expiration. South Africa has traditionally been a major producer of various minerals from which metal products are manufactured. The country also produces its own fuel, having the world's biggest synfuel (SASOL Pty. Ltd.) plant converting coal to petroleum products (Eberhard, 2011). Investigating more asset classes significantly important to the South African economy was essential for new literature, given that large sectors of the domestic economy are impacted by developments in the markets in which these commodities are traded. Lee, Hsu and Ke (2013) find agricultural

futures, by way of their unique harvesting and growing cycles, having distinct seasonal patterns quite distinct from the metal and energy commodity classes.

In terms of methodology for investigating contract maturity effects, this thesis accounts for the impact of traded volume, open interest and the bid – ask spread. This approach expands literature by extending from Kenourgios and Katevatis (2011), who included the two other explanatory variables, leaving out the bid – ask spread in their estimations. Further, the thesis accounts for both seasonality and multicollinearity, which is not easy to achieve when applying non-parametric analysis, as employed in Viljoen (2004). It should be noted that the Viljoen (2004) study did not find support for maturity effects in the wheat contract, contrary to findings in this thesis. Arguments as to why there would be differences between the two studies are comprehensively looked at both in the first and current chapters of this thesis. Owing to differences in both methodology and findings, the current study brings new perspectives to maturity effects literature.

## 5.3 Methodology and Data

### *5.3.1. Empirical Methodology*

Estimation of maturity effects in this paper is by ordinary least squares (OLS) with time-to-maturity as one of the explanatory variables to contract volatility. To derive return volatility, a variability estimator generated from daily high-low prices is used. This approach is similar to Garman and Klass (1980), Parkinson (1980) and Serletis (1992). The specification of volatility follows the relation

$$VAR_t = \frac{\left(\ln H_t - \ln L_t\right)^2}{4\ln 2} \tag{5.1}$$

Where $H_t$ and $L_t$ are high and low prices, respectively. In Serletis (1992), simple regression estimation has been used to check for the Samuelson effect as follows:

$$VAR_t = \alpha_0 + \alpha_1 \ln TTM_t + \varepsilon_t \quad (5.2)$$

Where $VAR_t$ is the volatility of futures prices or returns derived from daily high and low prices in Equation (5.1). Time-to-maturity on day *t* is captured in $TTM_t$ which decreases from the time a contract is listed to its maturity (when it becomes zero), and a random error is represented by $\varepsilon_t$ .

Similar to Kenourgios and Katevatis (2011), traded volume and open interest are introduced into the relations testing for the maturity effect using the following relation:

$$VAR_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \Delta \ln OI_t + u_t \quad (5.3)$$

Time-to-maturity, traded volume and change in open interest are captured respectively in $lnTTM_t$, $lnVol_t$ and $\Delta lnOI_t$. The paper makes an addition to literature by incorporating the bid-ask spread, an important liquidity variable in financial markets. This paper follows Corwin and Schultz (2012) who make use of daily high and low prices to derive the bid-ask spread. Roll (1984) postulates that the bid-ask spread is a reflection of transaction costs which themselves influence liquidity in futures markets. Corwin and Schultz (2012) acknowledge their bid-ask spread estimator is fairly easy to generate and use. The key relation for deriving the estimator is:

$$\left[\ln\left(H_t^0 / L_t^0\right)\right]^2 = \left[\ln\left(\frac{H_t^A\left(1+S/2\right)}{L_t^A\left(1-S/2\right)}\right)\right]^2 \quad (5.4)$$

Where the actual daily high and low prices are captured in $H_t^A(L_t^A)$, and $H_t^0(L_t^0)$ are observed daily high and low prices, on trading day *t*. The bid-ask spread in Corwin and Schultz (2012) was defined by the simplified relation:

$$S = \frac{2\left(e^{\alpha}-1\right)}{1+e^{\alpha}} \quad (5.5)$$

Furthermore, simplification of the equations gives:

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}} \tag{5.6}$$

Parameters $\beta$, and $\gamma$ are elaborately defined in Corwin and Schultz (2012). The relation for $\beta$ is:

$$\beta = E\left\{ \sum_{j=0}^{1} \left[ \ln\left( \frac{H_{t+j}^{0}}{L_{t+j}^{0}} \right) \right]^2 \right\} \tag{5.7}$$

The parameter $\gamma$ can be estimated using the relation

$$\gamma = \left[ \ln\left( \frac{H_{t,t+1}^{0}}{L_{t,t+1}^{0}} \right) \right]^2 \tag{5.8}$$

In the above relation, $H_{t,t+1}$ is the high price for the 2 days *t* and *t+1*and $L_{t,t+1}$ is the low price during the 2 days *t* and *t+1*. Bid-ask spread estimates for 2-day periods are used in Corwin and Schultz (2012) to derive average monthly spreads.

The next step in this paper is to expand on the relation in Equation (5.3). Using the series for the bid-ask spread in Equation (5.5), the paper estimates:

$$VAR_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \Delta \ln OI_t + \beta_4 SP_t + \zeta_t \tag{5.9}$$

Where $SP_t$ is the bid-ask spread series for each contract. This brings into literature an extension to the relation introduced by Kenourgios and Katevatis (2011), which did not include the bid-ask spread. Given that trading-related variables are correlated, Equation (5.9) could have multicollinearity problems. For this reason, the paper makes provision for such adverse outcome thus improving the specification of the above relation.

In this process, the analysis explores the relationship between change in open interest and traded volume. Chamberlain (1989) used the following relation

$$Ln\Delta OI_t = \alpha_0 + \alpha_1 LnVol_t + \varepsilon_{1,t} \quad (5.10)$$

In the above $\alpha_1$ provides the extent of influence of changes in traded volume on change in open interest. Residuals $\varepsilon_{1,t}$ are saved to become a regressor in the next relation estimating the bid-ask spread.

$$SP_t = \alpha_0 + \alpha_1 \ln Vol_t + \hat{\varepsilon}_{1,t} + \varepsilon_{2,t} \quad (5.11)$$

Where $SP_t$ is the spread as defined by the estimator in Corwin and Schultz (2012). To account for multicollinearity in Equation (5.9), change in open interest and spread are replaced by their residuals in the modified relation as follows:

$$VAR_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \hat{\varepsilon}_{1,t} + \beta_4 \hat{\varepsilon}_{2,t} + \upsilon_t \quad (5.12)$$

Proxies for $ln\Delta OI_t$ and $SP_t$ are respectively, $\hat{\varepsilon}_{1,t}$ and $\hat{\varepsilon}_{2,t}$.

Finally, seasonality at daily and monthly levels has been taken into account to model volatility and the residuals (from the seasonality relation) have been taken as the new volatility series to replace that used in Equation (5.12). The respective relations used are elaborately outlined in equations (5.14) and (5.15) below.

### *5.3.2. Data*

End of day futures trade close prices, daily high and low prices as well as daily traded volume and open interest for white maize, yellow maize, wheat, silver and WTIO crude have been used. Daily data was collected through Thompson Reuters and DataStream for various periods depending on respective contract listing. Returns were calculated using the relation

$$R_t = 100 * \ln\left(P_t \Big/ P_{t-1}\right) \quad (5.13)$$

Where $R_t$ is the futures contract return and the price and lagged price series are respectively given in $P_t$ and $P_{t-1}$. Prices are expressed in Rands (the South African currency) per ton, and returns are expressed in percentage terms.

Contract specifications and maturity months for futures in this study are provided in Table 5.1. Agricultural commodity contracts have maturities in March, May, July, September and December. Energy and metals contracts mature in March, June, September and December. SAFEX trading hours are from 9.00 am to 12.00 pm during business days.

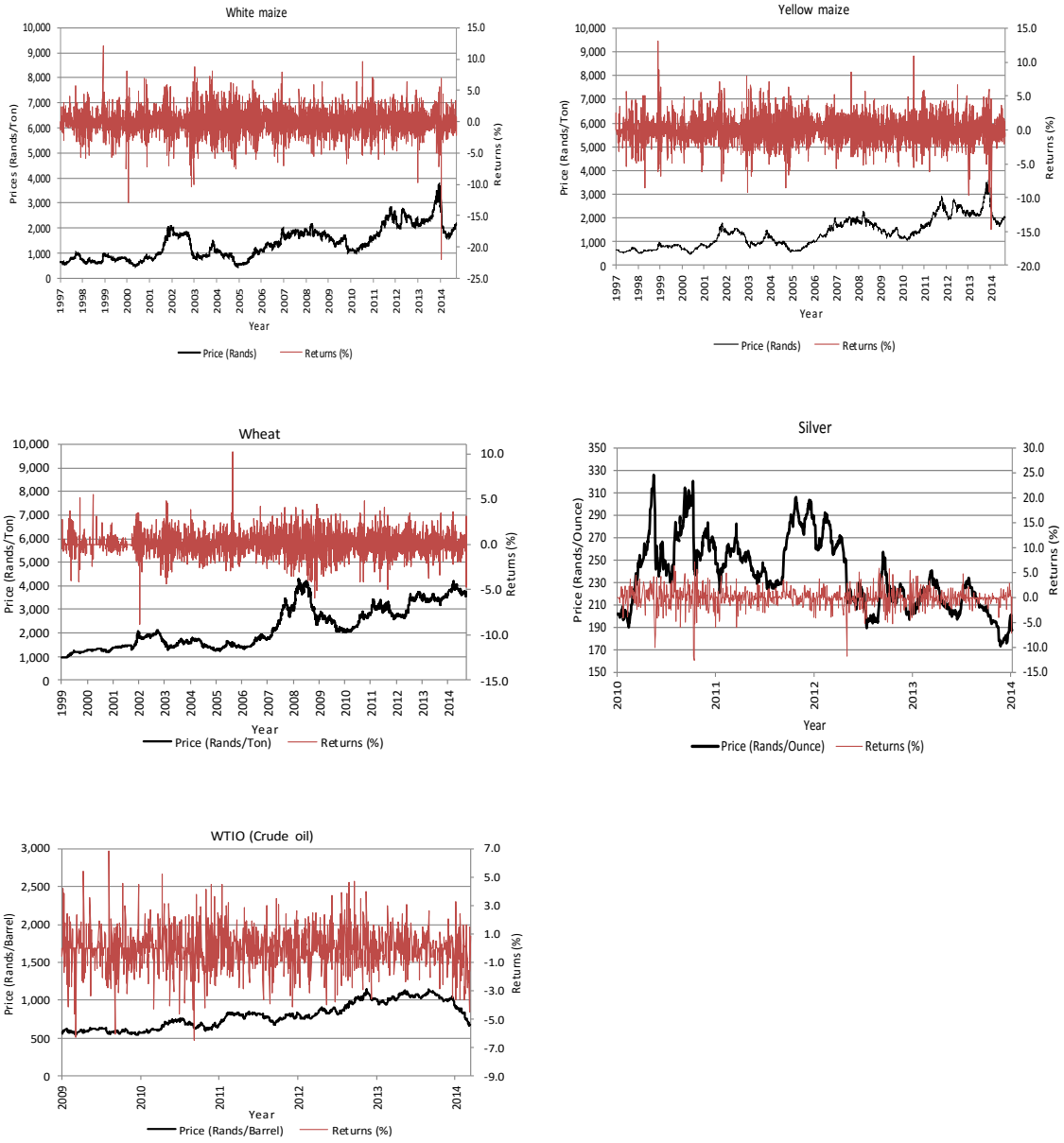
**Table 5.1: Contracts descriptive information**

| Commodity | Beginning | End | Observations | Maturity months | Year of Listing |
|---|---|---|---|---|---|
| *Agricultural commodities* | | | | | |
| White maize | 01/04/1997 | 22/12/2014 | 4425 | 3,5,7,9,12 | 1997 |
| Yellow maize | 01/04/1997 | 28/11/2014 | 4416 | 3,5,7,9,12 | 1997 |
| Wheat | 01/01/1999 | 23/09/2014 | 3937 | 3,5,7,9,12 | 1997 |
| *Metals commodities* | | | | | |
| Silver | 14/12/2010 | 19/12/2014 | 995 | 3,6,9,12 | 2010 |
| *Energy commodities* | | | | | |
| WTIO | 12/10/2009 | 22/12/2014 | 1297 | 3,6,9,12 | 2009 |

Descriptive information on the contracts in this study is presented in the table. The months January,…., December are represented under the column "Maturity months" as respectively 1,…,12. Contracts are categorized as agricultural, metals and energy contracts.

In Figure 5.1, the graphs for each contract show the price and returns series from the beginning of each contract's sample to about December 2014. Peak maize and wheat prices around mid-2008 coincide with the global economic downturn. For white and yellow maize, an additional notable peak in prices (beyond R3,000.00 per ton) was recorded in early 2014. The high prices were attributable to globally tight supply conditions compounded by poor earlier rainfall in South Africa. White and yellow maize prices subsequently collapsed to a trough below R2,000.00 per ton around harvest time (about mid-2014) before climbing gradually upwards.

**Figure 5.1: Graphs on price and return series by commodity**




Graphs for the daily price and returns series for white maize, yellow maize, wheat, silver and WTIO (crude oil) traded on SAFEX are presented. Daily contract prices are expressed in Rands and returns are presented in percentage terms. The horizontal axis presents the time period over which data for respective contracts has been collected.

Silver and WTIO have primary listings on Chicago Mercantile Exchange (CME) in the USA. This means these contracts simultaneously trade on SAFEX and CME in Rands and US Dollars respectively. As such, prices for these contracts are strongly related with international levels. Silver prices have been flat since listing before declining marginally in

the second half of the graph. WTIO contract prices on SAFEX have been gradually rising since listing only to start falling significantly in the second half of 2014.

## 5.4 Results and Discussion

Firstly, we look at whether contracts support the Samuelson effect using ordinary least squares estimation. Table 5.2 gives the results of the tests using Equation (5.2).

**Table 5.2: Test for maturity effects using daily high and low prices**

| Commodity | $\alpha_0$ | $\alpha_1$ | $R^2$ | Adj. $R^2$ |
|---|---|---|---|---|
| White maize | 0.00022*** [0.0000] | -0.00001 [0.3104] | 0.0002 | 0.0000 |
| Yellow Maize | 0.00030*** [0.0000] | -0.00005*** [0.0000] | 0.0115 | 0.0112 |
| Wheat | 0.00021*** [0.0000] | -0.00005*** [0.0000] | 0.0223 | 0.0220 |
| Silver | -0.00002 [0.6770] | 0.00003** [0.0406] | 0.0089 | 0.0068 |
| WTIO | 0.08924 [0.2883] | -0.01934 [0.4562] | 0.0007 | -0.0006 |

Ordinary least squares estimation of volatility is presented, with the daily high-low price volatility estimator. The regression estimated in the table is specified as:

$$VAR_t = \alpha_0 + \alpha_1 \ln TTM_t + \varepsilon_t$$

P-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively.

Here we make use of daily high and low prices to generate the volatility estimator in Equation (5.1). In this estimation, yellow maize and wheat support the maturity effect at 1 % level of significance while silver has a positive and significant coefficient at 10 % level, suggesting volatility declines as time-to-maturity decreases.

We present the analysis for Equation (5.9) in Table 5.3. Traded volume, open interest and bid-ask spread are each introduced in stages, finding influences of respective liquidity variables on volatility and time-to-maturity. Three panels have been used to present the results. Panel A gives the estimation explaining volatility using time-to-maturity and traded volume. For Panel B, volatility is expressed in terms of time-to-maturity, traded volume and change in open interest. Panel C additionally brings bid-ask spread to the analysis to complete the estimation envisaged in Equation (5.9).

**Table 5.3: Maturity effect: volume, change in open interest and spread**

| Description | W/Maize | Y/Maize | Wheat | Silver | WTIO |
|---|---|---|---|---|---|
| *Panel A: Maturity effect and volume* | | | | | |
| $\beta_0$ | 0.00006 | 0.00020*** | 0.00013*** | -0.00012*** | 0.11254 |
| | [0.3544] | [0.0000] | [0.0000] | [0.0062] | [0.3210] |
| $\beta_1$ | 0.00000 | -0.00004*** | -0.00004*** | 0.00003*** | -0.03866 |
| | [0.8163] | [0.0000] | [0.0000] | [0.0073] | [0.2252] |
| $\beta_2$ | 0.00002*** | 0.00002*** | 0.00001*** | 0.00006*** | 0.01276 |
| | [0.0010] | [0.0004] | [0.0000] | [0.0000] | [0.4055] |
| *Adj. $R^2$* | 0.0024 | 0.0141 | 0.0280 | 0.0890 | 0.0002 |
| *Panel B: Maturity effect, volume and change in open interest* | | | | | |
| $\beta_0$ | 0.00003 | 0.00019*** | 0.00013*** | -0.00012*** | 0.11170 |
| | [0.6015] | [0.0000] | [0.0000] | [0.0087] | [0.3255] |
| $\beta_1$ | -0.00000 | -0.00004*** | -0.00004*** | 0.00003** | -0.03962 |
| | [0.6225] | [0.0000] | [0.0000] | [0.0108] | [0.2156] |
| $\beta_2$ | 0.00003*** | 0.00002*** | 0.00001*** | 0.00006*** | 0.01390 |
| | [0.0000] | [0.0005] | [0.0000] | [0.0000] | [0.3685] |
| $\beta_3$ | 0.00001 | -0.00000 | -0.00000 | 0.00002 | 0.06873 |
| | [0.6815] | [0.9259] | [0.7691] | [0.2719] | [0.3541] |
| *Adj. $R^2$* | 0.0090 | 0.0122 | 0.0272 | 0.0897 | -0.00002 |
| *Panel C: Maturity effect, volume, change in open interest and spread* | | | | | |
| $\beta_0$ | -0.00016*** | 0.00003 | 0.00005 | -0.00024*** | 0.14435 |
| | [0.0010] | [0.4884] | [0.1046] | [0.0007] | [0.2533] |
| $\beta_1$ | -0.00000 | -0.00003*** | -0.00004*** | 0.00005** | -0.04710 |
| | [0.7925] | [0.0003] | [0.0000] | [0.0208] | [0.1839] |
| $\beta_2$ | 0.00003*** | 0.00002*** | 0.00001*** | 0.00005*** | 0.00942 |
| | [0.0000] | [0.0018] | [0.0084] | [0.0004] | [0.5851] |
| $\beta_3$ | -0.00000 | -0.00002 | 0.00000 | 0.00001 | -0.00584 |
| | [0.9024] | [0.1518] | [0.6914] | [0.7039] | [0.9431] |
| $\beta_4$ | 0.00936*** | 0.00783*** | 0.00754*** | 0.00425*** | -0.04099 |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.9244] |
| *Adj. $R^2$* | 0.1247 | 0.0940 | 0.0956 | 0.2674 | -0.0036 |

Ordinary least squares (OLS) estimation for the influence on volatility of time-to-maturity, traded volume, change in open interest and the bid-ask spread is presented. Panel A introduces time-to-maturity and traded volume while Panel B additionally includes change in open interest. Furthermore, Panel C introduces an estimator of the bid-ask spread to estimate the relation:

$$VAR_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \Delta \ln OI_t + \beta_4 SP_t + \zeta_t$$

Volatility in the relation is derived from daily high and low prices using Equation (5.1). The estimator of the bid-ask spread, $SP_t$ is derived using daily high and low prices. P-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively.

In Panel A, evidence of the Samuelson effect is shown at 1% level for yellow maize and wheat. There is no support for the maturity effect in white maize and WTIO while volatility in silver actually decreases with diminishing time-to-maturity. An investigation was also conducted into the support for the mixture of distributions hypothesis (MDH), which suggests a direct relation between volatility and traded volume. MDH was found to hold in contracts

inclusive of white maize, yellow maize, wheat and silver. Results for these contracts are in agreement with Epps and Epps (1976) who first proposed the MDH, also later supported by findings in Bessembinder and Seguin (1993) and Andersen (1996). Neither volume nor time-to-maturity has explanatory power on the volatility of the WTIO contract.

In Panel B of Table 5.3, traded volume is significant at 1% level in explaining volatility in white maize, yellow maize, wheat and silver. Change in open interest has insignificant explanatory power for white maize, yellow maize, wheat, silver and WTIO crude. Yellow maize and wheat remain in support of the Samuelson effect after inclusion of change in open interest in Panel B. Findings on open interest in Kyle (1985) and Madarassy (2003) have been asset return volatility has a significant relation with open interest. Open interest has been acknowledged as a possible proxy for market depth in Madarassy (2003)[25]. Bessembinder and Seguin (1993) found an inverse relationship between volatility and market depth.

Bid-ask spread is introduced in Panel C. In this panel, both traded volume and bid-ask spread have a positive significant relationship at 1 % level with white maize, yellow maize, wheat and silver. Yellow maize and wheat still support the Samuelson effect while silver volatility declines with decreasing period to maturity. Inclusion of all 3 liquidity variables in Equation (5.9) does not diminish maturity effects in yellow maize and wheat. In all 3 panels examined, white maize and WTIO have insignificant volatility changes as contract maturity approaches.

Looking at liquidity variables in Equation (5.9), it was necessary to address multicollinearity in the case that it existed. Given possible relationships among explanatory variables, the

[25] Market depth is defined in Madarassy (2003) as order flow capable of moving financial asset prices by one unit.

next step was to construct a table of cross-correlation coefficients. There is evidence of significant cross-correlations between volume and change in open interest for white maize, wheat and WTIO crude, as shown in Table 5.4. Significant positive cross-correlation between traded volume and bid-ask spread is observed in white maize, wheat and silver. Change in open interest and bid-ask spreads are significantly positively correlated in the case of white maize and yellow maize. Cross-correlations among explanatory variables in Equation (5.9) confirmed there was need to account for multicollinearity. Iterative regressions in equations (5.10) and (5.11) were estimated generating the residuals series from relations of change in open interest and bid-ask spread, respectively denoted as $\hat{\varepsilon}_{1,t}$ and $\hat{\varepsilon}_{2,t}$.

**Table 5.4: Cross-correlations: volume, open interest, spread**

| Description | | $lnVol_t$ | | $\Delta lnOI_t$ | |
|---|---|---|---|---|---|
| White maize | $\Delta lnOI_t$ | 0.04510*** | [0.0047] | 1.00000 | |
| | $SP_t$ | 0.06290*** | [0.0001] | 0.03270** | [0.0406] |
| Yellow maize | $\Delta lnOI_t$ | 0.01620 | [0.3238] | 1.00000 | |
| | $SP_t$ | 0.01010 | [0.5381] | 0.06610*** | [0.0001] |
| Wheat | $\Delta lnOI_t$ | 0.07390*** | [0.0002] | 1.00000 | |
| | $SP_t$ | 0.06250*** | [0.0014] | -0.02970 | [0.1281] |
| Silver | $\Delta lnOI_t$ | -0.09530 | [0.1189] | 1.00000 | |
| | $SP_t$ | 0.31990*** | [0.0000] | 0.06510 | [0.2873] |
| WTIO Crude | $\Delta lnOI_t$ | -0.12850*** | [0.0013] | 1.00000 | |
| | $SP_t$ | 0.04360 | [0.2755] | -0.05620 | [0.1600] |

The table shows cross-correlations among traded volume, change in open interest and bid-ask spread. $SP_t$ represents bid-ask spread generated using the estimator in Corwin and Schultz (2012). As there are significant cross-correlation coefficients, the need arises for modifying estimations to account for the impact of multicollinearity. P-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively.

Equation (5.12) is the estimated model with results presented in Table 5.5. Findings show that yellow maize and wheat support maturity effects at 1% significance level after accounting for multicollinearity.

Residuals of change in open interest ($\hat{\varepsilon}_{1,t}$) have no significance in explaining volatility for any of the 5 contracts.

**Table 5.5: Maturity effect: traded volume, residuals of change in open interest, spread**

| Description | W/Maize | Y/Maize | Wheat | Silver | WTIO |
|---|---|---|---|---|---|
| $\beta_0$ | 0.00000 | 0.00017*** | 0.00014*** | -0.00017** | 0.14317 |
| | [0.9758] | [0.0000] | [0.0000] | [0.0184] | [0.2570] |
| $\beta_1$ | -0.00000 | -0.00003*** | -0.00004*** | 0.00005** | -0.04710 |
| | [0.7925] | [0.0003] | [0.0000] | [0.0208] | [0.1839] |
| $\beta_2$ | 0.00003*** | 0.00002*** | 0.00001*** | 0.00008*** | 0.00948 |
| | [0.0000] | [0.0011] | [0.0005] | [0.0000] | [0.5810] |
| $\beta_3$ | 0.00001 | -0.00000 | 0.00000 | 0.00003 | -0.00530 |
| | [0.5822] | [0.8230] | [0.9214] | [0.2531] | [0.9481] |
| $\beta_4$ | 0.00936*** | 0.00783*** | 0.00754*** | 0.00425*** | -0.04099 |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.9244] |
| *Adj.* $R^2$ | 0.1247 | 0.0940 | 0.0956 | 0.2674 | -0.0036 |

Presented in the table is ordinary least squares (OLS) estimation for the influence on volatility of time-to-maturity, traded volume and residuals from the change in open interest and bid-ask spread relations. The model estimated is:

$$VAR_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \hat{\varepsilon}_{1,t} + \beta_4 \hat{\varepsilon}_{2,t} + \upsilon_t$$

Residuals for change in open interest and bid-ask spread are respectively, $\hat{\varepsilon}_{1,t}$ and $\hat{\varepsilon}_{2,t}$. Volatility in the relation is derived from high and low prices using Equation (5.1). P-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively.

## 5.5 Seasonality and maturity effects

Milonas (1986) and Choi and Longstaff (1985) suggest the Samuelson effect has secondary impact subordinate to seasonality. We attempt to filter out seasonality in futures contracts while determining maturity effects in Table 5.6.

To account for seasonality, the following relation is used:

$$VAR_t = \alpha + \sum_{i=2}^{5} \delta_i D_{i,t} + \sum_{m=2}^{12} \theta_m M_{m,t} + \xi_t \qquad (5.14)$$

Daily and monthly dummies are given by $D_{i,t}$ and $M_{m,t}$ respectively. Residuals series $\xi_t$, is saved as the new volatility series $nv_t$. The following regression is then estimated in Table 5.6:

$$nv_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \hat{\varepsilon}_{1,t} + \beta_4 \hat{\varepsilon}_{2,t} + \eta_t \qquad (5.15)$$

Findings on this estimation provide evidence that wheat still supports the Samuelson hypothesis after accounting for daily and monthly seasonality. White maize and silver have a significant coefficient for the time-to-maturity term, but with a positive sign. Both of these

contracts therefore experience lower volatility as maturity nears. A key observation is that inclusion of seasonality has not affected support for maturity effects in wheat but that which was earlier detected in yellow maize.

**Table 5.6: Maturity effects – accounting for multicollinearity and seasonality**

| Description | W/Maize | Y/Maize | Wheat | Silver | WTIO |
|---|---|---|---|---|---|
| $\beta_0$ | -0.00029*** | -0.00009** | 0.00001 | -0.00028*** | 0.09291 |
| | [0.0000] | [0.0262] | [0.8340] | [0.0001] | [0.4570] |
| $\beta_1$ | 0.00002* | -0.00001 | -0.00002*** | 0.00006*** | -0.04008 |
| | [0.0775] | [0.5136] | [0.0030] | [0.0013] | [0.2529] |
| $\beta_2$ | 0.00004*** | 0.00002*** | 0.00001*** | 0.00007*** | 0.00893 |
| | [0.0000] | [0.0000] | [0.0001] | [0.0000] | [0.5991] |
| $\beta_3$ | 0.00001 | 0.00000 | 0.00000 | 0.00003 | -0.01912 |
| | [0.5769] | [0.9657] | [0.7795] | [0.2478] | [0.8127] |
| $\beta_4$ | 0.00847*** | 0.00706*** | 0.00740*** | 0.00373*** | -0.02590 |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.9516] |
| *Adj. $R^2$* | 0.1103 | 0.0779 | 0.0837 | 0.2506 | -0.0045 |

Ordinary least squares (OLS) estimation of maturity effects is presented. Seasonality at the daily and monthly levels is taken into account by way of dummy variables. The seasonality relation is:

$$VAR_t = \alpha + \sum_{i=2}^{5} \delta_i D_{i,t} + \sum_{m=2}^{12} \theta_m M_{m,t} + \xi_t$$

Residuals $\varepsilon_t$ are saved as the new volatility series $nv_t$. The relation estimated in this table is:

$$nv_t = \beta_0 + \beta_1 \ln TTM_t + \beta_2 \ln Vol_t + \beta_3 \hat{\varepsilon}_{1,t} + \beta_4 \hat{\varepsilon}_{2,t} + \eta_t$$

Residuals derived from change in open interest, and bid-ask spread are respectively represented as $\hat{\varepsilon}_{1,t}$ and $\hat{\varepsilon}_{2,t}$. P-values are shown in parenthesis. Significance levels at 1%, 5% and 10% are depicted by ***, ** and * respectively.

Findings in this study are in disagreement with those of Viljoen (2004) who found support for the Samuelson hypothesis in white maize, but not in yellow maize and wheat using data from 1997 to 2003. Differences in findings are partly attributable to the different timeframes over which data was sampled. Approaches used in the two studies are also not similar.

## 5.6 Implications and possible market applications

Derivative market positions are susceptible to volatility risks that manifest in unexpected change in value. Volatility swaps in the form of a forward or futures contract on realized or implied volatility have traditionally been used to manage these risks. Speculators trading volatility would benefit from its increase. Participants holding a physical or underlying futures

position may need to hedge the risk for example, using a straddle option similar to Brenner, Ou and Zhang (2006). This could be the case for particularly silo facility owners holding their own physical wheat stocks leading up to maturity in the futures contract.

Wheat experiences an increase in volatility as maturity nears and hence a delta neutral position should be more difficult to achieve as changes in volatility make traders vulnerable. The reverse scenario applies to white maize and silver, whose volatility reduces as maturity nears. It is worth noticing that the value of an option in the Black – Scholes formula increases (either call or put) with higher volatility levels and the ability to predict volatility levels places a trader in a profitable position (see also Bakshi and Madan (2000)). Furthermore, the strategy in Brenner, Ou and Zhang (2006) trades volatility changes which linearly correspond to variation in the value of the proposed “at-the-money-forward straddle”.

Cooper (2013) postulates traditional volatility investing entails trading in options, futures or variance swaps. Volatility stylized facts are i) volatility is predictable, and ii) investors are prepared to pay a premium for their risk to be shifted to a third party. Strategies crafted around volatility derive their profits from these volatility risk premiums, which are paid by hedgers. As pointed out in Bueno, de Olmo, Ivorra, and de Master (2012), the value of an option is dependent on the future standard deviation of volatility. The profit of investment in an option is the value at the time of sale less the value at the time of purchase.

A possible strategy is to buy and hold wheat options in anticipation of the increase in value till maturity, where the position may then be lifted. In this regard therefore, it appears the value of white maize and silver options is bound to decrease as maturity approaches. In this case, a prudent strategy would be to sell white maize and silver options which are bound to end up out-of-the-money, allowing the option writer to earn the full premium paid.

## 5.7 Concluding Remarks

Maturity effect estimations are carried out in this paper using five futures contracts in the agricultural, metals and energy categories. The Samuelson hypothesis suggests volatility increases as time-to-maturity diminishes (Samuelson, 1965). Following Kenourgios and Katevatis (2011), the paper looked at the joint effect of traded volume, change in open interest and time-to-maturity on return variability. An extension was introduced to additionally include bid-ask spread as a liquidity explanatory variable. By replacing change in open interest and the bid-ask spread with respective residuals, estimation of maturity effects took account of multicollinearity, to give better specified results. After these adjustments, yellow maize and wheat showed evidence of support for maturity effects. Finally, seasonality was accounted for in the robustness analysis finding daily and monthly seasonality not affecting maturity effects in wheat. Yellow maize no longer supported maturity effects after taking into account seasonality. WTIO crude oil has shown no support for maturity effects at all, while white maize and silver volatility decline as time-to-maturity decreases. Findings in this paper are of interest to a range of market participants in-so-far as contract volatility is an input in pricing futures or options, hedging, speculation and setting margins on the SAFEX market.

Margins for wheat should be increased proportionately as the contract approaches maturity in the months of March, May, July, September and December.

# 6 MARGIN ADEQUACY AND EXTREME VALUE ANALYSIS ON SAFEX

## 6.1 Introduction

Extreme value analysis (EVA) is suitable in modelling rare occurrences whose consequences are substantial (Gilli and Këllezi, 2003). EVA can be used in finance where assets experience sharp drops or sudden jumps in prices over time (Jondeau & Rockinger, 1999). A margin is a good faith deposit protecting financial market participants from default. Optimal margins ensure the likelihood of transaction losses exceeding margin provisions is kept minimal. This chapter looks at margins on the South Africa Futures Exchange (SAFEX) using extreme value theory with and without price limit events. It provides insight to the probability of margin depletion in white maize, yellow maize, wheat, silver and crude oil (WTIO) within the SAFEX settlement period. To the best of our knowledge, margin exceedances in contracts on SAFEX have not been looked at in depth in both the academic and professional literature.

Margins are central to risk minimization and market stability. Figlewski (1984) concludes the purpose of minimum margins is protecting investors from too much leverage while supporting price stability. Margin setting entails balancing costs of trading while reducing the probability of default (Dewachter & Gielens, 1999). This guarantees fulfilment of futures positions taken by the traders and investors. While sufficient margins protect futures market integrity, excessive margins make a futures market unattractive. Inadequate margins lead to defaults as previously experienced on financial markets in Paris, Kuala Lumpur and Hong Kong (Booth, Broussard, Martikainen, & Puttonen, 1997). Longin (1999) postulates that substantial price shifts potentially cause a margin account to be wiped out resulting in a margin call. If an investor reneges on the call, default will result. The view in Warshawsky

(1989) is that margins should cover 98 to 99% of futures market price movements. Dutt and Wein (2003) suggest margins must cover at least 95 % of an asset's price movements.

Mechanisms to protect against futures market failure include margins supported by daily marking-to-market, price limits and futures market circuit breakers (Broussard, 2001). The process of default prevention should however not compromise market liquidity as this is detrimental to efficient price discovery. Margins should allow for competitiveness of the exchange while protecting default risk (Cotter, 2001). Ultimately, competitiveness of an exchange is gauged by trading cost levels referred to as the hypothesis of efficient contract design in Brennan (1986).

The contribution of this chapter to margin exceedance literature is four fold. Firstly, the study examines the impact of price limits on margin violation probabilities on SAFEX. While taking account of price limit events, the chapter directly provides functional information on margin-setting. A price limit event occurs where price changes exceed the set limit levels. Such event constitutes a mechanism allowing traders time to raise funds for variation margins (Longin, 1999). Barriers to large price movements are imposed by price limits without halting trading. Chou, Lin, and Yu (2000) acknowledge price limits may help reduce market default while lowering required margin levels. Brennan (1986) argues price limits are a partial substitute for margin requirements. By inhibiting potentially mutually beneficial transactions beyond set limits, price limits constitute an additional cost to traders. A key downside to price limits is the impediment to price discovery (Chou et al., 2000). It is suggested in Longin (1999) that price limits should be set above margin levels. The study concentrates on whether SAFEX contracts are consistent with this guideline and if price limits impact margins or the probability of margin violation on SAFEX.

Secondly, the study uses extreme value analysis (EVA), a superior approach grounded on in-depth statistical theory that precisely models tails of a distribution (Lux, 2001). By not imposing any assumptions on the overall shape of returns distribution, extreme-value estimation is a more powerful approach than methods based on the normal distribution. The normality assumption is rejected in literature for a wide range of commodity returns (Cornew, Town, & Crowson, 1984; Venkateswaran, Brorsen, and Hall 1993). This is in agreement with Warshawsky (1989), Kofman (1992), Longin (1995), Booth, Broussard, et al. (1997) and Broussard and Booth (1998) in confirming normality in financial market data is unlikely. Fama (1963) and Mandelbrot (1967) had earlier noticed that the normal distribution was insufficient in characterizing stock returns. Observations in Figlewski (1984), Gay, Hunter, and Kolb (1986), and Broussard and Booth (1998) point out that assuming normality results in margins being set conservatively.

Thirdly, this study incorporates asymmetry across long and short positions in estimating margins and their likelihood of violation. The key question is whether margins for long and short positions should be identical and if risk is asymmetric? It stands to reason that if there are asymmetric positive and negative returns, setting similar margins for short and long positions could result in trading costs that may be unwarranted.

Furthermore, the study hypothesizes that extreme value estimation improves futures contract margin-setting. In a recent study by Hedegaard (2011), the impact of margin levels on a number of market variables is examined. The increase in margins is found leading to reduction in traded volume, market open interest and liquidity. Higher margins are also found increasing the price-impact cost as measured using Amihud (2002)'s illiquidity measure. Hedegaard (2011) also finds margin changes impacting long-term prices of futures contracts.

This study will therefore find out how the margin-setting trade-offs have been balanced for the 5 contracts.

Fourthly, this chapter provides examples on how margin violation probabilities can be applied to set futures margins. A comparison on the differences in margins set using the parametric VaR, historical VaR and EVT approaches is given. Currently, the JSE and SAFEX use the parametric VaR approach to margin-setting and are in transition adopting the historical VaR method. An increase in margins reduces trading activity effectively decreasing brokers' commissions and the income of the exchange itself (Longin, 1999).

Briefly, the results shows that price limits reduce the shape parameter estimates for white maize, yellow maize and wheat using the extreme value approach. EVA is found ideal for estimating margin violation probabilities of large price changes. This is partly because asymmetry of negative and positive price changes is taken into account generating different margin levels for long and short positions. EVT violation probability graphs are found closely tracking the curves of the empirical distributions similar to Booth, Broussard, et al. (1997). Instances where margins could be set more liberally are revealed.

The paper is organized as follows. Section 2 reviews futures returns literature with extreme value theory applications. Section 3 gives the theoretical background on extreme value theory and the methodology for the paper. The data used in the paper is described in Section 4 while the main results are presented in Section 5. Consistency and potential applicability of the results is gauged by comparing EVA and SAFEX margin methodologies in Section 6. Section 7 concludes.

## 6.2 Literature Review

Margins protect the financial integrity of a futures contract. The initial margin requirement (IMR) is the maximum anticipated upward or downward price movement in a day as per the set confidence levels (SAFCOM, 2013). In the case of SAFEX, value-at-risk (VaR) is used to calculate this margin. Margin exceedances occur when daily price movements are higher than the IMR. All risks have an unobservable probability distribution and the likelihood of extreme events is characterised in the tails (McNeil, 1999). Financial markets data has been associated with fat tails, volatility clustering and paretian distributions (Ghose & Kroner, 1995). Tail risks examined in literature have included market, credit, operational and insurance risks (McNeil, 1999). Measures of risk include VaR and expected shortfall. The need to analyse tails of a distribution separately from the central parts is identified in DuMouchel (1983). The extreme value approach has been used to derive optimal margins using tails of returns (Cotter, 2001; Lehikoinen, 2007; Zhao, Scarrott, Oxley, & Reale, 2011). This allows for extension outside the sample used to generate distribution parameters (Gençay, Selçuk, & Ulugülyagci, 2001). As such, historically unobserved exceedances can be estimated.

Many papers have focussed on linkages between margins, futures trading levels and market volatility (Bahram Adrangi & Chatrath, 1999; Fishe, Goldberg, Gosnell, & Sinha, 1990; Hardouvelis, 1990; Hardouvelis & Kim, 1995; Kupiec, 1993, 1998). A finding in Bahram Adrangi and Chatrath (1999) is that excessive margins impact trading volume negatively. This is in agreement with various scholars including Kupiec (1993) who found support for a positive relationship between margin changes and price volatility. Leading scholars in literature have used extreme value analysis to understand extreme returns in futures prices. Tomek (1984) examined appropriateness of margins in agricultural, metals and government securities between 1970 and 1980 finding margins conservative. Margin adequacy in

agricultural, metals and US Government securities are investigated in Gay et al. (1986) with data covering the 1970's and 1980's. Margin levels were concluded to be conservative. The study also observed numerous exceedances of margins which were set at around 5%.

Longin (1999) examined margins for the silver contract on COMEX using extreme value approaches. Daily data from 1975 to 1994 was used to derive margin levels corresponding to probability of margin violation ranging from 0.5 to 0.001. For long positions, appropriate margin levels for probability of violation of 0.50 and 0.001 calculated to 4.30% and 9.29% respectively. With asymmetry in the returns data, a 0.5 probability of violation for a short position required an ideal margin of 7.83%. The optimal common margin level for long and short positions disregarding asymmetry at a probability of exceedance of 0.05 was found to be 8.49%. It is worth noticing that the margin level set by COMEX on 30 April 1998 was 9.59%.

Broussard (2001) analysed extreme asset returns in the CBOT corn and T-Bond contracts using EVA. Evidence was found that extreme movements in the two contracts were from the Fretchet distribution. Chen (2002) found margin levels inversely related to price limits after examining the British Pound, Deutschemark, copper, gold and the S&P 500. Hsiao and Shanker (2014) examined margins for corn, soybeans, soybean meal and wheat on CBOT[26] as well as canola and western barley on the ICE[27] market in Canada. Findings suggested an inverse relationship between return volatility and margin requirements after taking into account price limits.

[26] CBOT is the Chicago Board of Trade
[27] ICE is the International Commodity Exchange

## 6.3 Methodology

The distribution of extreme price movements is independent of the underlying distribution of all price changes (Longin, 1999). Two methods are used for analysing extreme values (Dewachter & Gielens, 1999; Edwards & Neftci, 1988; Longin, 2000). The first entails using the maximum observation within a block period (block maxima method).[28] The second approach identifies a minimum cut-off point (threshold) beyond which all values are included in the analysis.

Going by the block maxima method, the margin, $M_n$, has the following relation

$$M_n = \max\{R_1, \ldots\ldots R_n\} \tag{6.1}$$

$$P_{short} = P\{M_n > r_{short}\} = P\{R_1 > r_{short}, \ldots, R_n > r_{short}\} = 1 - F_{\max}{}^{n}\{r_{short}\} \tag{6.2}$$

Asset returns are represented by $R_1, \ldots, R_n$. Equation (6.2) gives the margin level for a short position, captured in $r_{short}$. $P_{short}$ is the probability that a given margin is higher than the margin for a short position. In the case of a long position, we have

$$Min\{R_1, \ldots\ldots R_n\} = -Max\{-R_1, \ldots\ldots, R_n\} \tag{6.3}$$

$$P_{long} = P\{M_n < r_{long}\} = P\{R_1 < r_{long}, \ldots\ldots, R_n < r_{long}\} = F_{\min}{}^{n}(r_{long}) \tag{6.4}$$

This thread of literature looks at the convergence of the maxima, $M_n$, to the $H$-distribution in the following relation:

$$\frac{M_n - d_n}{c_n} \xrightarrow{d} H \tag{6.5}$$

Where $c_n > 0$ and $d_n$ is part of the non-degenerate distribution $H$ belonging to extreme distributions defined by 3 limit laws. The Fisher-Tippert theorem gives these 3 laws, namely

[28] A block could be a day, a week, a month or a year (Gilli & Këllezi, 2003).

i) Fretchet $(\phi_\alpha)$, ii) Weibull $(\psi)$ and iii) Gumbel (∧) (Fisher & Tippett, 1928). These distributions are as follows:

$$Fretchet: \phi_\alpha(x) = \begin{cases} 0 & x \le 0 \\ e^{-x^{-\alpha}} & x > 0 \end{cases} \text{ where } \alpha>0 \tag{6.6}$$

$$Weibull: \psi_\alpha(x) = \begin{cases} e^{-(-x)^{\alpha}} & x \le 0 \\ 1 & x > 0 \end{cases} \text{ where } \alpha>0 \tag{6.7}$$

$$Gumbel: \Lambda\phi_\alpha(x) = e^{-e^{-x}}, \text{ where } -\infty < x < \infty \tag{6.8}$$

In Von Mises (1936) and Jenkinson (1955), one-parameter representation of the three standard extreme value distributions gives the generalized extreme value distribution (GEV). With improvement in notation, the GEV is presented in McNeil (1999), Cotter (2005) and, Lehikoinen (2007) and Zhao et al. (2011) as

$$G(z) = \exp\left[-\left\{1+\xi\left(\frac{z-\mu}{\sigma}\right)\right\}_+^{-1/\xi}\right] \tag{6.9}$$

This derivation sets $\xi$, the shape parameter, as $\xi=\alpha^{-1}$, in the Fretchet, or $\xi=-\alpha^{-1}$ in the Weibull. In the above, $y_+=max(y,0)$, $\sigma>0$, $\xi<\infty$ and $-\infty<\mu$. The scale and location parameters are $\sigma$ and $\mu$ respectively. When $\xi = 0$, we have the Gumbel, and when $\xi<0$, we have the Weibull distribution. The Gumbel has an exponential tail decline and is derived as $\xi\to0$ with the relation:

$$G(z) = \exp\left[-\exp\left\{-\left(\frac{z-\mu}{\sigma}\right)\right\}\right], \quad -\infty < z < \infty. \tag{6.10}$$

If $\xi > 0$, then we have the Fretchet distribution, described in Cotter (2005) as characterised by fat tails. Broussard and Booth (1998) explain the Fretchet tail distribution decays slowly. The Weibull distribution (when $\xi < 0$) has a bounded upper tail at $z_u=\mu-\sigma/\xi$ (Gilleland & Katz, 2013).

Three methods are identified for the estimation of parameters $\sigma$, $\mu$ and $\xi$, the non-linear least squares approach, the maximum log likelihood function and the non-parametric Hill estimator (McNeil & Frey, 2000). The Hill estimator is generally known to generate inefficient and unstable quantile estimators. Non-parametrically, if $r_{(1)} \leq r_{(2)} \leq \ldots\ldots\ldots \leq r_{(T)}$ are ordered returns and $k$ is a positive integer, the Hill estimator is

$$\hat{\xi}(k) = 1/k \sum_{i=1}^{k} \left( \ln r_{(T-j+1)} - \ln r_{(T-k)} \right) \tag{6.11}$$

As a result of the perceived limitations of the Hill estimator, the GEV has been more preferable in quantile estimation.

Booth, Broussard, et al. (1997) show the violation probabilities $\pi^{long}$ and $\pi^{short}$ respectively for long and short positions as

$$\pi^{long} = 1 - \exp\left[ -\left\{ 1 - \xi^{\min} \frac{\left( r^{\min} - \mu^{\min} \right)}{\sigma^{\min}} \right\}^{-1/\xi^{\min}} \right] \tag{6.12}$$

$$\pi^{short} = 1 - \exp\left[ -\left\{ 1 + \xi^{\max} \frac{\left( r^{\max} - \mu^{\max} \right)}{\sigma^{\max}} \right\}^{-1/\xi^{\max}} \right] \tag{6.13}$$

Thus, margin violation is dependent on the shape parameter $\xi$, the dispersion $\sigma$ and the location, $\mu$ (Booth et al., 1997). A general rule in Broussard and Booth (1998) says the margin increases as $\sigma$ and $|\mu|$ rise and when $\xi$ is more positive. Lastly, in Gilleland and Graybill (2009), the formula for calculating the number of possible exceedances per year is given as:

$$\hat{\lambda} = 365.25 * \frac{No..X_i > u}{No..X_i} \tag{6.14}$$

Where $\hat{\lambda}$ represents the number of margin exceedances and $u$ is similar to the threshold in the GPD approach.

The return level gives the margin level exceeded only once every *T* periods (return period) (Gilleland & Katz, 2013). The probability of exceeding this return value is *1/T*. One period is typically a block length; in this study, one day. Expressed as $z_p$, this is the margin level exceeded with probability *p* once every day. The extreme level exceeded once every day is given by *1/p*.[29] The relation for $z_p$ in Gilleland and Katz (2013) is as follows:

$$z_p = \begin{cases} \mu - \sigma/\xi\left[1 - \{-\ln(1-p)\}^{-\xi}\right], & \xi \neq 0 \\ \mu - \sigma \ln\{-\ln(1-p)\}, & \xi = 0 \end{cases} \quad (6.15)$$

Gilleland and Katz (2014) used the *pextRemes* function to find the probability of exceeding given return levels.[30] Software described in Gilli (2006), Gilleland (2012) and Gilleland (2015), based on the *R* programming language, is used for the analysis.

## 6.4 Data

SAFEX market contracts examined are white maize, yellow maize, wheat, silver and WTIO (crude oil). The data includes daily open prices, close prices, daily high and daily low prices. Contracts have sample sizes of different length in accordance with times of listing on SAFEX. JSE and SAFEX have provided raw data on historical margin levels. Literature on methodologies for calculating daily margins was provided in SAFCOM (2013). Historical price limit levels and limit changes for white maize, yellow maize and wheat were sourced from SAFEX. No price limits are in place for silver and crude oil (WTIO contract).

In Table 6.1, descriptive information on the features of the data samples is provided. The minimum sizes per each contract traded by SAFEX are presented as well as the margin

[29] For example, if you have a 100 year return level of 1.5 and the blocks are equivalent to a year, the probability of exceeding 1.5 is 1/100, which gives 0.01 (Gilleland & Katz, 2013).
[30] An example is: "pextRemes(fit, q=c(20,40,60,100), lower.tail = FALSE)"

levels that applied on the last day in the sample of each contract. SAFCOM has been using the parametric VaR method to generate daily margin levels on SAFEX (SAFCOM, 2013).

**Table 6.1: Contracts descriptive information**

| Contract | Sample | | Nominal Quantity | Margin | Margin |
|---|---|---|---|---|---|
| | Beginning | End | Per Contract | (%) | Date |
| White maize | 01/04/1997 | 22/12/2014 | 100 tons | 9.9811 | 22/12/2014 |
| Yellow maize | 01/04/1997 | 28/11/2014 | 100 tons | 9.1811 | 28/11/2014 |
| Wheat | 01/01/1999 | 23/09/2014 | 50 tons | 4.6935 | 23/09/2014 |
| Silver | 14/12/2010 | 19/12/2014 | 500 ounces | 9.3021 | 19/12/2014 |
| WTIO | 12/10/2009 | 22/12/2014 | 100 barrels | 13.868 | 12/22/2014 |

Descriptive information on the contracts in this study is presented in the table. The 5 contracts have different sample sizes and their beginning and end dates are shown in the table. SAFEX trades minimum contract sizes per contract shown in the column "Nominal quantity per contract". Margins have been provided for the last day in the sample of each contract as depicted above. The JSE and SAFEX have been using the parametric VaR method to generate daily margins.

### *6.4.1.Summary Statistics*

Before investigating asymmetry in returns, the paper first presents contract summary statistics. Daily close-to-close returns[31] are generated with the relation:

$$R_t = 100 * \ln\left(P_t / P_{t-1}\right) \tag{6.16}$$

Where, the daily price, and lagged price are $P_t$ and $P_{t-1}$ respectively. Table 6.2 presents the summary statistics for the contracts examined.

Panel A presents the results for each contract over the sampled period while Panel B separates for each contract, statistics for positive and for negative returns. In Panel A, skewness levels for white maize (-0.1064), yellow maize (-0.0218), wheat (0.0980), silver (-0.9468) and WTIO (-0.0930) are fairly different from zero. Further, for most of the contracts, the kurtosis significantly differs from 3. The Jarque-Bera and Kolmogorov-Smirnov tests provide evidence for the rejection of normality for the five SAFEX contracts.

[31] Asymmetry tests are carried out on these returns.

Panel B of Table 6.2 looks at the summary statistics for the separated positive excess returns and negative excess returns. Normality is also rejected for these returns.

**Table 6.2: Summary Statistics**

| Summary Statistics | Returns | W/Maize | Y/Maize | Wheat | Silver | WTIO |
|---|---|---|---|---|---|---|
| *Panel A: Entire Returns Set* | | | | | | |
| Maximum | | 12.071 | 13.142 | 10.208 | 7.182 | 6.851 |
| Minimum | | -12.968 | -14.692 | -8.883 | -12.611 | -6.471 |
| Mean | | 0.040 | 0.046 | 0.045 | -0.033 | -0.017 |
| St. dev | | 1.944 | 1.778 | 1.125 | 1.916 | 1.419 |
| Skewness | | -0.1064 | -0.0218 | 0.0980 | -0.9468 | -0.0930 |
| Kurtosis | | 2.789 | 4.021 | 4.712 | 6.337 | 2.135 |
| Jarque-Bera (normality) | | 1445.1*** | 2980.9*** | 3655.9*** | 1823.8*** | 250.10*** |
| Kolmogorov-Smirnov (normality) | | 0.1208*** | 0.0999*** | 0.1249*** | 0.0946*** | 0.0636*** |
| *Panel B: Separated Positive and Negative Returns* | | | | | | |
| Maximum | Positive | 12.031 | 13.096 | 10.163 | 7.215 | 6.868 |
| | Negative | -0.002 | 0.000 | -0.001 | -0.002 | -0.001 |
| Minimum | Positive | 0.001 | 0.001 | 0.004 | 0.008 | 0.017 |
| | Negative | -13.008 | -14.738 | -8.928 | -12.578 | -6.454 |
| Mean | Positive | 1.483 | 1.404 | 0.938 | 1.084 | 0.890 |
| | Negative | -1.305 | -1.121 | -0.632 | -1.443 | -1.150 |
| St. dev | Positive | 1.337 | 1.274 | 0.8554 | 1.265 | 0.9711 |
| | Negative | 1.377 | 1.249 | 0.7963 | 1.667 | 1.024 |
| Skewness | Positive | 1.749 | 1.998 | 2.103 | 1.615 | 1.775 |
| | Negative | -2.057 | -2.317 | -2.261 | -2.906 | -1.616 |
| Kurtosis | Positive | 4.908 | 7.609 | 10.360 | 2.672 | 4.363 |
| | Negative | 7.072 | 10.720 | 9.072 | 12.700 | 3.481 |
| Jarque-Bera | Positive | 3142.7*** | 6045.4*** | 8293.5*** | 419.73*** | 970.49*** |
| | Negative | 6579.7*** | 13989*** | 10090*** | 3509.9*** | 537.26*** |
| Kolmogorov-Smirnov | Positive | 0.5060*** | 0.5049*** | 0.5018*** | 0.5044*** | 0.5068*** |
| | Negative | 0.5147*** | 0.5143*** | 0.5086*** | 0.5007*** | 0.5005*** |

Summary statistics for SAFEX futures contract returns are presented above. For this analysis, daily close-to-close prices have been used to calculate returns which are represented in the table. Sample data for the various contracts commences at different times as shown in Table 6.1. Panel A shows statistics for the full returns set for each contract while Panel B summarizes the features of the returns separated into positive and negative excess returns. The Jarque-Bera and Kolmogorov-Smirnov are normality tests. Significance levels at 1%, 5% and 10% are respectively represented by ***, ** and *.

### *6.4.2. Symmetry tests of negative and positive returns*

Peiró (2004) observes when there is symmetry between positive and negative returns; the median coincides with the mean, and becomes the axis of symmetry. In testing for symmetry therefore, the mean is subtracted from the entire returns dataset. After this transformation process, negative excess returns are given by the following:

$$R_t^- : \left\{ R_t - \overline{R} \middle| R_t < \overline{R} \right\} \tag{6.17}$$

Positive excess returns are represented as follows:

$$R_t^+ : \left\{ R_t - \overline{R} \middle| R_t > \overline{R} \right\} \tag{6.18}$$

When setting margins on SAFEX, is there the presumption of symmetry in the distribution of returns? For the asymmetry analysis, negative excess returns are first converted to absolute terms. The null hypothesis states positive and negative returns have equal distributions. Typical two-sample distribution-free tests include: Wilcoxon (W) test, Siegel-Tukey (ST), Kolmogorov-Smirnov (KS) test and the Mann Whitney (MW) test.

Results of symmetry tests are presented in Table 6.3. Findings are that there is no evidence of symmetry between positive and negative excess returns for the 5 SAFEX contracts. Mean levels for returns on either side of the distribution are found significantly different at 1 % level for each contract. Siegel-Tukey tests provide evidence that the variances for positive and negative returns are significantly different at 1 % level. Distributions of all positive and negative returns are found significantly different at 1% level using the Wilcoxon and Kolmogorov-Smirnov tests.

**Table 6.3: Symmetry tests between negative and positive returns**

| Test | W/Maize | Y/Maize | Wheat | Silver | WTIO |
|---|---|---|---|---|---|
| t-test | -4.3503*** | -8.2337*** | -12.947*** | 2.3494*** | 4.6715*** |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.0000] |
| Wilcoxon (W) | 2700000*** | 2900000*** | 2400000*** | 99000.0*** | 170000*** |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.0000] |
| Siegel-Tukey (ST) | 5.6431*** | 9.8987*** | 12.382*** | 3.3607*** | 4.6543*** |
| | [0.0000] | [0.0000] | [0.0000] | [0.0008] | [0.0000] |
| Mann Whitney (MW) | 7.1999*** | 12.302*** | 19.441*** | 3.1793*** | 6.2165*** |
| | [0.0000] | [0.0000] | [0.0000] | [0.0015] | [0.0000] |
| Kolmogorov-Smirnov (KS) | 0.1492*** | 0.2038*** | 0.3317*** | 0.2348*** | 0.1989*** |
| | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.0000] |

The *t-test* is for testing the equality of means between the absolute negative and the positive returns. W, ST and KS are respectively the Wilcoxon, Siegel-Tukey and the Kolmogorov-Smirnov two-sample test statistics for the equality of distributions. *P-values* are included in parenthesis and significance at 1%, 5% and 10% is shown by ***, **, *. Of the two samples tested, one derives from absolute negative excess returns while the second are the positive excess returns for each contract.

Further, the study looks at symmetry of positive and negative excess returns across intervals, for instance, 0% to 0.5%, 0.5% to 1.0%, and so on. Frequencies of both positive and negative returns in each range are generated. Table 6.4 presents the frequencies of positive and negative returns in each range. For negative excess returns, absolute values are used. The premise in Peiró (2004) is a symmetric distribution follows a binomial distribution with parameters *n* and *p*. The value of *p* is set at 0.5 if there is symmetry in a given interval. Our test is therefore:

Ho: p=0.5

H1: p≠0.5

In general, binomial tables have values of *p* where $n \leq 20$. It is possible to approximate the binomial with the normal distribution where parameters *n* and *p* can respectively be substituted by *np* and *np(1-p)* (Peiró, 2004). The rank statistic generated is:

$$\text{Test statistic} = 2\left[1-\phi\left(\frac{Max\left(n^{+},n^{-}\right)+0.5-np}{\sqrt{np\left(1-p\right)}}\right)\right] \qquad (6.19)$$

The number of negative and positive excess returns is given respectively by $n^{-}$ and $n^{+}$ such that $n^{-} + n^{+} = n$. The cumulative standard normal distribution function is represented by $\phi$. Results for the analysis are given in Table 6.4.

For the 5 contracts, positive and negative excess returns in the range 0% and 0.5% are significantly different at 1% level. It is noted however that excess returns beyond the threshold of 4% do not appear to be different for all the 5 contracts. However, as most excess returns for each contract are in the range 0% to 0.5%, the overall tests aggregating all returns suggest asymmetry for all the contracts at 1% level of significance.

**Table 6.4: Tests of equal probability for negative and positive excess returns**

| Intervals | W/Maize | | | *Y/Maize* | | | Wheat | | | Silver | | | WTIO | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Neg. | Pos. | P | Neg. | Pos. | P | Neg. | Pos. | P | Neg. | Pos. | P | Neg. | Pos. | P |
| 0.0%, 0.5% | 808 | 508 | 0.0000*** | 998 | 496 | 0.0000*** | 1367 | 598 | 0.0000*** | 150 | 255 | 0.0000*** | 173 | 322 | 0.0000*** |
| 0.5%, 1.0% | 444 | 461 | 0.5496 | 439 | 463 | 0.4052 | 417 | 415 | 0.9172 | 70 | 84 | 0.2268 | 149 | 152 | 0.8177 |
| 1.0%, 1.5% | 323 | 297 | 0.2782 | 328 | 295 | 0.1731 | 256 | 253 | 0.8593 | 63 | 72 | 0.3894 | 83 | 109 | 0.0513* |
| 1.5%, 2.0% | 242 | 246 | 0.8209 | 231 | 226 | 0.7790 | 166 | 141 | 0.1378 | 41 | 49 | 0.3428 | 61 | 61 | 0.9279 |
| 2.0%, 2.5% | 170 | 173 | 0.8290 | 161 | 162 | 0.9114 | 66 | 88 | 0.0638* | 29 | 33 | 0.5254 | 42 | 42 | 0.9131 |
| 2.5%, 3.0% | 110 | 131 | 0.1564 | 118 | 118 | 0.9481 | 38 | 43 | 0.5050 | 22 | 24 | 0.6583 | 24 | 16 | 0.1547 |
| 3.0%, 3.5% | 100 | 94 | 0.6153 | 68 | 70 | 0.7984 | 20 | 28 | 0.1939 | 11 | 16 | 0.2482 | 12 | 10 | 0.5224 |
| 3.5%, 4.0% | 47 | 59 | 0.2067 | 40 | 45 | 0.5152 | 7 | 10 | 0.3320 | 13 | 12 | 0.6892 | 10 | 7 | 0.3320 |
| >4.0% | 110 | 102 | 0.5365 | 74 | 85 | 0.3413 | 15 | 10 | 0.2301 | 28 | 23 | 0.4008 | 12 | 12 | 0.8383 |
| All | 2354 | 2071 | 0.0000*** | 2457 | 1960 | 0.0000*** | 2352 | 1586 | 0.0000*** | 427 | 568 | 0.0000*** | 566 | 731 | 0.0000*** |

For each contract and for each interval, the column *Neg. (Pos.)* indicates the number of negative (positive) excess returns whose absolute values are included in a given interval. *P-values* are given in the column P. Essentially a test of equal probability of occurrence of negative and positive excess returns is being carried out. Significance levels at 1%, 5% and 10% are respectively represented by ***, ** and *.

### *6.4.4. Extreme value analysis data*

Similar to studies including Nadarajah (2005), the study uses extreme positive and negative returns calculated as high-to-close and low-to-close price changes. This is in line with the block maxima method described above (GEV approach). Minimum values were modelled using:

$$\min\{x_1,\ldots\ldots,\ x_n\} = -\max\{-x_1,\ldots\ldots\ldots.,-x_n\} \tag{6.20}$$

High-to-close and low-to-close returns are calculated respectively using the relations $100*\ln\left(P_t^{high}/P_t^{close}\right)$ and $100*\ln\left(P_t^{low}/P_t^{close}\right)$, where $P_t^{close}$ are close prices and $P_t^{high}$ and $P_t^{low}$ are high and low prices on day *t*.

## 6.5 Main Results

The analysis looks at EVT parameters for negative (minimal) and positive (maximal) returns. The minima are fit as the negative maxima. High-to-close and low-to-close returns have one-day blocks. Evidence is provided in Table 6.5 that the extreme distributions for the 5 contracts follow the Fretchet distribution. Most standard errors are substantially lower than 0.05, save for the shape parameters for silver and WTIO crude. This suggests high levels of

support for the GEV by extreme returns of the SAFEX contracts. Maximal returns are linked to high-to-close returns while minimal returns are linked to low-to-close returns. It should be noted that high-to-close returns correspond to short positions while low-to-close returns impact margins for long positions. We follow Broussard (2001) who looked at margins with price limits as well as without price limits. Table 6.5 is presented with two panels. Panel A gives GEV estimates for the original returns while Panel B gives parameters when bounds are placed at price limit levels. Since no price limits have been imposed on silver and WTIO, these contracts have similar parameters for both panels A and B.

**Table 6.5: Estimated parameters for minimal and maximal returns**

| Commodity | Shape $\xi$ | | Scale $\sigma$ | | Location $\mu$ | | Log Likelihood | |
|---|---|---|---|---|---|---|---|---|
| | Min Low-close | Max High-close | Min Low-close | Max High-close | Min Low-close | Max High-close | Min | Max |
| *Panel A: Data with price limit events* | | | | | | | | |
| White maize | 0.4556 | 0.4842 | 0.4241 | 0.4213 | 0.4925 | 0.4788 | 3561 | 3577 |
| | [0.0192] | [0.0195] | [0.0078] | [0.0079] | [0.0084] | [0.0083] | | |
| Yellow maize | 0.4035 | 0.4698 | 0.4123 | 0.4138 | 0.4875 | 0.4768 | 3079 | 3134 |
| | [0.0195] | [0.0205] | [0.0076] | [0.0081] | [0.0085] | [0.0087] | | |
| Wheat | 0.4477 | 0.4949 | 0.2877 | 0.2937 | 0.3290 | 0.3268 | 1344 | 1402 |
| | [0.0241] | [0.0257] | [0.0066] | [0.0071] | [0.0072] | [0.0075] | | |
| Silver | 0.4490 | 0.5166 | 0.4300 | 0.4596 | 0.4474 | 0.4527 | 225.7 | 250.5 |
| | [0.0780] | [0.0804] | [0.0315] | [0.0350] | [0.0342] | [0.0364] | | |
| WTIO | 0.4168 | 0.4502 | 0.3132 | 0.3246 | 0.3380 | 0.3436 | 329.0 | 362.1 |
| | [0.0577] | [0.0590] | [0.0156] | [0.0165] | [0.0173] | [0.0179] | | |
| *Panel A: Data bounded by price limits* | | | | | | | | |
| White maize | 0.4058 | 0.4323 | 0.4228 | 0.4199 | 0.4988 | 0.4853 | 3448 | 3458 |
| | [0.0196] | [0.0198] | [0.0076] | [0.0077] | [0.0084] | [0.0084] | | |
| Yellow maize | 0.3639 | 0.4220 | 0.4118 | 0.4127 | 0.4927 | 0.4828 | 3001 | 3038 |
| | [0.0198] | [0.0209] | [0.0075] | [0.0079] | [0.0086] | [0.0087] | | |
| Wheat | 0.3825 | 0.4454 | 0.2868 | 0.2927 | 0.3348 | 0.3310 | 1253 | 1333 |
| | [0.0246] | [0.0261] | [0.0064] | [0.0070] | [0.0072] | [0.0075] | | |
| Silver | 0.4490 | 0.5166 | 0.4300 | 0.4596 | 0.4474 | 0.4527 | 225.70 | 250.50 |
| | [0.0780] | [0.0804] | [0.0315] | [0.0350] | [0.0342] | [0.0364] | | |
| WTIO | 0.4168 | 0.4502 | 0.3132 | 0.3246 | 0.3380 | 0.3436 | 329.00 | 362.10 |
| | [0.0577] | [0.0590] | [0.0156] | [0.0165] | [0.0173] | [0.0179] | | |

Parameters for minimal (*low-to-close*) and maximal (*high-to-close*) price returns (%) are generated by estimating the GEV distribution. Asymptotic standard errors are included in the parenthesis. Log Likelihood is the log likelihood value obtained using the maximum likelihood estimation (MLE) approach. An alternative dataset with price limit consideration is generated to use for the analysis incorporating price limits. Panel A uses all the data while Panel B places limits on the returns corresponding to the price limits imposed by SAFEX over time.

A key observation is the lower shape parameters for price-limit-bounded data suggesting returns are less extreme because of the limits. By incorporating price limits, some extreme and rare risks are removed in the datasets. Another finding from both panels A and B is that maximal (high-to-close) shape parameters are higher than those for minimal (low-to-close) movements. This means there is higher likelihood to observe larger positive price changes than negative ones. This is fairly consistent with symmetry tests carried out in the previous section.

A margin violation table gives the probability of violation for a given margin level (Longin, 1999). Tables 6.6 and 6.7 give probabilities for margin violation generated using both extreme value analysis and actual empirical return levels for the 5 contracts. Table 6.6 provides this analysis before price limits while Table 6.7 gives results with data not exceeding price limits. The way to read either table involves selecting a given margin level in the first column. The return type is selected either, low-to-close or high-to-close.

The theoretical value column gives the probability of the margin being violated from extreme value calculations. The column “Empirical” gives the number of returns lower (higher) than the margin for negative (positive) returns (%) as a proportion of total number of returns. Probabilities of margin violation are provided for given margin levels over a margin range from 1% to 30%.

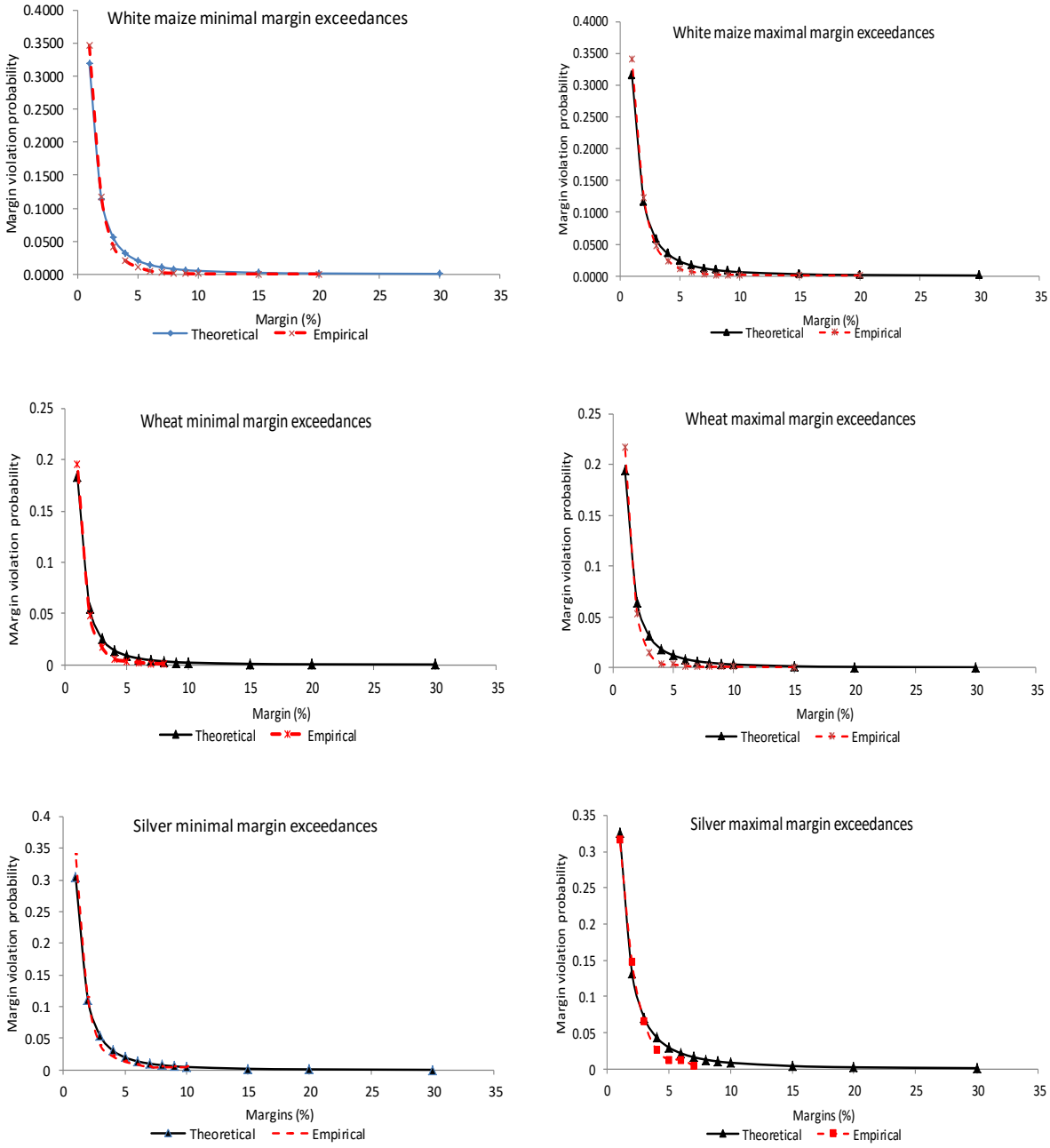
**Table 6.6: Empirical distributions from extreme value analysis**

| Margin | Returns | W/maize | | Y/maize | | Wheat | | Silver | | WTIO | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Level | | Theoretical | Empirical | Theoretical | Empirical | Theoretical | Empirical | Theoretical | Empirical | Theoretical | Empirical |
| *Panel A: Data with price limit events* | | | | | | | | | | | |
| 30 | Low-to-close | 0.0005 | na | 0.0002 | na | 0.0002 | na | 0.0004 | na | 0.0001 | na |
| | High-to-close | 0.0007 | na | 0.0005 | na | 0.0004 | na | 0.0011 | na | 0.0002 | na |
| 20 | Low-to-close | 0.0011 | 0.0003 | 0.0006 | na | 0.0004 | na | 0.0011 | na | 0.0004 | na |
| | High-to-close | 0.0015 | 0.0006 | 0.0012 | na | 0.0008 | na | 0.0023 | na | 0.0006 | na |
| 15 | Low-to-close | 0.0021 | 0.0003 | 0.0012 | na | 0.0008 | na | 0.0020 | na | 0.0007 | na |
| | High-to-close | 0.0026 | 0.0008 | 0.0023 | na | 0.0014 | 0.0004 | 0.0040 | na | 0.0011 | na |
| 10 | Low-to-close | 0.0050 | 0.0005 | 0.0031 | na | 0.0020 | na | 0.0048 | 0.0044 | 0.0018 | na |
| | High-to-close | 0.0059 | 0.0017 | 0.0052 | 0.0018 | 0.0031 | 0.0009 | 0.0085 | na | 0.0027 | 0.0019 |
| 9 | Low-to-close | 0.0062 | 0.0008 | 0.0039 | 0.0003 | 0.0025 | na | 0.0060 | 0.0044 | 0.0023 | na |
| | High-to-close | 0.0073 | 0.0019 | 0.0064 | 0.0021 | 0.0039 | 0.0009 | 0.0103 | na | 0.0033 | 0.0019 |
| 8 | Low-to-close | 0.0079 | 0.0016 | 0.0052 | 0.0009 | 0.0033 | 0.0009 | 0.0077 | 0.0044 | 0.0030 | na |
| | High-to-close | 0.0092 | 0.0019 | 0.0082 | 0.0024 | 0.0049 | 0.0009 | 0.0128 | na | 0.0043 | 0.0019 |
| 7 | Low-to-close | 0.0104 | 0.0022 | 0.0070 | 0.0027 | 0.0044 | 0.0013 | 0.0101 | 0.0044 | 0.0041 | na |
| | High-to-close | 0.0120 | 0.0033 | 0.0107 | 0.0031 | 0.0063 | 0.0009 | 0.0163 | 0.0043 | 0.0057 | 0.0019 |
| 6 | Low-to-close | 0.0142 | 0.0052 | 0.0100 | 0.0033 | 0.0061 | 0.0022 | 0.0139 | 0.0087 | 0.0058 | na |
| | High-to-close | 0.0161 | 0.0066 | 0.0145 | 0.0055 | 0.0085 | 0.0018 | 0.0215 | 0.0130 | 0.0077 | 0.0039 |
| 5 | Low-to-close | 0.0206 | 0.0107 | 0.0151 | 0.0081 | 0.0089 | 0.0035 | 0.0201 | 0.0131 | 0.0087 | 0.0020 |
| | High-to-close | 0.0229 | 0.0110 | 0.0208 | 0.0095 | 0.0121 | 0.0031 | 0.0296 | 0.0130 | 0.0115 | 0.0039 |
| 4 | Low-to-close | 0.0319 | 0.0203 | 0.0246 | 0.0137 | 0.0141 | 0.0056 | 0.0312 | 0.0218 | 0.0142 | 0.0039 |
| | High-to-close | 0.0347 | 0.0242 | 0.0320 | 0.0193 | 0.0184 | 0.0040 | 0.0436 | 0.0261 | 0.0180 | 0.0039 |
| 3 | Low-to-close | 0.0552 | 0.0422 | 0.0451 | 0.0328 | 0.0253 | 0.0169 | 0.0539 | 0.03930 | 0.0261 | 0.0059 |
| | High-to-close | 0.0585 | 0.0471 | 0.0547 | 0.0419 | 0.0314 | 0.0148 | 0.0705 | 0.0652 | 0.0319 | 0.0116 |
| 2 | Low-to-close | 0.1138 | 0.1178 | 0.0999 | 0.1006 | 0.0556 | 0.0477 | 0.1104 | 0.1135 | 0.0590 | 0.0355 |
| | High-to-close | 0.1166 | 0.1233 | 0.1113 | 0.1150 | 0.0645 | 0.0534 | 0.1325 | 0.1478 | 0.0682 | 0.0446 |
| 1 | Low-to-close | 0.3194 | 0.3470 | 0.3059 | 0.3299 | 0.1833 | 0.1957 | 0.3041 | 0.3406 | 0.1972 | 0.2209 |
| | High-to-close | 0.3157 | 0.3414 | 0.3097 | 0.3339 | 0.1943 | 0.2175 | 0.3265 | 0.3174 | 0.2114 | 0.2345 |

Theoretical probabilities are derived using formulae for $F^{max}$ and $F^{min}$. Margin levels are given in the first column in percentage terms and exceedances are calculated from these margin levels. The two columns for each contract give theoretical and empirical probabilities respectively.

As an example, the probabilities of violating margin levels of 30% for the low-to-close and high-to-close returns for white maize are 0.0005 and 0.0007 respectively. On the lower end, probabilities for violating margins of 1% for low-to-close and high-to-close returns are 0.3194 and 0.3157 respectively.

## Figure 6.1: Initial margins and violation probabilities




The graphs give a comparisom of empirical and theoretical margins and violation probabilities for both minimal and maximal returns, linked to long and short positions respectively. Theoretical margin violation probabilities are estimated using the GEV distribution, using respectively low-to-close and high-to-close prices. Price limits are not taken into account, and graphs for only three contracts are provided owing to limitations in space.

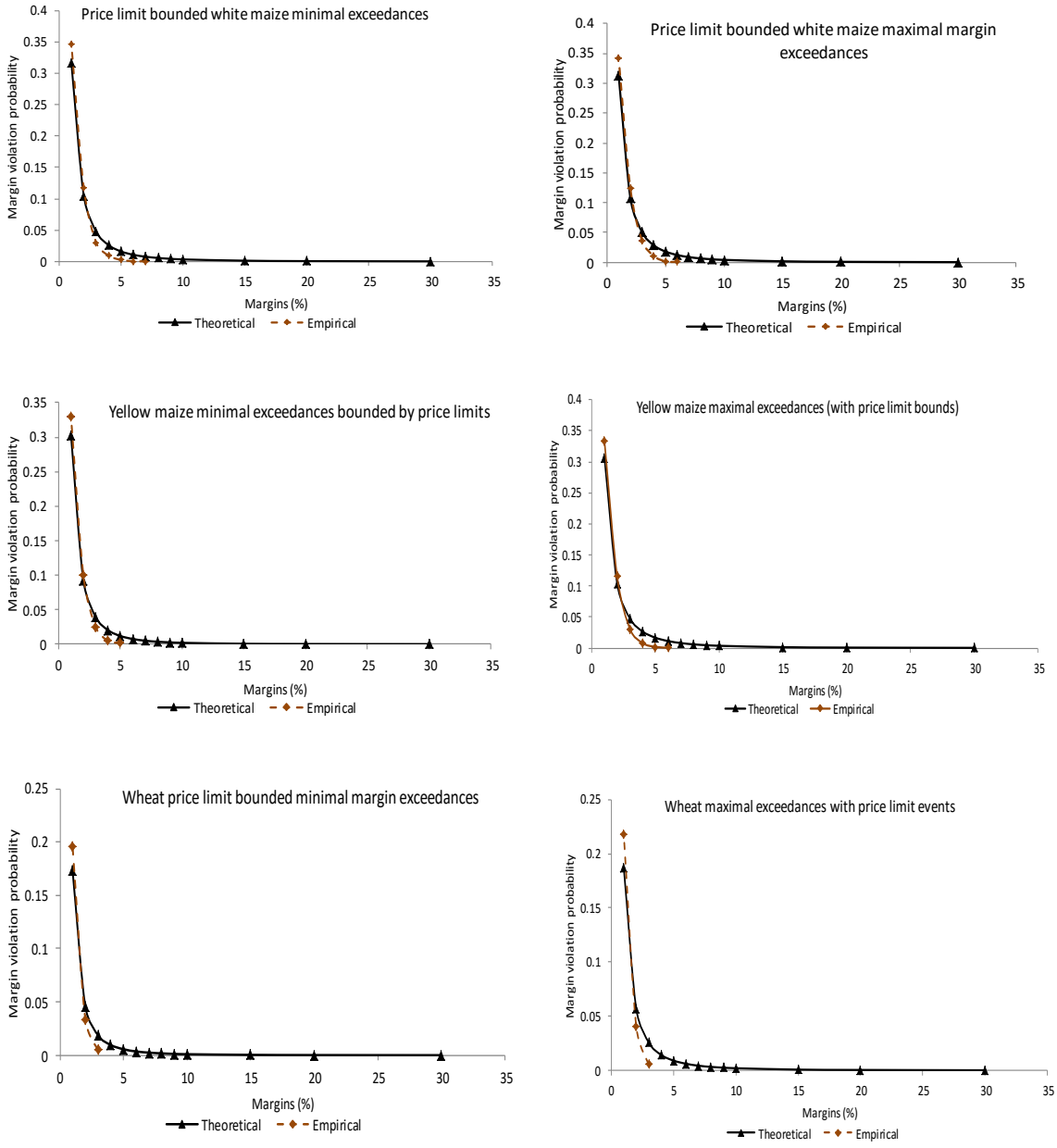
**Table 6.7: Empirical distributions from extreme value analysis**

| Margin | Returns | W/maize | | Y/maize | | Wheat | |
|---|---|---|---|---|---|---|---|
| Level | | Theoretical | Empirical | Theoretical | Empirical | Theoretical | Empirical |
| *Panel B: Data bounded by price limits* | | | | | | | |
| 30 | Low-to-close | 0.0002 | na | 0.0001 | Na | 0.0001 | na |
| | High-to-close | 0.0003 | na | 0.0003 | Na | 0.0002 | na |
| 20 | Low-to-close | 0.0006 | na | 0.0003 | Na | 0.0002 | na |
| | High-to-close | 0.0009 | na | 0.0007 | Na | 0.0005 | na |
| 15 | Low-to-close | 0.0013 | na | 0.0007 | Na | 0.0004 | na |
| | High-to-close | 0.0017 | na | 0.0014 | Na | 0.0008 | na |
| 10 | Low-to-close | 0.0033 | na | 0.0021 | Na | 0.0010 | na |
| | High-to-close | 0.0041 | na | 0.0036 | Na | 0.0021 | na |
| 9 | Low-to-close | 0.0043 | na | 0.0028 | Na | 0.0013 | na |
| | High-to-close | 0.0051 | na | 0.0046 | Na | 0.0026 | na |
| 8 | Low-to-close | 0.0056 | na | 0.0037 | Na | 0.0018 | na |
| | High-to-close | 0.0066 | na | 0.0059 | Na | 0.0033 | na |
| 7 | Low-to-close | 0.0076 | 0.0003 | 0.0052 | Na | 0.0025 | na |
| | High-to-close | 0.0088 | na | 0.0080 | Na | 0.0044 | na |
| 6 | Low-to-close | 0.0107 | 0.0005 | 0.0077 | Na | 0.0036 | na |
| | High-to-close | 0.0123 | 0.0006 | 0.0112 | 0.0006 | 0.0062 | na |
| 5 | Low-to-close | 0.0161 | 0.0025 | 0.0120 | 0.0018 | 0.0057 | na |
| | High-to-close | 0.0181 | 0.0017 | 0.0166 | 0.0018 | 0.0091 | na |
| 4 | Low-to-close | 0.0262 | 0.0096 | 0.0205 | 0.0051 | 0.0097 | na |
| | High-to-close | 0.0286 | 0.0107 | 0.0266 | 0.0080 | 0.0144 | na |
| 3 | Low-to-close | 0.0478 | 0.0301 | 0.0396 | 0.0251 | 0.0188 | 0.0052 |
| | High-to-close | 0.0507 | 0.0366 | 0.0477 | 0.0309 | 0.0259 | 0.0058 |
| 2 | Low-to-close | 0.1050 | 0.1178 | 0.0930 | 0.1006 | 0.0459 | 0.0339 |
| | High-to-close | 0.1075 | 0.1233 | 0.1030 | 0.1150 | 0.0569 | 0.0404 |
| 1 | Low-to-close | 0.3161 | 0.3470 | 0.3033 | 0.3299 | 0.1731 | 0.1957 |
| | High-to-close | 0.3120 | 0.3414 | 0.3063 | 0.3339 | 0.1868 | 0.2175 |

Theoretical probabilities are derived using formulae for $F^{max}$ and $F^{min}$. Margin levels are given in the first column in percentage terms and exceedances are calculated from these margin levels. The two columns for each contract give theoretical and empirical probabilities respectively. To identify price limit events that are corrected for, high and low prices are compared to the previous close prices similar to Broussard (2001). These movements are compared with the price limits imposed by the futures exchange. An alternative dataset with price limit consideration is generated for use in the above analysis.

Wheat has the lowest probabilities of violation for margins at 1% for low-to-close (0.1833) and high-to-close (0.1943) returns. To give better insight into margin exceedances and probabilities of violation, Figure 6.1 gives graphical presentation for the 5 contracts. The graphs compare the theoretical and empirical probabilities of contract margin exceedance. The graphs show that theoretical probabilities closely track the empirical probabilities of margin violation.

## Figure 6.2: Initial margins and violation probabilities with price limits




The graphs give a comparison of empirical and theoretical margins and violation probabilities for both minimal and maximal returns, linked to long and short positions respectively. Theoretical margin violation probabilities are estimated using the GEV distribution, which uses respectively low-to-close and high-to-close prices. Price limits are taken into account, and graphs for the contracts subject to price limits are presented. The empirical margin graphs are therefore terminated at the incidences of the price limit events.

Tables 6.7 looks at margin violation probabilities for white maize, yellow maize and wheat, accounting for price limits.

As expected, probabilities of violation in price limit-bounded returns are lower than for data without limits (given in Table 6.6). This confirms that price limits have an effect on extreme value-based margin violation probabilities. Broussard (2001) found that price limits resulted in the likelihood of margin violation being more conservative when compared to exclusion of limits. Graphs corresponding to Table 6.7 are presented as Figure 6.2. In Figure 6.2, margin exceedance graphs for white maize, yellow maize and wheat account for price limits.

It is observed that empirical violation curves particularly in the tails are lower than for the theoretical graphs. Further, the truncation of the graphs for empirical violation probabilities is attributable to price limits at the points where the limit events occur. In general, the graphs confirm that tail estimates from extreme value analysis occur at larger probabilities than values deriving from empirical observations. This means there is the possibility of understating likelihood of margin exceedance if only historical empirical violation probabilities are used.

Table 6.8 gives the probability of margin violation and related price changes generated using theoretical and empirical approaches.[32] This table is read with set violation probabilities in the left-most column and corresponding price changes in the middle of the table. In this case, long positions are affected by negative movements while short positions are linked to positive price movements, hence the differences in signs. A margin violation probability of 0.100 corresponds to long position price changes between -1.4463% and -2.1566% across

[32] This table is somewhat a reverse of the earlier graphs.

the 5 contracts. For short positions, price moves for the same violation probability range between 1.5408% and 2.4082%.

**Table 6.8: Price changes given margin violation probabilities for SAFEX contracts**

| Margin Violation Probabilities | Distribution | W/maize Long | W/maize Short | Contract Y/maize Long | Contract Y/maize Short | Price Changes Wheat Long | Price Changes Wheat Short | (%) Silver Long | Silver Short | WTIO Long | WTIO Short |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Data with price limit events* | | | | | | | | | | | |
| 0.100 | Estimated | -2.1567 | 2.1956 | -1.9992 | 2.1313 | -1.4463 | 1.5408 | -2.1202 | 2.4082 | -1.5063 | 1.6084 |
| | Empirical | -2.1340 | 2.1990 | -2.0050 | 2.1277 | -1.4205 | 1.5815 | -2.0450 | 2.4000 | -1.1050 | 1.5192 |
| 0.050 | Estimated | -3.1639 | 3.2744 | -2.8530 | 3.1514 | -2.1156 | 2.3143 | -3.1239 | 3.6898 | -2.1780 | 2.3684 |
| | Empirical | -2.8630 | 2.9525 | -2.6650 | 2.8000 | -1.9500 | 2.0162 | -2.5800 | 3.6950 | -1.5950 | 1.9825 |
| 0.040 | Estimated | -3.5589 | 3.7029 | -3.1800 | 3.5540 | -2.3770 | 2.6231 | -3.5162 | 4.2065 | -2.4367 | 2.6657 |
| | Empirical | -3.0700 | 3.1800 | -2.8600 | 3.0550 | -2.0990 | 2.1925 | 3.0000 | 3.7250 | -1.7180 | 2.2022 |
| 0.030 | Estimated | -4.1294 | 4.3266 | -3.6458 | 4.1378 | -2.7539 | 3.0737 | -4.0820 | 4.9648 | -2.8067 | 3.0945 |
| | Empirical | -3.3925 | 3.5600 | -3.1220 | 3.4150 | -2.3800 | 2.4000 | -3.4200 | 3.9000 | -1.9500 | 2.3500 |
| 0.020 | Estimated | -5.0690 | 5.3643 | -4.3990 | 5.1040 | -3.3729 | 3.8263 | -5.0117 | 6.2411 | -3.4078 | 3.7994 |
| | Empirical | -4.0300 | 4.2815 | -3.5350 | 3.9220 | -2.9000 | 2.6450 | -4.2500 | 4.5050 | -2.1000 | 2.6500 |
| 0.010 | Estimated | -7.1316 | 7.6794 | -6.0044 | 7.2423 | -4.7258 | 5.5157 | -7.0449 | 9.1416 | -4.6985 | 5.3421 |
| | Empirical | -5.1050 | 5.100 | -4.5300 | 4.8000 | -3.4500 | 3.3350 | -6.7000 | 6.2000 | -2.4050 | 3.5000 |
| 0.005 | Estimated | -9.9546 | 10.912 | -8.1233 | 10.198 | -6.5671 | 7.8922 | -9.8149 | 13.2837 | -6.4180 | 7.4457 |
| | Empirical | -6.1500 | 6.400 | -5.4000 | 6.1500 | -4.1705 | 3.8000 | -10.150 | 7.900 | -2.7500 | 3.6500 |
| 0.004 | Estimated | -11.069 | 12.205 | -8.9409 | 11.373 | -7.2918 | 8.8471 | -10.906 | 14.9641 | -7.0854 | 8.2743 |
| | Empirical | -6.3050 | 6.7108 | -5.8900 | 6.7000 | -4.5250 | 4.1000 | na | na | -2.8680 | 6.5000 |
| 0.003 | Estimated | -12.684 | 14.091 | -10.109 | 13.080 | -8.3391 | 10.244 | -12.482 | 17.436 | -8.0424 | 9.4729 |
| | Empirical | -6.500 | 7.1500 | -6.5000 | 7.1000 | -5.1000 | 4.5850 | na | na | -2.8699 | 6.6000 |
| 0.002 | Estimated | -15.350 | 17.236 | -12.004 | 15.913 | -10.064 | 12.583 | -15.080 | 21.607 | -9.6014 | 11.448 |
| | Empirical | -7.0500 | 7.8500 | -7.4550 | 9.1150 | -6.1825 | 5.2850 | na | na | -5.2000 | 12.200 |
| 0.001 | Estimated | -21.218 | 24.273 | -16.053 | 22.199 | -13.843 | 17.846 | -20.777 | 31.107 | -12.959 | 15.783 |
| | Empirical | -8.6250 | 11.800 | -7.9500 | 11.500 | -7.8000 | 7.9000 | na | na | na | na |
| 0.0005 | Estimated | -29.264 | 34.113 | -21.408 | 30.904 | -18.996 | 25.261 | -28.552 | 44.695 | -17.440 | 21.704 |
| | Empirical | -12.750 | 22.500 | -8.5406 | 13.450 | -8.1500 | 16.005 | na | na | na | na |
| 0.0004 | Estimated | -32.443 | 38.051 | -23.476 | 34.365 | -21.025 | 28.242 | -31.616 | 50.210 | -19.180 | 24.038 |
| | Empirical | -13.500 | 23.000 | -9.3500 | 13.550 | na | na | na | na | na | na |
| 0.0003 | Estimated | -37.048 | 43.798 | -26.432 | 39.397 | -23.959 | 32.605 | -36.046 | 58.327 | -21.677 | 27.414 |
| | Empirical | -20.500 | na | na | Na | na | na | na | na | na | na |
| 0.0002 | Estimated | -44.655 | 53.385 | -31.226 | 47.750 | -28.791 | 39.911 | -43.347 | 72.022 | -25.745 | 32.981 |
| | Empirical | na | na | na | Na | na | na | na | na | na | na |
| 0.0001 | Estimated | -61.402 | 74.833 | -41.476 | 66.287 | -39.382 | 56.354 | -59.360 | 103.22 | -34.507 | 45.198 |
| | Empirical | na | na | na | Na | na | na | na | na | na | na |

Presented above are percentage price changes that occur at margin violation probabilities given in the left-most column of the table. Parameters already generated for each contract and for long and short position scenarios are used to carry out the estimation using the relation:

$$z_p = \mu - \sigma/\xi\left[1 - \left\{-\ln\left(1-p\right)\right\}^{-\xi}\right]$$

given $\xi$ is estimated not equal to zero (Gilleland & Katz, 2013). The shape, scale and location parameters are respectively captured in $\xi$, $\sigma$ and $\mu$. Exceedances of margins for long positions are on the downside hence the negative sign in front of the respective price changes. Comparable tables are also given in a number of studies on extreme values theory (Broussard, 2001; Broussard & Booth, 1998). Extreme value distribution is applied to generate theoretical price change levels for respective margin violation probabilities.

## Table 6.9: Price changes given margin violation (with price limits)

| Margin Violation Probabilities | Distribution | W/maize | | Contract Y/maize | Price | Changes Wheat | (%) |
|---|---|---|---|---|---|---|---|
| | | Long | Short | Long | Short | Long | Short |
| 0.100 | Estimated | -2.0536 | 2.0835 | -1.9276 | 2.0327 | -1.3583 | 1.4643 |
| | Empirical | -2.1279 | 2.1900 | -2.0050 | 2.1255 | -1.4225 | 1.5550 |
| 0.050 | Estimated | -2.9345 | 3.0215 | -2.6962 | 2.9300 | -1.9203 | 2.1411 |
| | Empirical | -2.6500 | 2.7480 | -2.5950 | 2.6825 | -1.7800 | 1.8760 |
| 0.040 | Estimated | -3.2721 | 3.3854 | -2.9852 | 3.2764 | -2.1335 | 2.4052 |
| | Empirical | -2.8250 | 2.9425 | -2.7250 | 2.8274 | -1.9035 | 2.0020 |
| 0.030 | Estimated | -3.7536 | 3.9079 | -3.3927 | 3.7725 | -2.4355 | 2.7857 |
| | Empirical | -3.0050 | 3.1540 | -2.8950 | 3.0250 | -2.0350 | 2.1340 |
| 0.020 | Estimated | -4.5325 | 4.7612 | -4.0424 | 4.5799 | -2.9202 | 3.4101 |
| | Empirical | -3.3050 | 3.5150 | -3.1435 | 3.2785 | -2.2325 | 2.3450 |
| 0.010 | Estimated | -6.1950 | 6.6101 | -5.3965 | 6.3188 | -3.9413 | 4.7730 |
| | Empirical | -3.9019 | 4.0700 | -3.6000 | 3.8550 | -2.6680 | 2.7650 |
| 0.005 | Estimated | -8.3928 | 9.0997 | -7.1352 | 8.6438 | -5.2693 | 6.6251 |
| | Empirical | -4.4250 | 4.5500 | -4.0150 | 4.3500 | -3.0500 | 3.0700 |
| 0.004 | Estimated | -9.2418 | 10.073 | -7.7944 | 9.5483 | -5.7769 | 7.3532 |
| | Empirical | -4.6950 | 4.6900 | -4.3150 | 4.5500 | -3.1225 | 3.1350 |
| 0.003 | Estimated | -10.456 | 11.474 | -8.7268 | 10.847 | -6.4985 | 8.4050 |
| | Empirical | -4.8950 | 4.7200 | -4.3500 | 4.6105 | -3.1650 | 3.2000 |
| 0.002 | Estimated | -12.425 | 13.768 | -10.218 | 12.967 | -7.6599 | 10.135 |
| | Empirical | -5.1500 | 4.9825 | -4.9000 | 4.8500 | -3.3250 | 3.2500 |
| 0.001 | Estimated | -16.641 | 18.752 | -13.335 | 17.545 | -10.113 | 13.923 |
| | Empirical | -5.6950 | 5.5300 | -5.2500 | 5.5400 | -3.4000 | 3.4050 |
| 0.0005 | Estimated | -22.226 | 25.477 | -17.346 | 23.677 | -13.311 | 19.078 |
| | Empirical | -6.4000 | 6.2250 | -5.8000 | 6.3250 | -3.5000 | 3.7000 |
| 0.0004 | Estimated | -24.384 | 28.107 | -18.868 | 26.064 | -14.535 | 21.107 |
| | Empirical | -6.6000 | 6.9500 | -5.8500 | 6.6000 | -3.6500 | 3.7140 |
| 0.0003 | Estimated | -27.471 | 31.894 | -21.021 | 29.493 | -16.274 | 24.037 |
| | Empirical | -7.3000 | na | 5.9000 | na | na | na |
| 0.0002 | Estimated | -32.482 | 38.098 | -24.465 | 35.090 | -19.074 | 28.860 |
| | Empirical | na | na | na | na | na | na |
| 0.0001 | Estimated | -43.211 | 51.580 | -31.668 | 47.182 | -24.991 | 39.417 |
| | Empirical | na | na | na | na | na | na |

Presented above are percentage price changes that occur at margin violation probabilities that are given in the left-most column of the table. Parameters already generated for each contract and for long and short position scenarios are used to carry out the estimation using the relation:

$$z_p = \mu - \sigma/\xi\left[1 - \left\{-\ln\left(1-p\right)\right\}^{-\xi}\right]$$

given $\xi$ is estimated not equal to zero (Gilleland & Katz, 2013). The shape, scale and location parameters are respectively captured in $\xi$, $\sigma$ and $\mu$. Exceedances of margins for long positions are on the downside hence the negative sign in front of the respective price changes. Comparable tables are also given in a number of studies on extreme values theory (Broussard, 2001; Broussard & Booth, 1998). Extreme value distribution is applied to generate theoretical price change levels for respective margin violation probabilities.

For violation probability of 0.0001, silver has notably dissimilar price changes for long (-59.360%) and short (103.22%) positions. While price changes associated with short positions (we are looking here at price increases) can breach the 100% mark, the same is not possible for long positions. Of all the contracts, WTIO has the lowest price changes corresponding to violation probability levels of 0.0001 for both long and short positions.

Table 6.9 incorporates price limits into the analysis of price changes associated with various violation probabilities. Price changes in Table 6.9 are lower than those in Table 6.8 as expected. Compared to theoretical price changes, empirical changes are much lower in Table 6.9 as price limits inhibit the movements. Please note that where empirical values are unobserved, no price changes are provided.[33]

## 6.6 SAFEX Initial Margins Methodology

To check the consistency of our results, some comparisons with SAFEX margin requirements methodologies were drawn. The JSE[34] and SAFEX approach to margins is outlined in SAFCOM (2013) pointing out the on-going process of transition from the parametric VaR method to the historical VaR approach[35]. In this section, two angles are pursued, collecting actual margins from the SAFEX historical database, and calculating margins using the new method being adopted by SAFCOM.

Table 6.10 makes a comparison of the time-to-margin violation derived using the historical VaR compared to the parametric VaR approach. Exceedance corresponding to the probability of margin violation is used to calculate the amount of time in months or years

[33] In this case “na” is used.
[34] SAFEX is a subsidiary of the JSE and clearing for the former and the latter is conducted by the SAFEX Clearing Company (Pty) Ltd (SAFCOM).
[35] See Appendix I.

before violation occurs.[36] These computations use violation probabilities derived from extreme value theory results.

In general, long positions have a longer time to margin violation compared to short positions. Of all the positions without price limit considerations, the WTIO long position experiences the longest period to margin violation (56.20 months), using the parametric VaR method. Wheat has the shortest times to margin violation (without price limits) when using the parametric VaR for both long (4.73 months) and short (3.53 months) positions. When bounded by price limits, times to margin violation increase for white maize, yellow maize and wheat. As an example, white maize time to margin violation for the historical VaR increases from 8.65 months to 12.70 months for the long position. The margin violation time for white maize short position increases from 7.25 months to 10.48 months when price limit bounds are introduced.

**Table 6.10: Expected years or months to margin violation**

| Commodity | Margin Approach | Observed Margin (%) | | Number of months to margin violation | | | |
|---|---|---|---|---|---|---|---|
| | | | | Without price limit events | | Bounded by price limits | |
| | | Long | Short | Long | Short | Long | Short |
| White maize | Historical VaR | 9.4704 | 9.4704 | 8.65 | 7.25 | 12.70 | 10.48 |
| | Parametric VaR | 9.9811 | 9.9811 | 9.67 | 8.04 | 14.35 | 11.76 |
| Yellow maize | Historical VaR | 10.847 | 10.847 | 18.89 | 10.89 | 28.00 | 15.99 |
| | Parametric VaR | 9.1811 | 9.1811 | 8.12 | 6.82 | 18.22 | 10.99 |
| Wheat | Historical VaR | 4.8708 | 4.8708 | 5.11 | 3.79 | 7.94 | 5.01 |
| | Parametric VaR | 4.6935 | 4.6935 | 4.73 | 3.53 | 7.27 | 4.63 |
| Silver | Historical VaR | 8.3988 | 8.3988 | 6.92 | 4.11 | 6.92 | 4.11 |
| | Parametric VaR | 9.3021 | 9.3021 | 8.57 | 4.96 | 8.57 | 4.96 |
| WTIO | Historical VaR | 7.5243 | 7.5243 | 13.75 | 9.82 | 13.75 | 9.82 |
| | Parametric VaR | 13.868 | 13.868 | 56.20 | 36.28 | 56.20 | 36.28 |

SAFCOM (2013) confirms that SAFEX assumes margins are the same for long and short positions. The probability of margin violation (which is generated using EVA) can be converted into the number of days (months, years) it would take for a violation to occur. The number of years for violation is generated using the assumption of approximately 250 trading days per year (Booth et al., 1997).

[36] Margin violation probabilities primarily pertain to the return period for the initial margin, which is one day. This probability can then be converted into the number of days it would take for a violation to occur. The number of years for violation is generated using the assumption of approximately 250 trading days per year (Booth, Broussard, et al., 1997).

Further, the paper also calculates the possible margins using extreme value approaches. If given a probability of margin violation, *p*, Longin (1999) estimates the optimal margin to be set by the exchange as:

$$M = \mu - \frac{\sigma}{\xi}\left(1 - \left(-\log(1-p)\right)^{-\xi}\right) \tag{6.21}$$

Where *M* is the margin, $\mu$ is the location parameter, $\sigma$ is the scale and $\xi$ is the shape parameter. We include this margin level for comparison with the parametric VaR and historical VaR. Thus, Table 6.11 makes a comparison of margins using the parametric VaR, the historical VaR and EVA. For EVA margins, five probabilities of margin violation are used (0.5; 0.1; 0.05; 0.01 and 0.005). The question is what would be the plausible margin violation probability the exchange should work with? The margin committee only has to choose this probability of violation consistent with the exchange's risk profile.

**Table 6.11: Comparative margins using three approaches**

| Contract | | Parametric VaR | Historical VaR | Extreme value margins (@ various violation probabilities) | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Margin (%) | Margin (%) | (Prob=0.50) (%) | (Prob=0.10) (%) | (Prob=0.05) (%) | (Prob=0.01) (%) | (Prob=0.005) (%) |
| White maize | Short | 9.9811 | 9.4704 | 1.1461 | 3.1990 | 4.5442 | 9.6906 | 13.261 |
| | Long | 9.9811 | 9.4704 | 1.1528 | 3.0995 | 4.3352 | 8.9089 | 11.992 |
| Yellow maize | Short | 9.1811 | 10.847 | 1.1280 | 3.0991 | 4.3749 | 9.1933 | 12.499 |
| | Long | 9.1811 | 10.847 | 1.1127 | 2.8377 | 3.8788 | 7.5367 | 9.8919 |
| Wheat | Short | 4.6935 | 4.8708 | 0.7956 | 2.2698 | 3.2510 | 7.0670 | 9.7524 |
| | Long | 4.6935 | 4.8708 | 0.7718 | 2.0246 | 2.7979 | 5.5782 | 7.4053 |
| Silver | Short | 9.3021 | 8.3988 | 1.2172 | 3.9406 | 5.9124 | 14.300 | 20.673 |
| | Long | 9.3021 | 8.3988 | 1.1315 | 3.3151 | 4.7747 | 10.477 | 14.505 |
| WTIO | Short | 13.868 | 7.5243 | 0.8605 | 2.5133 | 3.6197 | 7.9475 | 11.010 |
| | Long | 13.868 | 7.5243 | 0.8260 | 2.3043 | 3.2553 | 6.8235 | 9.2583 |

A comparison of margin levels derived using the parametric VaR, historical VaR and EVA approaches is presented. Several margin violation probabilities (0.5; 0.1; 0.05; 0.01 and 0.005) are used with the EVA methodology. EVA margins are estimated using the Longin (1999) relation, which is:

$$M = \mu - \frac{\sigma}{\xi}\left(1 - \left(-\log\left(1-p\right)\right)^{-\xi}\right)$$

The approach to EVT margins enables the margin committee to select the violation probability in line with the risk profile of the futures exchange.

For all contracts, EVA has lower margins for long positions compared to short positions. According to EVA and at any probability of margin violation, silver has the highest margin levels while wheat has the lowest. It should also be remembered that EVA parameters for silver and WTIO have not incorporated price limits as none exist for these contracts. The analysis finds EVA probability of margin violation of 0.01 interesting as it gives margins closely tracking the parametric VaR and the historical VaR methods (at least for the largest contracts on SAFEX).

## 6.7 Concluding Remarks

The paper contributes to literature on extreme value application to futures contracts accounting for the impact of price limits. Significant evidence of asymmetry is found between the distributions of negative and positive returns for all the contracts examined. This suggests setting different margins for long and short positions may be plausible to increase margin prudentiality while reducing market trading costs. Further, it is a key finding of this study that price limits have an influence on extreme contract movements on SAFEX. It is observed that differences exist in parameter estimates between contracts with price limits and those without.

Empirical exceedance curves were observed lower than those for theoretical margin violation probabilities. This suggests margin-setting based on historical returns observations could underestimate the potential for large price changes. Further, empirical curves are actually truncated by price limits suggesting there is room to allow less conservative margins to promote liquidity and price discovery. At the same time, theoretical probabilities were generally higher than empirical probabilities in the tails especially for data taking price limit events into account.

The extreme value approach can therefore be used with parameter estimates consistent with price limits allowing more prudent margins to be set. It has also been seen that the EVT approach enables different margins to be set for short and long positions. The margins committee has to select the probability of margin violation matching the risk profile of the exchange.

Optimization of margins may increase trading activity, brokers' commissions and SAFEX revenues. Extreme value estimation enables this to be done without overlooking the likelihood of margin exceedance, hence protecting exchange integrity.

**APPENDIX 6.1: Calculation of VaR and IMR: The proposed SAFCOM (2013) approach**

The proposed approach incorporates a look-back period of 750 days and a stressed period of about 250 days (SAFCOM, 2013). Returns in for the look-back period are generated with the relation:

$$R(i)=\left|\frac{x_{t-i}}{x_{t-i-m}}-1\right|, \text{ for } i=0,1,2,\ldots..,n-1 \tag{A1}$$

Where *t* is the day and *m* is the number of days in holding period. Stressed period returns are:

$$R^{*}(i)=\left|\frac{x^{*}_{\tau-i}}{x^{*}_{\tau-i-m}}-1\right|, \text{ for } i=0,1,2,\ldots..,\eta-1 \tag{A2}$$

The vector $R^c$, formed as an $((n+\eta)x1)$ is calculated as:

$$R^{c}(i)=\begin{cases} R^{*}(i), & i<\eta \\ R(i-\eta), & i\geq\eta \end{cases}, \text{ for } i=0,1,2,\ldots..,n+\eta-1 \tag{A3}$$

Volatility scaling in SAFCOM (2013) uses continuously compounded return, $u_t$ on day *t*, as:

$$u_t=\ln\left(\frac{x_t}{x_{t-1}}\right) \tag{A4}$$

This is used to calculate for day *t*, the 90-day realized volatility using:

$$\sigma_t=\sqrt{\frac{1}{90-1}\sum_{i=1}^{90}\left(u_{t-i}-\hat{u}_2\right)^2}, \text{ where, } \hat{u}_t=\frac{1}{90}\sum_{i=1}^{90}u_{t-i} \tag{A5}$$

Scaling the vector Rc, the relation is:

$$R^{c}(i)\Leftarrow R^{c}(i)*\max\left(0.7,\frac{\sigma_{t-(m-1)}}{\sigma_{i-(m-1)}}\right) \qquad \begin{matrix} i<\eta \\ i\geq\eta \end{matrix}, \text{ for } i=0,1,2,\ldots..,n+\eta-1 \tag{A6}$$

VaR is then defined by SAFCOM (2013) as the $y^{th}$ largest element of $R^c$, where *y* is:

$$y=\max\left\{z\in \mathrm{N}: z\leq\alpha(n+\eta)\right\} \tag{A7}$$

# 7 CONCLUSIONS, MARKET IMPLICATIONS AND RECOMMENDATIONS

## 7.1 Introduction

Four major empirical themes guided the analysis on futures contracts in this thesis. Firstly, the study looked at seasonality in returns and volatility on SAFEX with focus on the wheat contract. Calendar effects considered are day-of-the-week, monthly, pre-holiday, post-holiday, as well as the impact of KCBT holidays on the wheat market. Given the identified anomalies, the next step was to develop trading rules exploiting market inefficiencies and testing for strategy profitability. Monte Carlo simulation was used for the tests accommodating round-trip trading costs in the out-of-sample period.

Secondly, information transmission between SAFEX and selected international futures markets was examined using cointegration analysis, VAR estimation and multiple regressions. The study looked at whether price shocks in wheat futures markets on diverse continents impacted on the SAFEX market. Of interest was to find markets' sensitivity to receiving information and the ability of each market to transmit information thereby influencing other markets. The analysis revealed market linkages between SAFEX and major global exchanges and the direction of information flows across four futures markets.

Thirdly, maturity effects in SAFEX contracts were examined determining volatility behaviour as contract maturity nears. This was carried out accounting for the influence of traded volume, the bid-ask spread and change in open interest. In the robustness analysis, the effects of multi-collinearity and seasonality were accounted for.

Fourthly, extreme value analysis was applied to examine margins in five contracts on the SAFEX market. The analysis firstly looked at asymmetry in negative and positive returns determining if margins should be equal for long compared to short contract positions. The effect of price limits is accounted for using data bounded by price limit events. Margin violation probabilities are estimated using the GEV approach both with and without price limit events. Comparative margins are generated using the parametric VaR method, historical VaR and EVT, highlighting the strengths of the EVT approach. The study investigated optimization of margins using EVT to improve margin-setting and enhance price discovery and market integrity.

In this thesis, the empirical analysis focused on futures return volatility, market anomalies, information transmission, maturity effects and margins of contracts on SAFEX. The overall motivation is to guide risk management on SAFEX for the investors and for the exchange while pointing out profitable trading opportunities. This helps to achieve the futures market objectives of increasing liquidity and price discovery, which lead to higher market activity and consequently higher brokers' commissions and revenue for the exchange. Understanding commodity volatility also assists in mitigating its adverse effects while exploiting profitable opportunities arising from price movements. Increased volatility entails higher costs of hedging, which, when passed on to the commodity end-users, causes higher price inflation.

## 7.2 Empirical Findings

### *7.2.1. Wheat Market Seasonality Analysis*

Chapter 3 examined market inefficiencies in the wheat contract finding if they could be exploited for financial gain. Significant evidence of market anomalies in the wheat contract is found. Analysis results showed the highest mean daily returns occurring on Mondays and the lowest (and negative) returns on Tuesdays. The study does not find evidence of pre-

holiday and post-holiday effects in the wheat contract. However, wheat returns are significant on KCBT holidays. Further, seasonality in wheat returns and volatility revealed the contract does not support the efficient market hypothesis. In addition, non-parametric and parametric-based techniques are used to study sample regimes before and after the peak in wheat prices which occurred during the global economic crisis in 2008. Seasonal patterns occur largely in the second sample (after the global crisis) of the wheat dataset. Furthermore, it is observed that volatility diminished after the global financial crisis.

A trading strategy was developed which entailed taking long positions on Mondays, short positions on Tuesdays and long positions on KCBT holidays. Financial profit is achieved by this trading rule, net of round-trip trading costs. Validation of the strategy is carried out using out-of-sample Monte Carlo simulation, proving to be both profitable and superior to any trading approach based on chance.

### *7.2.2. Wheat Market Information Flows*

Chapter 4 investigated the extent of information transmission across SAFEX, ZCE, KCBT and Euronext/Liffe. Broadly, this chapter gives an insight on whether prices on SAFEX are influenced by foreign markets. To begin with, close linkages amongst Euronext/Liffe, KCBT and SAFEX are found using cross-correlation analysis. ZCE is found to be unrelated to the other markets. Three approaches for studying information flows among non-synchronous markets are applied in this chapter; cointegration techniques, VAR analysis, and multiple regression proposed in Peiró et al. (1998). Going by cointegration analysis, no evidence of long-run relationships in the wheat prices on ZCE, SAFEX, Euronext/Liffe and KCBT is found. The study proceeds by applying the VAR and the multiple regression approach in Peiró et al. (1998).

Using VAR, the most exogenous wheat market contributing the most to variance prediction for SAFEX, KCBT and ZCE is Euronext/Liffe. The markets with the largest impact on the other markets are Euronext/Liffe and KCBT. The last stage was the application of the multiple regression approach to find markets' sensitivity to receiving information as well as the ability to influence other markets. After arranging the markets according to closing times, the Peiró et al. (1998) approach finds KBCT the most influential and most sensitive of the 4 wheat markets. SAFEX is found to be a significant receiver of information but does not influence the other markets. ZCE is both the least influential and least sensitive market. Evidence is found that participation on the Chinese wheat market by state-owned entities diminishes linkages of the ZCE with the global wheat system. As such, wheat prices on ZCE are out of sync with the other 3 markets.

### *7.2.3. Maturity Effects in SAFEX Contracts*

Volatility behaviour of white maize, yellow maize, wheat, silver and WTIO as the contracts approach maturity is investigated in Chapter 5. The study is looking at support for the Samuelson hypothesis by the SAFEX contracts. Characterizing volatility patterns is of interest in hedging, speculation and margin-setting. Estimation of the Samuelson effect is by ordinary least squares (OLS) approach using the volatility estimator in Garman and Klass (1980), Parkinson (1980) and Serletis (1992). The analysis simultaneously tests for the Samuelson effect while establishing significance of traded volume, change in open interest and bid-ask spread on intraday volatility. After accounting for multicollinearity and seasonality, evidence is found that wheat experiences maturity effects or otherwise supports the Samuelson hypothesis. White maize and silver experience significant diminishing volatility as contract maturity approaches.

### *7.2.4. Margin Adequacy on SAFEX*

Finally, margin-setting on SAFEX is investigated using extreme value analysis (EVA) in Chapter 6. The aim is to find out if EVA may be a more suitable approach to calculating margins given that the normal distribution is not assumed in its implementation. Considerations by a futures margin committee when setting margins include volatility, traded volume, existing market conditions and price limit levels (Bahram Adrangi & Chatrath, 1999; Fishe et al., 1990; Kupiec, 1998). The initial analysis looks at whether it would be beneficial to incorporate asymmetry into the calculation of margins. Given white maize, yellow maize, wheat, silver and WTIO have asymmetric returns, the study findings support the setting of different margin levels for long and short positions. EVA is found suitable for setting the different opposite margins. Further, it is found long positions should have lower margins than short positions of similar magnitude for the five SAFEX contracts.

Price limits are found impacting extreme contract movements and reducing the probability of margin violation. Unlike EVA, margin-setting approaches using historical (empirical) data or based on the normal distribution are found potentially underestimating the likelihood of extreme price movements. Margin violation probabilities are estimated given a range of margin levels. Exceedances at given margin levels are used to calculate the amount of time before margin violation occurs, for lower and upper tail distributions. Margin violation curves generated using GEV parameters show empirical exceedance lower than the theoretical curves. This further confirms setting margins using historical returns may underestimate extreme movements. Actual margin levels fixed by SAFEX are examined estimating corresponding violation probabilities.

It is found EVA allows better margin optimization which could increase trading activity, brokers' commissions and the revenues of the exchange. With theoretical margin violation curves located above those for the empirical distribution, EVA is less likely to underestimate the likelihood of margin exceedance compared to current SAFEX approaches.

## 7.3 Contributions to Literature

The thesis develops a new trading rule exploiting market inefficiencies in the wheat contract on SAFEX. Validated by Monte Carlo simulation, the suggested trading strategy is both more superior to the buy-and-hold approach and is better than any strategy based on chance. The rule also gives financial profits significantly higher than round-trip trading costs. The study therefore shows inefficiencies on the SAFEX market can enable SAFEX investors to make economic profits.

Using VAR analysis and a technique accounting for non-synchronous trading on four wheat markets, this thesis finds KCBT the most influential and sensitive market of the four exchanges considered. Euronext/Liffe is the most exogenous market within the group. It is also found that SAFEX is vulnerable to price shocks that may be experienced in the global wheat markets as opposed to ZCE, which is not adversely impacted by these shocks.

The paper extends on an approach in Kenourgios and Katevatis (2011) in the investigation of maturity effects in white maize, yellow maize, wheat, silver and WTIO. Wheat is found robustly in support of the Samuelson hypothesis. It would be prudent for wheat margins to be proportionately increased and those for white maize and silver to be decreased towards contract maturity. Presently margins do not take into account maturity effects from contract inception to maturity.

Price limits are found reducing margin violation probabilities on SAFEX, but also effectively inhibiting price discovery. EVA is found more superior than methods using the normal distribution assumption, particularly as SAFEX contracts' returns are found asymmetric. EVA is found ideal for margin-setting to enhance prudentiality while minimising trading costs. The results in Chapter 6 are important in showing how to optimise margin-setting to both reduce trading costs while increasing market integrity. Achieving this could increase market traded volume and market liquidity improving price discovery.

## 7.4 Futures Market Implications

The wheat contract does not obey the efficient market hypothesis. Armed with suitable trading strategies, market inefficiencies could see more investors, particularly speculators, increasing participation levels on SAFEX. Traders may make use of the rule developed in this thesis to time position-taking or they could time previously planned purchases to be on Mondays or planned sales to be on Tuesdays. Such opportunities may make the market more attractive for some participants enhancing trading levels. Increased investment could however reduce profit opportunities in the long run as demand and supply forces lead to price re-alignment.

South Africa has increasingly been depending on imported wheat as domestic production of the cereal started declining after market liberalization in 1996. Policies supporting local production of wheat in South Africa would reduce import requirements by increasing local market supply. This reduces vulnerability to global markets and sensitivity to receiving information (which may be adverse) potentially stabilising domestic prices. Increasing local wheat production could also complement South Africa's inflation-targeting framework which prescribes inflation bands that should not to be breached. Furthermore, enhancing local

wheat production could also increase information flows out of the country rather than into it, smoothening food prices and increasing food security.

The leading role of the USA futures markets in the global system and its importance in world commodities and financial systems is revealed in Chapter 5. The openness of the SAFEX market supports linkages with the global wheat system. The vulnerability of the SAFEX wheat contract to global price shocks is made worse by the dependence of South Africa on wheat imports to meet approximately half of domestic demand. South Africa requires better incentives for wheat farmers to increase production, create employment and reduce local bread and wheat prices while conserving hard currencies. China barely experienced price peaks at the height of the global financial crisis, unlike the other markets. State-owned entities participate in the food markets in China leading to the disconnection with the global system.

As wheat supports the Samuelson Hypothesis, margins should be set higher as the contract approaches maturity. There should also be better opportunities to trade volatility for wheat nearer maturity if investors are trading volatility. As such, the price of options should generally increase towards maturity of the contract. Hedgers are expected to proportionately adjust hedge ratios as volatility increases while speculators could profitably exploit price fluctuations for financial gain.

Extreme market movements are linked to market corrections, crashes, financial collapses and foreign currency crisis. Further optimisation of margin approaches could reduce trading costs and increase market efficiencies. Higher market competitiveness will attract both local and international investors enhancing market liquidity and price discovery.

## 7.5 Recommendations for Further Research

A number of areas for further research to add to empirical findings in this thesis have been identified. An opportunity exists for future research to investigate seasonality in maize, soybeans, sunflower as well as the metals and energy contracts listed on SAFEX. Trading strategies deriving out of any anomalies may be tested in the out-of-sample period finding if net positive returns are realisable.

As the study focussed on commodity futures on SAFEX, there is the opportunity to investigate the options markets for market anomalies, information flows, maturity effects and margin adequacy. Some of the methods used here or suitable variations would be worthwhile for use in future studies. The study predominantly used daily data. It would be interesting to find out if using higher frequency data would substantially change the findings.

Information transmission could be investigated in SAFEX contracts like maize, soybeans, silver and crude oil. Market linkages could be investigated with other markets such as Australia, India and Canada. It would be interesting in future research to incorporate regimes finding out information transmission across time. This could allow comparison of information flows before the global crisis as distinguished from the post-crisis years.

Further, research on maturity effects could also consider if regimes have an impact on the result. An opportunity is presented to develop trading strategies exploiting volatility predictability particularly in the wheat contract. This profitability could be validated in an out-of-sample period confirming trading rule viability. Further research in new studies will enable clearer guidelines to be developed on the use of trading rules on SAFEX.

The futures markets in South Africa are still in the growth phase and there may be limitations on the amount and extent of information that can be gathered when compared to the CME. SAFEX operates daily for 3 hours only while the CME is functional across the entire business day. This makes it difficult to effect certain direct comparisons. There is still need for SAFEX to in future report on similar information as that coming from the CFTC on the CME market. This information provides the positions held by large traders on the futures markets and splits market trades by trader category. This information is required when carrying out studies in future research on speculation levels and their impact on market behaviour. Without this information, further research on the determinants and behaviour of volatility may need to modify existing models in literature to adapt to the information available on SAFEX.

It would be worthwhile for future research to forecast extreme market movements in an out-of-sample period and back-test the GEV parameters for the major SAFEX contracts. There is an opportunity to split samples into regimes and compare shape, scale and location estimates. It is also worthwhile to investigate whether EVA would have been able to predict notable market movements, for example, extreme movements linked to the global financial crisis.

The study also focussed on the initial margin requirements on SAFEX. Further research concentrating on variation and the newly introduced concentration margins would provide a more complete picture. Variation margins could be investigated using weekly data similar to Booth, Broussard, et al. (1997). Further research could investigate the behaviour of the other contracts on SAFEX not covered here, particularly the oilseeds. Indeed, the sunflower seed and soybean contracts on SAFEX have not been extensively looked at in both the professional and academic literature.

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## Attachment I: Literature Review Summary on Commodity Price Spill-over Studies[37]

| Study | Data | Method | Commodity | Key findings |
|---|---|---|---|---|
| Baffes (2007) | 1960-2005 (annual) | OLS | Crude oil, 35 commodities | Changes in oil prices spill into non-energy commodity indices |
| Harri & Hudson (2009) | 2003-2009 (daily) | Causality | Crude oil, maize, soy | Pass-through from oil to maize after global economic downturn |
| Krichene (2008) | 2000-2007 (daily) | LPGH | Crude oil | Expansionary policies impact on crude oil prices |
| Alghalith (2010) | 1974-2007 (annual) | NOLS | Crude oil, food Commodities | Volatility passes from crude oil to food commodities |
| Baffes (2010) | 1960-2000 (annual) | OLS | Energy, non-energy indices | Spill-over from energy, to fertilizer to the metals |
| Busse et. al (2010) | 2002-2009 (weekly) | MS-VECM | Biodiesel, rapeseed, Soy, crude oil | substantial pass-through, crude oil to biodiesel, to rapeseed oil |
| Chang & Su (2010) | 2000-2008 (daily) | EGARCH | Crude oil, maize, soy | Volatility flows from crude oil to maize and soy prices |
| Zhang et. al (2010) | 1989-2008 (monthly) | VECM | Ethanol, maize, rice Soy, sugar, wheat Gasoline, crude oil | No long-tern relationships were found between energy and food commodities |
| Alom et. al (2011) | 1995-2010 (daily) | VAR | Crude oil, food price Index | Positive volatility linkages, oil and food prices, with differences in levels by country |
| Cevik & Sedik (2011) | 1990-2010 (monthly) | OLS | Crude oil, fine wine | Macroeconomic factors had larger influence on prices |
| Du et. al (2011) | 1998-2009 (weekly) | SVM | Crude oil, maize, wheat | Pass-through between crude oil, maize and wheat |
| Serra (2011) | 2000-2009 (monthly) | SP-GARCH | Ethanol, crude oil Sugar | Variability from crude oil and sugar prices affects ethanol positively |
| Serra (2011) | 1990-2008 (monthly) | ST-VECM | Ethanol, corn, oil gasoline | Spill-over is determined for energy and food prices in the long-term |
| Kristoufek et. al (2012) | 2003-2011 (weekly) | MS-HT | Biodiesel, ethanol, | Food and fuel impact biofuels while the other way round is limited |

[37] Source: the table is adapted and expanded from the one presented in Mensi et al. (2013). BMCMC is Bayesian markov chain Monte Carlo, OLS is ordinary least squares, NOLS is non-ordinary least squares, SVM is stochastic volatility models, SP-GARCH is semi-parametric GARCH, LPGHT is Levy process of generalized hyperbolic type, MS & HT is minimal spanning & hierarchical trees, MLLR is multivariate local linear regression, ST-VECM is smooth transition vector error correction, MS-VECM is markov switch vector error correction

| Study | Data | Method | Commodity | Key findings |
|---|---|---|---|---|
| Hassouneh et. al (2012) | 2006-2010 (weekly) | MLLR | Biodiesel, sunflower crude oil | Long-run impact across various commodities identified |
| Nazlioglu et. al (2012) | 1986-2011 (monthly) | CIV | Oil, soy, maize, wheat, sugar | Oil price volatility passes-through food prices post-global crisis |
| Mensi et. al (2013) | 2000-2011 (monthly) | VAR-GARCH | S&P 500, energy, gold, food products | Significant pass-through exists between S&P 500 and commodity markets |

## Attachment II: Literature Review Summary on South African Financial Markets Studies[38]

| Study | Data | Method[39] | Financial assets | Key Findings |
|---|---|---|---|---|
| Fedderke & Joao (2001a) | 1996-1998 (daily) | VECM, cointegration | Spot, future ALSI40 | There exists cost-of-carry arbitrage link between the spot and the futures prices for the ALSI |
| Fedderke & Joao (2001b) | 1996-1998 (daily, intra-day) | Unstructured VAR | South African stock index, spot | Futures lead spot prices |
| Coutts & Sheikh (2003) | 1987-1997 (daily) | Dummy regression | All gold index | Anomalies not found; weekend, January, pre-holiday effects all not significant. |
| Floros (2009) | 2002-2006 (daily) | Cointegration, VECM, GCT, ECM, TGARCH | Stock index futures, spot stock prices | Cointegration and bidirectional co-movement exists between stock index futures and daily spot prices. |
| Phukubje & Moholwa | 2000-2003 (daily) | Randon walk test | Wheat, sunflower seed | Future prices are predictable to some extent from past prices for wheat and sunflower seed |
| Viljoen (2003) | 1996-2000 (daily) | Cointegration, non-parametric tests | White, yellow maize, wheat | Day-of-the-week, time-of-the-year, turn-of-the-month and maturity effects were found in the maize, and only the turn-of-the-month-effect was found in wheat. |
| Smith & Rogers (2006) | 1998-2005 (weekly) | Variance ratio tests | Stock index futures, 36 SSFs | Random walk confirmed for four stock index futures and 25 SSFs |
| Adelegan (2009) | 2001-2008 (daily) | None | Equity, futures, options | Rapid growth in derivatives has been seen in South Africa helping price assets and transfer risk |
| Motladiile & Smit (2003) | 1998-2001 (daily) | CCH model | Stock index futures, spot price indices | Basis has an inverse relationship to index volatility, open interest is positively linked to volatility |
| Moholwa (2005) | 1999-2003 (daily) | Randon walk test | White, yellow maize | There is partial predictability of white and yellow maize prices from past price data. |
| Jordaan et. Al (2007) | 1997-2006 (daily) | ARIMA, GARCH | Maize, wheat, sunflower seed, soybeans | Volatilities for commodities ranked in order of intensity follow the order; maize, sunflower seed, soybeans and wheat |

[38] Source: project research findings

[39] VECM stands for vector error correction method, GCT stands for Granger Causality test, ECM is error correction method, SSFs are single stock futures. CCH model stands for the model developed in Chen, Cuny and Haugen (1995). ALSI stands for All Share Index with forty of the largest counters on the JSE. ARIMA stands for autoregressive integrated moving average, GARCH stands for generalized autoregressive conditional heteroskedasticity and VAR stands for vector autoregression.

## Attachment II: (Cont.)

| Study | Data | Method[40] | Financial assets | Key Findings |
|---|---|---|---|---|
| Mashamaite & Moholwa (2005) | 1996-2003 (daily, weekly) | PAM[41] | White, yellow maize, wheat, sunflower seed | Wheat prices emerged as asymmetric responding more drastically and faster to price decline than increase. |
| Strydom & McCullough (2013) | 1996-2009 (2 obs. per contract) | ECM, VECM | White maize | Long-run cointegration exists between SAFEX futures and spot prices for white maize |
| Wiseman et. al (1999) | 1997-1998 (daily) | Cointegration analysis | White maize | No long-run linkage between futures and spot prices found for 1997, but significant relationship existed in 1998. |
| Geyser & Cutts (2007) | 2001-2006 (monthly) | Correlation analysis | Maize, exchange rate, gold | South African volatility is explained more by fundamental factors than linkages with the international markets |
| Boshoff (2006) | 1997-2002 (daily) | Multivariate regression | JSE top-forty stocks | The financial crises in Asia, Russia and Argentina had insignificant impact on firms on the JSE. |
| Van Wyk (2012) | 1997-2011 (daily) | EGARCH | White, yellow maize | Spill-over of volatility from the CME not statistically significant for white and yellow maize |

[40] VECM stands for vector error correction method, GCT stands for Granger Causality test, ECM is error correction method, SSFs are single stock futures. CCH model stands for the model developed in Chen, Cuny and Haugen (1995). ALSI stands for All Share Index with forty of the largest counters on the JSE. ARIMA stands for autoregressive integrated moving average, GARCH stands for generalized autoregressive conditional heteroskedasticity and VAR stands for vector autoregression.
[41] PAM stands for price asymmetric model.