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Sayed, Ayesha

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SCHOOL OF ECONOMICS AND FINANCE

FACULTY OF COMMERCE, LAW AND MANAGEMENT



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Price Volatility in Maize Futures of Major Exporters

Name: Ayesha Sayed

Student number: 0507725E

Degree: Doctor of Philosophy

School of Economics and Finance

Supervisor: Professor Christo Auret

A thesis submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand in fulfilment of the requirements for the degree of Doctor of Philosophy in Finance.

Johannesburg, South Africa

I had always looked on 'futures' as the creatures of wild speculation and eminently uncertain, and I could not avoid a feeling of wonder that such operations could be reduced within the dominion of scientific investigation, which alone is a great step in advance.

Remarks by Sir Francis S. Powell, M. P., Chairmain at a meeting of the Royal Statistical Society, London, April 24, 1906.

Price Volatility in Maize Futures of Major Exporters

General Abstract

Futures markets provide a platform for risk management and price discovery. Significant structural changes have taken place in futures markets over the last two decades transforming them into a volatile and fast paced trading environment, with heightened volatility expected to continue. Increased volatility in grain futures markets is of special concern to farmers, traders, academics, and policy makers as it impacts food security, renewable energy and the regulation of futures exchanges. Price volatility is investigated for maize futures listed in South Africa on the South African Futures Exchange (SAFEX), in the United States on the Chicago Board of Trade, in Argentina on the Mercado a Termino de Beunes Aires and in Brazil on the Brazilian Mercantile and Futures Exchange. A particular focus is placed on South African white maize futures, given its liquidity on SAFEX, its uniqueness as the only listed white maize contract traded on a futures exchange globally, and the importance of white maize as South Africa's largest produced field crop and main staple food. This thesis investigates the effectiveness of price limits which are found to be ineffective in curbing volatility, and instead found to accelerate prices towards their limits prematurely, exacerbate volatility and impair market liquidity. The impact of sentiment as measured through volatility indices is also studied using a time-varying vector autoregressive framework. The results confirm the influence of sentiment on trading behaviour in white maize futures, and subsequently on price volatility. The level of speculative activity and its impact on price volatility is also examined using Granger-causality, variance decomposition and impulse response functions. Finally, volatility spillovers among key major exporters of maize is investigated using four multivariate GARCH models and a DCC-GARCH Connectedness approach, with the results confirm significant own and cross volatility spillovers and time-varying interdependence. This thesis makes novel contributions to the field of futures risk management. The work covered in this thesis is among the first to investigate price limits on SAFEX, the first to include SAVI White Maize in an empirical analysis, the first to quantify the level of speculative activity in the white maize futures market and the first to investigate spillover and dynamic connectedness in maize futures among key maize exporters .

Keywords: *futures, price volatility, white maize, speculation, price limits, dynamic connectedness, volatility spillover*

Declaration

I, Ayesha Sayed, declare that this thesis is my own work and that I have correctly acknowledged the work of others. It is submitted to fulfil the requirements for the degree of Doctor of Philosophy in Finance at the University of the Witwatersrand, Johannesburg. I declare that this thesis has not been submitted for any other degree or examination in this or any other institution.

Ayesha Sayed

Ayesha Sayed

June 2023

Declaration - Publications

I, Ayesha Sayed, declare that the following papers have been published from this thesis:

- Sayed, A., & Auret, C. (2018). The effectiveness of price limits in the South African white maize futures market. *Investment Analysts Journal*, *47*(3), 193-208. https://doi.org/10.1080/10293523.2018.1475591
- Sayed, A., & Auret, C. (2019). Volatility transmission in maize futures markets of major exporters. *Investment Analysts Journal*, *48*(3), 173-187. https://doi.org/10.1080/10293523.2019.1626602
- Sayed, A., & Auret, C. (2020). Volatility transmission in the South African white maize futures market. *Eurasian Economic Review*, *10*(1), 71-88. https://doi.org/10.1007/s40822-019-00128-y
- Auret, C., & Sayed, A. (2020). The effects of uncertainty on investor expectations and volatility in the South African white maize futures market. *Investment Analysts Journal*, *49*(3), 165-179. https://doi.org/10.1080/10293523.2020.1776503
- Sayed, A., & Auret, C. (2023). Speculative ratios and returns volatility in the South African white maize futures market. *Cogent Economics & Finance*, 11(1), 2160127. https://doi.org/10.1080/23322039.2022.2160127

Ayesha Sayed

June 2023

Declaration – Conference Presentations

I, Ayesha Sayed, declare that the following papers have been presented at the following conferences:

- Sayed, A. and Auret, C. (2017). Volatility, volume and market depth in the South African white maize futures market. Presented at the Eurasian Business and Economics Society (EBES) conference, September 2017, Madrid, Spain.
- Sayed, A. and Auret, C. (2018). The effect of circuit breakers and trading limits in grains futures markets – overreaction vs stability. Presented at the Southern African Finance Association conference, January 2018, Cape Town, South Africa.
- Sayed, A and Auret, C. (2018). Mean and volatility transmission for white maize futures. Presented at the Eurasian Business and Economics Society (EBES) conference, October 2018, Prague, Czech Republic.
- Sayed, A. and Auret, C. (2019). Heat waves or meteor showers? Examining volatility transmission in maize futures markets. Presented at the Southern African Finance Association conference, January 2019, Cape Town, South Africa.
- Sayed, A. and Auret, C. (2019). Speculative ratios and price volatility in the South African white maize futures market. Presented at the Eurasian Business and Economics Society (EBES) conference, October 2019, Lisbon, Portugal.
- Sayed, A. and Auret, C. (2020). The effects of uncertainty on investor expectations in the South African white maize futures market. Presented at the Southern African Finance Association conference, January 2020, Cape Town, South Africa. .

Ayesha Sayed

June 2023

Ethical clearance

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

Registration number: REC-101114-044

13 August 2020

Re: Ms. Ayesha Sayed (0507725E)

Waiver letter number: HRECNMW20/08/05

To whom it may concern,

Ms. Sayed is currently registered as a PhD student at the School of Economics and Finance at the University of the Witwatersrand, Johannesburg. This letter is to confirm that, at the time of writing, Ms. Sayed does not need ethical clearance for her PhD study entitled *'Price volatility in maize futures of major exporters'*. This decision has been reached based upon a description of the project supplied by Ms. Sayed to the University Human Research Ethics Committee (Non-Medical), which has been evaluated by the Chairs and Deputy Chairs. If, however, Ms. Sayed changes the methods of data collection and analysis for this study, this decision may no longer be valid. If such changes take place, this should be communicated to the University Human Research Ethics Committee (Non-Medical) as soon as possible. This waiver letter is valid until 12 August 2023.

Please feel free to contact me should you require any further information.

Thank you.

Yours sincerely,
S Schoeman

Acknowledgements

I would like to thank the Almighty for blessing me with the opportunity to seek knowledge, and I pray that this journey will serve to benefit myself and others.

I would also like to thank and acknowledge the unconditional and unwavering support of my parents, brothers and husband. To my husband in particular, your dedication as a father to our kids has been vital to the completion of this degree.

To my son, Muhammad Salmaan, and my daughter, Salma Tahseen, you have been a strong motivation to complete this thesis and I pray this serves to motivate and guide you towards a strong work ethic and a sincere appreciation for the gift of knowledge.

Mostly, I would like to give a heartfelt thanks to my supervisor, Prof Christo Auret, without whom I would not be the Academic I am today. Your support, guidance and mentorship over the last six years has been invaluable.

Finally, I would also like to thank all my peers both at Wits and UCT for all their support and encouragement.

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Glossary of Terms

ARCH: Autoregressive conditional heteroskedasticity

BFAPB: Bureau for Food and Agricultural Policy

BIS: Bank for International Settlements

BMF: Brazilian Mercantile and Futures Exchange

CBOT: Chicago Board of Trade

CCC: Constant Conditional Correlation

CFTC: Commodity Futures Trading Commission

CIMMYT: The International Maize and Wheat Improvement Center

CME: Chicago Mercantile Exchange

CoCA: Census of Commercial Agriculture

COT: Commitment of Traders

DCC: Dynamic Conditional Correlation

FAO: Food and Agriculture Organization of the United States

GARCH: Generalized Autoregressive Conditional Heteroskedasticity

GFA: Grain Futures Administration

ICE: Intercontinental Exchange

IMF: International Monetary Fund

JSE: Johannesburg Securities Exchange

LME: London Metal Exchange

MACD: Moving Average Convergence Divergence

MATBA: Mercado a Termino de Beunes Aires

NALEDI: National Labour and Economic Development Institute

NAMC: National Agricultural Marketing Council

RSI: Relative Strength Index

ROC: Rate of Change

SA: South Africa

SAFEX: South African Futures Exchange

SAVI: South African Volatility Index

SDGs: Sustainable Development Goals

SOI: Southern Oscillation Index

UN: United Nations

US: United States

USDA: United States Department of Agriculture

UNDP: United Nations Development Programme

VAR: Vector Autoregressive

VAT: Value-Added Tax

WASDE: World Agricultural Supply and Demand Estimates

WFP: World Food Program

CHAPTER ONE: INTRODUCTION AND OVERVIEW OF THESIS

1.1INTRODUCTION

1.1.1 Background of the problem

The United Nations lists food security, nutrition and sustainable agriculture as one of its key sustainable development goals (Pérez-Escamilla, 2017). Food security is defined as the equal, physical and economic access to sufficient, safe and nutritious food that meets all dietary requirements for a healthy life (Fresco, 1997). Despite modern advancements in agriculture, such as harvest automation, autonomous tractors and temperature and moisture sensors, global food insecurity remains a reality. In a 2021 report on the State of Food Security and Nutrition in the World, the Food and Agriculture Organization (FAO) of the United Nations (UN) noted with concern that their Sustainable Development Goal (SDG) of ending hunger, achieving food security, and promoting sustainable agriculture was far off track, and would not be achievable by 2030 (World Health Organisation, 2021). They ascribe this to increased geographical conflict, rising fuel prices, economic slowdowns and downturns, and more notably, climate variability and extremes. To emphasise their concern, the report stated that if bold actions were not taken, the number of people facing hunger in 2030 could be close to triple the population of Brazil.

Like many emerging markets, South Africa has not been immune to either rising food prices or the increased volatility in commodity prices associated with it. In lights of these concerns, no industry is more critical to the economic success of a country or generation than that of agriculture. Mandle (1985) asserts that agriculture holds the key to the long sought-after goal

of ending dependency, while also promoting development in a region. Agriculture is even more crucial in emerging economies like South Africa as it meets the dual objectives of poverty eradication and food security. According to Gassner, Harris, Mausch, Terheggen, Lopes, Finlayson and Dobie (2019), agricultural development in Africa ensures food and nutritional security while also influencing significant increases in farm incomes and a contribution to wider economic growth. Cereals such as maize, rice and wheat are estimated to provide at least a third of the food calories to several billion people across roughly a hundred developing countries (Shiferaw, Prasanna, Hellin & Banziger, 2011). Maize is therefore critical to food security, especially in developing countries like South Africa.

The 2020 Trends in Agricultural Sector report released by the South African Department of Agriculture, Forestry and Fisheries highlights maize as accounting for 80% of cereal production in Southern Africa. According to Vink and Kirsten (2003) South Africa's agricultural sector is dualistic, consisting of both a commercial, large-scale farming sector as well as a less productive, smallholder sector. Aliber and Hart (2009) estimated the number of commercial large-scale farmers in South Africa to be around 39 900, producing roughly 95% of the country's agricultural output using an estimated 87% of total agricultural land. The FAO recommends agricultural census be conducted every 10 years (Nkosi & Sihlobo, 2019). In South Africa, Statistics South Africa (Stats SA) is responsible for carrying out a national Census of Commercial Agriculture (CoCA) every five years (Aguera, Berglund, Chinembiri, Cominos, Gilwald & Govan-Vassen, 2020). The CoCA is tasked with collecting data regarding farm size, farm use, farm loss, crop production, livestock numbers, machinery usage, employment, as well as financial information. The report however could not be conducted in 2012 due to insufficient funding, while the 2017 report was delayed until March 2020. This CoCA report for 2017, released by StatsSA on the 24th of March 2020 reported the total number

of farms involved in the commercial agriculture sector in South Africa in 2017 as 40 122. The largest production of farms in the report were listed as livestock, which was 33.9% of the total, followed by mixed farming at 31.1% and field crops made up the balance with 21.3%. The report also revealed maize to be the largest crop in metric tons, followed by sugarcane, potatoes and oranges. However, according to a news article published on the 27th of February 2019 by Professor Johann Kirsten, the director of the Bureau for Economic Research at Stellenbosch University, and Mr Wandile Sihlobo, the chief economist of the Agricultural Business Chamber of South Africa, the Agricultural Census by Stats SA underreports the number of farms involved in South Africa's commercial agricultural sector. They argue that StatsSA only includes farmers registered to pay VAT (VAT registration is compulsory for business turnover exceeding R 1 000 000). However, when one accounts for non-VAT registered farms then the total number of commercial farms is closer to 70 000 (Sihlobo & Kirsten, 2021). Furthermore, even though agriculture in South Africa only contributes 4% annually to GDP, figures released by Stats SA in September 2020 revealed agriculture to be the only sector in the South African economy to have reported a positive growth figure, despite the onset and implications of Covid-19. This reiterates the importance of managing the uncertainty, risks and incomes of commercial farmers in South Africa (and globally).

Price risk management is critical to the success of agriculture, as compared to the industrial sector, as it is exposed to many more unpredictable risks and uncertainties, be it by government policy, foreign exchange rates, climatic disasters or political and civil instability (Kang, 2005). Furthermore, agricultural performance is susceptible to several exogenous factors, from the supply chain, to crop output and productivity, which is also affected by climatic disruptions, natural hazards and pest attacks.

Price volatility linked to agricultural commodities like grains is therefore an integral topic for research, as periods of excessively high or low commodity prices have often been associated with periods of crises, posing significant challenges to farmers, producers, consumers, and policymakers (Kalkuhl, Braun & Torero, 2016). Price volatility exacerbates uncertainty in agricultural markets which leads to food emergencies, political crises and increased poverty (Wright, 2011). This is reiterated by Bellemare (2015) who investigated the relationship between food prices and social unrest, such as food riots. According to Bellemare (2015), food price volatility reduces food security (Ivanic & Martin, 2008) which in turn causes social and political instability. As cited by Ismail, Ihsan, Khan and Jabeen (2017), price volatility in agricultural commodities is said to adversely affect the economic growth of developing countries more than developed economies (Aizenman & Marion, 1993; Ramey & Ramey, 1995). In addition, Roache (2010) found price volatility in agricultural commodities to also have an adverse effect on a country's balance of payments, imports and exports, government budget, inflation and poverty levels.

One of the most significant agricultural commodities grown is maize. The maize plant (Zea mayas), is arguably the most important grain crop in the world (Nuss & Tanumihardjo, 2010). Its kernels contain essential components for plant reproduction and growth and includes starch, protein and several micronutrients required for sound human health. Ranum, Pena-Rosas and Garcia-Casal (2014) document the origins and uses of maize. According to them, maize is often referred to as corn in the United States, as this was the name given to the grain under early British and American trade. Maize is said to have originated in central Mexico almost 7 000 years ago and continues to be widely consumed given its makeup of 72% starch, 10% protein and 4% fat. It also has several industrial uses in products like sweeteners, oil, beverages, glue, industrial alcohol and as fuel in the context of ethanol.

According to an October 2020 report by the United States Foreign Agricultural Services, world maize production for the 2020/2021 period was forecast at almost 4% higher than that produced in 2019/2020. The report further listed the United States as contributing 32,5% to production, followed by 22% by China, 9,5% by Brazil, 6% by the European Union, and the balance of 30% being produced jointly by Argentina, South Africa, Ukraine, Mexico and India.

There are two variations of maize available: white maize and yellow maize. White maize is the staple food of South Africa for majority of the population. While, yellow maize is predominantly used in livestock feed. Most of the other major maize exporting countries, like the United States, Argentina and Brazil export the yellow maize variety. The market for white maize therefore is quite thin as most countries that produce this variety keep it for domestic consumption instead of exporting it. According to Watkinson and Makgetla (2002), the price of white maize predominantly hinges on the production and export levels of white maize in South Africa as the other major exporters of maize (like the United States, Argentina and Brazil) produce yellow maize instead, which is predominantly used for chicken and livestock feed. South Africans prefer to consume white maize. The size of maize harvests is highly dependent on rainfall and subject to severe annual fluctuations (Bernstein, 1996). White maize is biologically and genetically identical to yellow maize with the same production conditions and cultivation methods, although a difference of appearance is noted due to the absence of carotin oil pigments in the kernel (CIMMYT, 1997).

According to a 2020 report on the Agricultural Sector by the Department of Agriculture, Forestry and Fisheries, 57% of the maize produced in South Africa is white, while the remaining 43% is yellow maize. The ratios of areas planted is 62% white maize to 38% yellow

maize. Approximately 4,4% of the area planted to white maize is under irrigation, with the balance of 95,6% in dryland. For yellow maize, the area planted is 15% under irrigation and 85% in dryland. White maize is generally produced in the western parts of the maize belt, while yellow maize is planted in the eastern part. Furthermore, maize has been the largest contributor towards the gross value of field crops in South Africa over the past five seasons, followed by sugar cane, wheat, soybeans and sunflower seed. The gross value of maize for the 2019/2020 period amounted to R40 228 million, which was 43% more than the value for 2018/2019. The report also mentioned that the two main white-maize growing provinces in South Africa, namely Free States and the North West, produced roughly 81% of the white maize harvest in 2020. The report also highlighted that despite the impact of Covid-19 in 2020, the year itself was good for summer crops as by the time lockdown measures were imposed, the maize crops were almost ready for harvest, complimented with favourable weather conditions, particularly in the western production regions.

The report also makes mention of important seasonal considerations for maize. In South Africa, maize is planted during late spring or early summer with optimal planting months indicated as November and December. Any rainfall deficits in October and November therefore delay maize plantings and result in larger areas of land being sown outside of the optimal planting period. Rainfall in December and January however is welcomed as it leads to an increase in soil moisture reserves and minimises the impact of earlier dry weather conditions. The rainfall pattern and weather conditions therefore determine the planting period as well as the length of the growing season, Specifically, planting commences as early as October and can extend to January. Finally, most of the maize is harvested from late May up until the end of August. This is in contrast to the United States who harvest in October and November (CME Group, 2022).The U.S. grows the majority of the world's maize and is the world's leading corn

exporter. Their maize is planted in April and May in the area stretching from Minnesota to Missouri and from Nebraska to Ohio. Corn prices in the U.S. hits a low during November harvest with less trading throughout their winter, while their summer trade is very volatile due to crop sensitivity and the weather. Price volatility in the U.S. therefore hits its peak between late June and August.

The importance of risk management for farmers of maize in South Africa is compounded as white maize is the staple food for the majority of the population. Low-income households spend a considerable portion of their monthly income on white maize alone (National Labour and Economic Development Institute, 2002). According to a 2020 report by the Bureau for Food and Agricultural Policy (BFAP), South Africans on average spend up to 40% of their household budget on food, with low income groups reported to spend 12% of their household expenditure just on maize meal. Commercial maize farmers in South Africa are estimated at 9 000 and said to provide direct employment to an estimated workforce of over 120 000, with the number of developing agricultural farmers unknown (National Department of Agriculture, 2020) further highlighting the importance of price risk management for maize. The importance of commercial maize farming in South Africa in further reiterated by Pardey and Greyling (2019), who examined maize production in South Africa for the period 1904 to 2015. They found that South Africa increased its total maize production sixfold from 328 000 in 1904 to 12.2 million tons in 2015, despite a 36% reduction in the area planted. Pardey and Greyling (2019) also highlighted that 95% of the country's maize crop is produced by commercial farmers.

South Africa is a net exporter of maize, the most important agricultural commodity produced for domestic consumption in the country, with the central to eastern parts of the country reserved as the primary focus area for maize cultivation (Malherbe, Landman, Olivier, Sakuma & Luo, 2014). Over the north eastern provinces of South Africa, such as North West,

Mpumalanga, and Limpopo, dryland cultivation covers between ten and fifteen percent of the area where agricultural activity leans more towards commercial than subsistence agriculture. According to Fairbanks, Thompson, Vink, Newby, Van den Berg and Everard (2000) land use for crop cultivation covers about 12% of the surface area of South Africa. According to Grain SA (2016) maize requires between 500mm and 800mm of water to produce crops ranging from 3.5 tons per hectare to 6 tons per hectare depending on cultivar, soil potential and heat units received in a production area. The cultivation, harvesting and sale of maize therefore presents significant risks for farmers, millers and other commercial uses of the grain.

One of the ways that price risks in agriculture are managed is through the use of derivative contracts, knows as futures. Derivatives are financial contracts that derive their value from another underlying asset and offer an efficient mechanism to hedge pre-existing risk exposures (Overdahl, 2010). The Bank for International Settlements (BIS) define a derivative as a contract whose value depends on (or is derived from) the price of underlying assets, but which does not require any investment of principal in those assets. The exchange traded derivatives' market satisfies the requirements of transparency, liquidity and risk management. While derivatives can be divided into five types of contracts: swaps, forwards, futures, options and repo, this thesis focuses on futures. Futures contracts improve market efficiency and liquidity by lowering trading costs and information asymmetry, and the imposition of daily setting of margins (Oldani, 2003). Futures contracts therefore mitigate risk exposures by transferring risk from parties that desires less exposure to uncertainty, referred to as hedgers; to parties that are willing to accept it in exchange for an expected profit, referred to as speculators (Cifarelli and Paladino, 2015). Futures are a type of derivative contract that is traded on organised financial exchanges, like the South African Futures Exchange (SAFEX).

SAFEX was established from an informal market in April 1987 with option contracts subsequently introduced in October 1992, agricultural commodity futures in 1995 (following the deregulation of the agricultural market) and a fully automated trading system available from March 1, 1996 (Adelegan, 2009). SAFEX is overseen by the Financial Services Board which also regulates the JSE and operates under the Securities Services Act of 2004 (Mezui, Rutten, Sekioua, Zhang, N'Diaye, Kabanyane & Nekati, 2013). The flagship contract that facilitated the success of South Africa's agricultural futures market is the white maize contract. SAFEX's maize contracts are settled through physical delivery, requiring the involvement of major silo operators to register with the exchange. There are almost 20 registered silos operators, with 200 registered delivery points. Furthermore, SAFEX reports over 12 000 clients for its agricultural platform, estimating hedgers to account for majority of its open positions with the largest users made up of commercial farmers and processors (Mezui *et al.*, 2013). Not only are white maize futures contracts used for risk management by commercial maize traders, but these contracts also set the benchmark for spot prices that traders can ask for, or offer, in the daily trading of maize in the physical spot market (Chabane, 2002).

SAFEX also facilitates the use of futures and option contracts by traders to hedge or insure against price risk. The use of futures for price discovery and risk management was gradually adopted in South Africa relative to its longstanding and frequent use in countries like the United States. This adoption was initiated by the liberalisation of the maize market in 1996 through the termination of the Maize Board and the passing of the Marketing of Agricultural Products Act of 1996 (Vink & Kirsten, 2003). Before 1996, the Maize Board determined the buying and selling prices of maize for each marketing season (Bernstein, 1996). The liberalisation of the maize market in South Africa facilitated prices to fluctuate according to both local and

international conditions, as maize was now traded in a free market with prices set according to forces of supply and demand (Chabane, 2002).

The success of the liberalisation of South Africa's maize market and the adoption of futures by commercial participants for risk management is in itself an important case study to observe and examine. Other white maize producing (and consuming) countries, like Mexico, have struggled to make such a seamless transition. While the United States is the leading producer and exporter of maize (or as they call it, corn), they focus predominantly on the yellow maize variety with white maize cultivation accounting for a much smaller fraction of their total domestic corn output (Ranum *et al.,* 2014). This preference for yellow maize over white is also influenced by the feed industry as yellow maize is required for the manufacture of animal feed. In Mexico however, almost 90% of the corn produced and consumed is white maize (Martin, 2010). And while corn acreage in the United States continues to rise, Mexico's corn acreage continues to shrink. To address the concerns of profits by maize farmers several support programs were implemented by the government of Mexico. This included the Production for Wellbeing (Producción para el Bienestar) program which paid $50 to $85 per hectare on up to 20 hectares of maize and also established minimum prices for white maize (Martin, 2010). An important government-initiated program that has proven to be unsuccessful however, was the use of futures contracts by farmers in Mexico. The use of futures to achieve price stabilisation was advocated by the Mexican government as an alternative policy objective as previous administered commodity price schemes had proven unsuccessful. Despite the argued benefits of farmers adopting derivatives to hedge their price risk, relatively few Mexican farmers actually chose to hedge their crops this way. The Mexican hedging programme incorporates financial incentives to encourage the adoption of the use of derivatives listed on the CME by

Mexican farmers, however a low utilisation of futures contracts by these farmers has been documented by Benavides and Snowden (2006) and Cuautle-Parra and Riley (2018).

Between 1980 and the early 2000s several market liberalisation policies, like the ones discussed above, were widely adopted by governments in developing countries due to relatively low agricultural prices and the implementation of structural programs by the International Monetary Fund (IMF) (Guo & Tanaka, 2019). However, rapid price increases in agricultural commodities were observed between 2007 and 2008, and again in 2010, garnering renewed concern and urgent attention around price volatility. Headey and Fan (2008) link these global food crises to poor grain harvests, biofuel mandates, and energy price hikes. Von Braun, Akhter, Asenso-Okyere, Fan, Gulati, Hoddinott, Pandya-Lorch, Rosegrant, Ruel, Torero, Van Rheenen and Von Grebmer (2008) attributed it to a decline of investment in agricultural research and grain productivity and export restrictions. More notably for the context of this thesis, financial speculation was also listed as a determinant of these observed food crises (Cooke & Robles, 2009).

According to Roberts and Schlenker (2009) when aggregate stocks of wheat, rice and maize fall to minimal feasible levels, then prices become highly sensitive to small shocks, consistent with the economics of storage behaviour. Further, Cohen (1999) asserts that agricultural prices are structurally prone to fluctuations because of the short-run inelasticities of demand and supply for agricultural products. These inelasticities of supply and demand lead to large price changes and therefore heightened volatility, affecting farm incomes. Production for an agricultural commodity, like maize, is fixed in the short-run and highly sensitive to growing conditions and unexpected weather shocks which can vary greatly from one season to the next (Geyser & Cutts, 2007). Supply of agricultural commodities is therefore seasonal in nature as

crops are abundant at harvest and then drop during the balance of the year. The demand for basic commodities, however, remains consistently stable throughout the year, as it is affected by changes in income and tastes. Any small shift in either the supply or demand therefore causes a major increase in price volatility. Volatility increases not only the risk of paying higher prices for a specific commodity, but likewise also increases the cost of hedging in derivative instruments, as futures contracts become more expensive (Geyser & Cutts, 2007). Wright (2011) attributed the food crises observed between 2006 and 2009 to the fact that aggregate stocks of wheat, rice and maize declined due to the imposition of new and substantial biofuels mandates on markets subject to otherwise fairly normal ranges of shifts in yields and demands. He argued that these stocks were further strained by the fact that biofuel demands were in excess of mandates induced by spikes in petroleum prices which took place at the same time. This led key exporters to restrict supplies in 2007 which further exacerbated price increases in grain markets.

Despite several arguments, like the ones above, that attribute food price spikes to squeezes in supply brought on by poorly timed biofuel mandates, many policymakers linked these food price spikes instead to the financialisation of commodities. This was the term referred to by academics, practitioners and policymakers for the unprecedented growth in the use of commodity futures markets by index investors. According to a 2008 report by the U.S. Commodity Futures Trading Commission, the total value of several commodity index-related instruments bought by institutional investors grew from an estimated $15 billion in 2003 to at least $200 billion in mid-2008 (Masters, 2008). Tang and Xiong (2012) comprehensively examined index investment and the financialisation of commodities for the period 2004 to 2011. They found that, together with the surge in index investment in commodity markets from the early 2000s, prices of non-energy commodity futures shared high correlations with oil

prices, which exacerbated price volatility in agricultural futures prices. The financialisation of commodities in the early 2000s pinpointed a significant shift in the use, behaviour and performance of commodity markets. As noted by Tang and Xiong (2012), prior to this observance, commodity markets were partly segmented from outside financial markets and from each other. However, it was this recognition of the diversification benefits of commodity markets that attracted commodity index investment and with it a rise in the use of commodity futures by speculators, who had no sincere commercial interest in trading the underlying commodities. This in turn artificially inflated prices, especially for agricultural products, like maize, and increased both food prices and price volatility within these markets.

Policymakers therefore felt the need to regulate futures markets in order to protect it from market manipulation and excessive volatility. To this end, in the U.S., the Dodd-Frank Act was implemented. On Thursday, 4 November 2011, the Permanent Subcommittee on Investigations in Washington, called for a special hearing on excessive speculation in commodity markets (Subcommittee, 2011). The hearing followed an issuing by the Commodity Futures Trading Commission (CFTC) of a final rule to impose position and trading limits in order to clamp down on excessive speculation and price manipulation. The argument put forward contrasted the purpose of commodity markets against that of stock markets. It asserted that commodity markets enable producers and commercial traders to arrive at reasonable prices for their goods while hedging their price risks over time, and were not purported solely to attract investors. Subcommittee chairman, Carl Levin, argued that as stable, reasonable commodity prices are critical to economic recovery and jobs, gasoline and food prices (including that of corn, or maize) need to reflect supply and demand fundamentals, and not speculative activities. He reiterated that physical goods are used in business on a daily basis and are therefore susceptible to price manipulation if the market is cornered on the supply that is available. The Dodd-Frank

Wall Street Reform and Consumer Protection Act of 2010 directed the CFTC to therefore impose position limits that would prevent individual traders from holding more than a specified number of futures contracts or swaps at a specified time, which would in turn prevent excessive speculation and market manipulation. The CFTC argues that limits on the size of speculative positions in futures markets are necessary because they protect futures markets from excessive speculation that can cause unreasonable or unwarranted price fluctuations (NAMC, 2009).

In addition, price limits, that would constrain the range of price volatility allowed in a specific futures contract over a single trading day, were also imposed. According to Frank (1992), price limits are set to prevent the price in a futures contract from changing too rapidly in a volatile market. Price limits therefore force some time to pass before the price can move further which in turn gives traders time to react to sudden and expected price changes. Frank (1992) further explains that if the large shift in prices is as a result of unexpected supply and demand conditions, then the price will remain locked to the limit until equilibrium is once again reached. If instead, the increased price volatility is not market related, then speculators should notice this disequilibrium, and should counteract the price change through offsetting positions, thereby restoring equilibrium. The objective of price limits therefore is to allow traders the time to notice that the market is out of equilibrium and to avoid excessively large price swings. In addition, as price limits do not entirely halt trading, but merely force trading to continue at a fixed price, they also allow unexpected and sudden information to be adequately and gradually incorporated into prices, thereby also avoiding heightened price volatility. While the intentions of price limits have been to avoid excessive price volatility and panic-trading in the futures markets, their implementation has not always been met without contention. Evidence of this can be seen recently in the nickel futures market of the London Metals Exchange (LME). In March 2022, the benchmark three-month nickel contract trading on the LME hit several price

limits causing trading havoc and uncertainty as its price more than doubled in a matter of hours (CNBC, 2022). While the LME argued that it imposed the price limits in order to protect its brokers from huge margin calls following prices rising by 250% in under two days, many traders felt instead that its implementation created a liquidity crisis in the market for one of the world's most crucial industrial commodities. The use of price limits in futures markets remains disputed. Advocates of price limits maintain that they reduce price volatility, counter overreaction and do not impede liquidity (Wang, Ding & Hsin, 2018). While, opponents assert that they increase volatility on subsequent trading days, preventing futures prices from reaching their equilibrium levels, further delaying and distorting price discovery (Chan, Kim & Rhee, 2005).

While the disruption caused by the financialisation of commodities has reignited research concerning price limits and speculative activity in the last two decades, its foundations can be traced back to the early regulation of U.S. futures markets that took place in the 1920s and 1930s. In this regard, it is best to review the works of Paul Mehl and Holbrook Working at that time, which has been substantially outlined and examined by Berdell and Choi (2018). Paul Mehl directed the statistical analysis of order flows, trading volume, and positions that supported the Grain Futures Administration (GFA) early regulation of futures markets in the 1920s and 1930s; while Holbrook Working was among the first academics to note the nexus between hedging and speculation in commodity markets, as seen in Working (1933, 1948, 1949).

During the 1920s, farm prices and profits in the U.S. declined rapidly with the end of the first World War, and weak global demand, exacerbated by the mechanisation of grain production. This was followed by an increase in legislation in the agricultural sector. It is estimated that 253 bills were passed between 1907 and 1935 in order to regulate or prohibit speculative futures

trading (Romano, 1997). Much of this early regulation was implemented by the Grain Futures Administration (GFA), which was the predecessor of the Commodity Futures Trading Commission (CFTC). The GFA was established following the Grain Futures Act of 1922 which stated that:

the transactions and prices of grain on such boards of trade are susceptible to speculation, manipulation, and control, and sudden or unreasonable fluctuations in the prices thereof frequently occur as a result of such speculation, manipulation, or control, which are detrimental to the producer or the consumer … and render regulation imperative for the protection of such commerce and the national public interest therein. (Markham, 2015: p. 51).

On the 9th of July 1923, the Chicago Office of the GFA began collecting daily reports from the clearing member of CBOT which detailed open positions. Large price fluctuations in daily futures prices were observed (especially between 1924 and 1926) and these were associated with the trading and market manipulation of large speculators, as well as the inability of speculators holding smaller positions to meet the requirements of their margin calls. Most of the GFA documentation surrounding futures trading regulation is presented only with corporate authorship or signed by the then chief of the GFA, Mr J. W. T. Duvel and a consulting economist, Mr G. W. Hoffman. Once Duvel and Hoffman left the Chicago office for the Washington branch, the archival records were then dominated by Mr Paul Mehl. Paul Mehl commenced work at the GFA in 1924. According to Berdell and Choi (2018), Paul Mehl is largely unknown, despite the critical role he played in producing the GFA's analysis of the price impact of large traders and in formulating their policy prescriptions. It is important to note that Mehl is credited for the being the first to suggest curbing speculation by limiting the open commitments of large speculators. In his 1936 unpublished manuscript titled, *Controlling speculative activity by limiting the size of lines and trading*, Mehl argued for the imposition of

limits on open interest and daily trading volume for large speculative accounts, as well as tighter margin requirements in order to reduce market volatility and curb speculative activity. Most of Mehl's work analysed which types of traders and trading positions gave rise to price volatility in the Chicago grain market during the 1920s and 1930s. Mehl and the GFA believed that it was speculation and market manipulation, and not the fundamental forces of supply and demand, that were responsible for the heightened daily price volatility that they observed. Mehl, in particular, asserted that excessive trading due to speculation resulted in wider daily price swings (increased daily price volatility), and contributed to needless instability, especially when these changes were not born from fundamental shifts such as changes in crop conditions (Mehl, 1934).

Around the same time, Holbrook Working was approached by Chief Duval to develop a statistical measure of speculative and manipulative price pressure following the work he had done in his 1921 thesis titled, *The effect of price changes upon production and consumption of wheat*. Berdell and Choi (2018) credit Working as the most prominent academic analyst of futures markets to date. Working strongly contested the trading rules advocated by the GFA as destructive, and advocated for a more discretionary approach to regulation. Following Duval's request, Working developed the Working Curve. The Working Curve analysed agricultural futures prices and found that price fluctuations reflect changes in the marginal cost of grain storage. Specifically, Working argues that grain prices are volatile because the marginal cost of storage is quite sensitive to variations in supply and demand. Supply and demand are large gross flows, and small changes to them cause large changes in the net amount of grain going into storage. In his 1961 work, Working labelled his conception of the futures market as reliably anticipatory. This has been recognised as an important, but nuanced, contribution to the formulation of Fama's (1970) efficient market hypothesis. The details of Working's T-index

to measure excess-speculation in futures markets will also be discussed later in this thesis in much detail. For now, the important nexus to highlight is that the debate surrounding the cause of price volatility in grain futures as either a supply and demand shock, or, as a result of excessive speculation is not a new one, but instead dates back to the early 1920s in Chicago, where grain futures markets often trace their origins.

While the impact of the financialisation of commodities was not as intricately examined in South Africa as it was in the United States, South Africa, and its maize market in particular, also observed unprecedented price spikes that raised concerns. Many academics and practitioners argued that concentrated market participants were irresponsibly taking out large speculative positions in order to corner the market and drive futures prices away from fundamentals. One case in particular had substantial media coverage that highlighted the severity of excess speculation, market manipulation and its influence on price volatility, namely *WJ Morgan & Associates vs Joint Municipal Pension Fund.*

Between October 2002 and January 2003, the Joint Municipal Fund (henceforth referred to as The Fund), backed by ABSA, traded in maize futures contracts on SAFEX that led to losses of over R1,9 billion. WJ Morgan & Associates (henceforth referred to as Morgan) was, through a written mandate, appointed as the broker of The Fund and authorised to trade on their behalf on SAFEX, on a discretionary basis. The Fund accused Morgan of dishonestly transferring personal losses to their account on the 13th and 16th of November 2001 and on the 4th of December 2001 before continuing to make excessive trades that led to substantial losses on their account. It is estimated that Morgan dominated trade in the maize market during 2001 and 2002 that accounted for up to 60% of the total number of maize futures contracts traded on SAFEX for that period. The Fund later sued 25 defendants, including the JSE, for not alerting

them to Morgan's dishonest trading in time, as they argued they would have terminated the mandate immediately had the initial dishonest trades been brought to their notice. In response, the JSE carried out their own investigation and found Morgan to be guilty of market manipulation as they used The Fund's money to trade in both long and short position in maize futures contracts from the personal account of a senior executive of the firm. Following the investigation a disciplinary tribunal found that Morgan had cheated, defrauded and deceived The Fund in 2001. The JSE Securities Exchange thereafter terminated the brokerage license of Morgan and fined them R3.3 million.

Following this high profile case, several regulatory changes were implemented on SAFEX that are significant for the context of this thesis. Firstly, from the 1st of July 2003, the JSE instituted position limits for speculative positions on SAFEX-traded white maize futures contracts traded in order to prevent individual market participants from cornering the market (NAMC, 2009). From the Grain Contract Specifications outlined by the JSE (JSE, 2021), position limits for white maize include 800 contracts for the spot month limit, 3 000 contracts for the single limit, and a limit of 5 000 contracts for all the months combined. Secondly, as another regulatory change, SAFEX introduced price limits on all agricultural contracts traded, including yellow and white maize (NAMC, 2009). These price limits were implemented in the market on 30th November 2007. SAFEX initially agreed in principal that they should represent 2,5% of the value of the underlying commodity, as price limits on CBOT corn contracts represented a price change of 6% of the current CBOT price, whose prices were higher than that of SAFEX-traded maize. However, when the limits were instituted they were set at specific prices. For instance, from August 2008 the price limits on white maize were set at R50 per ton, with extended limits of R75 per ton. Price limits on white maize then increased in December 2010 to R80 per ton (with extended limits of R100 per ton), and again in March 2016 to R100 per ton (with extended

limits of R150 per ton). Currently price limits on white maize are set at R130/ton, with an extended limit of R195 per ton.

These changes in regulation would have a significant impact on the efficiency and liquidity of SAFEX, as white maize futures are not only the most liquidly traded contract on SAFEX to date, but SAFEX is also the only futures exchange in the world where white maize is traded. These regulatory changes would therefore also significantly impact the use of white maize futures contracts by all market participants, including farmers and other commercial uses of maize mentioned earlier. Despite all of these implications however, prior to this thesis, the effectiveness of price limits had not before been examined. Furthermore, despite the role and influence that perceived speculation in white maize futures has played in these regulatory changes being initiated and implemented, prior to this thesis; speculative activity in the South African white maize futures market had not before been examined. Lastly, according to Hernandez, Ibarra and Trupkin (2014), if a market is significantly influenced by exogenous volatility spillovers, then any regulatory initiative implemented in such a market will have limited efficiency. Hence, if a significant portion of the price volatility of South African white maize futures can be explained by spillovers in volatility from other maize futures markets, then this too would bring into question the effectiveness of implementing price and position limits on SAFEX-traded white maize futures. It is these gaps in the literature defined above that this thesis aims to fill.

Cifarelli and Paladino (2015) segment the function of futures markets into two distinct roles, namely price discovery and risk management. According to Garbade and Silver (1983) price discovery refers to the use of futures prices for pricing cash market transactions; while risk management refers to the transfer of risk from hedgers, who wish to mitigate against price risk,

to speculators, who are risk-augmenting and would like to profit from price risk. The hypothesis that futures prices are unbiased predictors of spot prices is a joint hypothesis that markets are efficient and that risk premia are absent (Beck, 1994). The cointegration between the spot price and futures price of a commodity is a necessary condition for market efficiency. This is because cointegration ensures that there exists a long-run equilibrium relationship between the spot price and futures price of a commodity which conforms with the theories of convergence and spot-futures parity theorem (Ameur, Ftiti & Louchichi, 2022). Price discovery and therefore testing market efficiency in the South African white maize futures market has been carried out by Strydom and McCullough (2013) and Muroyiwa and Mushunje (2018). Strydom and McCullough (2013) examined the efficiency of the futures market in South Africa for white maize using near spot and futures prices. They employed bot the Engle-Granger's and Johansen's tests for cointegration and found evidence to support that the white maize market in South Africa is at minimum, weak-form efficient. This was in contrast to Muroyiwa and Mushunje (2018) who examined price discovery in the white maize and wheat futures market in South Africa using a Vector Error Correction model. Their study failed to confirm both short-run and long-run causality from futures to spot prices, hence refuted the price discovery role of futures markets. While these previous studies have addressed the price discovery function of the South African white maize futures market, the risk management function has yet to be examined in detail, especially in the context of speculation and price limits, and this thesis seeks to make novel contributions to this body of knowledge.

Research investigating price volatility on SAFEX has been documented in earlier studies, most notably by Geyser and Cutts (2007), Auret and Schmitt (2008) and Monk, Jordaan and Grove (2010). Geyser and Cutts (2007) examined how fundamental factors influence the price levels and volatility of SAFEX maize over the period December 2001 to June 2006. They found that

daily SAFEX maize prices are more volatile than the Chicago Board of Trade (CBOT) market and that SAFEX price levels are determined by the CBOT, the Rand/Dollar exchange rate, weather patterns and domestic stock levels. Auret and Schmitt (2008) developed a model that explains South African white maize futures prices using data over the period March 1996 to December 2005. They found that the Southern Oscillation Index (SOI) as a weather indicator, import parity prices, the Johannesburg Stock Exchange (JSE) Top 40, and a lag of white maize futures prices significantly explains South African white maize futures prices at the 5% level. Monk *et al*., (2010) used an ARCH/GARCH approach to quantify volatility in the price of July white maize futures contracts traded on SAFEX over the period 26 February 1996 to 31 January 2007. They found that the release of new information on local and international growing conditions increases the level of volatility in the price of July white maize futures contracts, especially news regarding growing conditions such as the Crop Estimate Committee and USDA WASDE public reports.

1.1.2 Problem statement and research questions

The importance of grain price volatility is embedded in its intertwined relationship with global food security. The last two decades have witnessed unprecedented price spikes in agricultural commodities, paired with extreme weather and waning stocks, all contributing to historic levels of food price volatility. Despite maize being commonly consumed as a second cycle-produce through its use as livestock feed; it is also the main staple food for inhabitants in Africa and South America, boasting a global production higher than that of rice and wheat. A 2018 report by CIMMYT[1] designates maize as the preferred staple food for 900 million people worldwide who live on less than $2 a day, as well as the number one food crop is sub-Saharan Africa.

[1] The International Maize and Wheat Improvement Center (CIMMYT) is a global leader in publicly funded maize and wheat research and related farming systems.

South Africa is the main emerging market for price discovery of maize in Africa, with white maize being the largest and most liquid agricultural commodity futures contract traded on the South African Futures Exchange (SAFEX). Price volatility became significant in South African agricultural markets following its deregulation in 1997, as prices were no longer fixed seasonally by the respective grain boards (Monk *et al*., 2010). Several other significant structural changes have taken place in the South African grain futures market like the implementation of position and price limits. These developments have transformed grain futures markets into a more volatile and faster trading environment, with heightened volatility expected to continue.

Despite the importance of price volatility in maize, there is a scarcity of research available concerning the risk management function of futures markets, especially in emerging markets like South Africa. Van der Vyver and van Zyl (1989) were among the first to document not only the interdependent relationship between the futures market and the physical maize market in South Africa, but also the ability of the futures market to alleviate some of the price risks involved. Any factors affecting price volatility in grains like maize therefore continues to be an imperative area of research. This is reiterated by Louw, Geyser, Troskie, van der Merwe, Scheltema and Nicholson (2010) who argue that price variability is a crucial component of the grain farmer's planning as it impacts their profitability. Research examining price volatility in maize futures will therefore benefit not only the users of derivative instruments, but also has implications for practitioners, academics and policymakers.

This thesis investigates price volatility in maize futures of major exporters, with a particular focus on South African white maize futures, given its liquidity on SAFEX, and its uniqueness

as the only listed white maize contract traded on a futures exchange globally. This thesis also contributes significantly to the understanding of key aspects in futures risk management and hedging. Four interrelated, but standalone, chapters are presented. The first chapter entitled, *The effectiveness of price limits in the South African white maize futures market,* investigates the efficacy of daily trading limits imposed on white maize futures and questions whether or not price limits result in the intended stabilising effects, or if they instead cause overreaction in the market by accelerating price changes, consequently amplifying volatility instead of constraining it? This chapter examines four distinct hypotheses. Firstly, the volatility spillover hypothesis which tests if imposing price limits on a particular trading day, results in higher volatility levels on the trading days that follow. Secondly, the delayed price discovery hypothesis, which tests if price limits prevent futures prices from efficiently reaching their equilibrium level. Next, the liquidity interference hypothesis, which tests if trading limits impair liquidity. Finally, the gravitation or magnetic effect hypothesis which examines if the anticipation of an impending price limit causes prices to accelerate towards their limit prematurely. Despite the adoption of price limits in commodities by several exchanges, including SAFEX, which can be traced back to 2007, little to no research has been conducted to examine their effectiveness. There is an abundance of research on price limits for equities, however research in agricultural commodities remains scarce and the work covered in this chapter remains the only work to date published on price limits in South Africa. Through its investigation of circuit breakers in the form of price limits, this chapter also highlights the importance of traders relying on a futures exchange for both liquidity and price equilibrium. This reinforces the importance of not only evaluating trading behaviour on a futures exchange, but also being able to pre-empt traders' perceptions which would lead to changes in the direction of their trade. This shift in expectation would have subsequent influence on price volatility which is a problem that the second chapter addresses.

The second chapter is entitled, *The effects of uncertainty on investor expectations and price volatility in the South African white maize futures market*. This chapter examines price volatility in the context of behavioural finance by investigating the influence of sentiment in the market, as proxied by three South African Volatility Indices, namely, the SAVI Top 40, the SAVI Dollar, and the SAVI White Maize. While the JSE launched these indices as far back as 2007 for the SAVI Top 40 and SAVI Dollar and in 2009 for the SAVI White Maize, this is the first work to include these sentiment indices in an empirical analysis and therefore makes a novel contribution to the field of behavioural finance in an emerging commodity market. This chapter tests if a shift in sentiment influences trading behaviour in the South African white maize futures market at the daily level. Investor expectations are measured using three common technical indicators: the Moving Average Convergence Divergence (MACD), the Relative Strength Index (RSI), and the Rate of Change (ROC). This chapter also assesses the impact of sentiment, as proxied by the SAVI indices, on price volatility. An important question that is investigated in this chapter therefore is whether sentiment in the financial markets can cause day traders in the futures markets to change the direction and/or intention of their trade; and if this change in sentiment also influences price volatility in that futures market? As day traders are often viewed as speculative traders given that their motive to trade is more short-term in nature, this chapter also highlighted the importance to evaluate the level of speculative trade in the South African white maize futures market, a problem that the third chapter addresses.

The third chapter is titled, *Speculative ratios and price volatility in the South African white maize futures market*. According to Lehecka (2015) speculative pressures occur when (net) demand for long speculation exceeds (net) short hedging needs, which may result in changed price levels. Hedging pressure on the other hand, based on the normal backwardation theory of

Keynes (1930) and Hicks (1939), attempts to explain the price behaviour of futures in relation to hedgers' position data. It is hypothesised that if the (net) demand for short hedging exceeds the demand for (net) long speculation, then long speculators will require an additional risk premium to balance the excess demand for short hedging, resulting in price impacts. Both concepts of hedging and speculative pressure assume that movements in futures prices are directly affected by changes in hedgers' or speculators' open interest positions. A common metric that is used to test if speculation in futures markets destabilises commodity prices is the Working T-Index (Working, 1960). However, constructing this index requires open interest data that has been split into long and short commercial positions, as well as long and short non-commercial positions. The commercial positions would be held by the hedgers in the futures contract. While the non-commercial positions would be held by the speculators in the contract. Net long futures positions held by non-commercial participants (speculators) have been argued to artificially drive up commodity prices, inducing excessive price volatility. In the U.S. this split of open interest data is readily available and can be sourced from weekly Commitment of Trader Reports provided by the CFTC. In South Africa, and other emerging markets like those in China, the split of open interest data remains unattainable. This chapter therefore constructs a speculative ratio and hedging ratio by using trading volume and open interest data given the absence of these COT reports. These ratios measure the level of speculative activity present in the South African white maize futures market. This chapter further tests if the level of speculative activity has a statistically significant impact on price volatility in the South African white maize futures market. As the absence of COT reports makes it challenging to compute a direct measurement of speculation, the work covered in this chapter contributes to overcoming this problem and is among the first works to examine the level of speculative trading present in the South African white maize futures market. This is despite policy recommendations already being implemented in this market to prevent market manipulation and squeezing by

speculative traders. While the first three chapters investigate problems specific to the South African white maize futures market, it is also important to investigate the influence of cross markets in order to gain insights into the transmission of shocks and sentiments from different regions, which is addressed in the next chapter.

Contagion theory asserts that information shocks in one market often spillover onto the price and volatility of other markets (King & Wadhwani, 1990). While volatility in grain futures prices is often found to be time-varying and seasonal, it is equally as important to assess volatility transmissions to and from commodities from other markets. Research in the U.S. agricultural futures markets has found CBOT-traded corn to be the commodity that most broadly received and transmitted volatility transmissions (Grieb, 2015). The existence of volatility transmissions implies that one large shock increases the volatilities not only in its own asset or market but in other assets and markets as well (Kalu, 2014). Evidence of cross-commodity and external market spillovers and volatility transmission also has important implications for investors when modelling optimal portfolio allocations as well as commercial traders when creating hedging models and strategies. As hedging also assists in preventing the cost of risk-taking from filtering down to the price consumers pay for food, commercial traders are the most significant benefactors from efficiently functioning futures markets.

The fourth chapter therefore is entitled, *Volatility spillover and dynamic connectedness in maize futures of major exporters*. In this chapter volatility spillover and time-varying interdependence among several maize futures markets is examined. The methodology employed in this chapter also identifies which maize futures markets are the net receivers of volatility, and which are the net transmitters of volatility, and importantly, if price volatility in SAFEX-traded white maize futures is predominantly composed of own or cross-volatility

spillovers. The work covered in this chapter is the first to employ multivariate GARCH models in the study of white maize futures volatility as all previous studies had only used univariate analyses. Further, the use of the dynamic connectedness approach of Gabauer (2020) is also a novel contribution as this is the first work to identify net transmitters and net receivers of volatility in the maize market using this approach.

While the first three chapters focus on the South African white maize futures market only, the last chapter also includes yellow maize futures listed on SAFEX as well as maize futures traded in the U.S., Brazil and Argentina. The last chapter therefore examines price volatility in maize futures listed on the South African Futures Exchange (SAFEX), Chicago Board of Trade (CBOT), Mercado a Termino de Beunes Aires (MATBA) and the Brazilian Mercantile and Futures Exchange (BMF). These markets are included based on the role they play as leading maize exporters. According to the USDA WASDE September 2022 Report, the major exporters of corn (maize) globally are the United States, Argentina, Brazil, Ukraine, Russia, and South Africa (USDA Wasde, September 2022). The United States is reported to have exported 69.78 million metric tons of corn for the 2020/2021 period. They were followed by Argentina with corn exports of 40.94 million metric tons, the Ukraine with 23.86 million metric tons, Brazil with 21.02 million metric tons, Russia with 3.99 million metric tons and South Africa with 3.73 million metric tons of corn exported (USDA Wasde, September 2022). As there is no corn (maize) futures price data available for Russia and Ukraine, the last chapter only includes maize futures data for the United States, Brazil, Argentina and South Africa in the analysis.

Apart from the food security role played by white maize, price volatility in SAFEX white maize in particular is important to investigate, as it has also been found to exhibit higher price

volatility than the maize futures markets of CBOT-corn and SAFEX-yellow maize. Geyser and Cutts (2007) compared price volatility between SAFEX maize and CBOT corn for the purpose of better understanding how fundamental factors influence price levels and volatility for SAFEX maize. The 10-day annualised volatilities for SAFEX white maize, SAFEX yellow maize and CBOT corn were calculated over the period December 2001 to June 2006. Their results showed daily SAFEX maize prices to be 61% more volatile than their counterpart on the CBOT-market. When compared at a production season level, they found the South African market to be more strongly affected by domestic stock levels and weather than CBOT. They attributed this stronger relationship with weather than in the U.S market to the inherent variability of African weather patterns. They concluded that SAFEX maize price levels were determined by the price of CBOT corn, the Rand-Dollar Exchange Rate, weather patterns and domestic stock levels.

1.1.3 Data Description

The central focus of this thesis is to empirically assess price volatility in the maize futures of major exporters, with a particular focus on SAFEX-listed white maize futures. According to Treat (2004), price volatility is the single most important criterion for assessing futures trading. It provides the basic economic justification for futures trading, which is to provide protection to the hedger against adverse price fluctuations. It is also necessary to attract risk capital from speculators, thereby ensuring sufficient liquidity to maintain the market. Treat (2004) argues further that if a commodity were characterised by price stability, there would be no need for a corresponding futures market on such a commodity While the concept and measure of volatility may differ from one academic to the next, the concept of price volatility in this thesis aligns more closely with the definition of Butler (1999), who defines volatility as the statistical

measurement of the change in price of an instrument. Specifically, the degree of price movements in futures contracts will be measured and assessed.

As argued by Poon (2005), although volatility can be considered a risk metric, there is a clear distinction between risk and volatility and this difference should not be overlooked. Risk assumes the probability of suffering a loss while volatility allows for the possibility of positive outcomes as well (Poon, 2005). This is reiterated by Geyser and Cutts (2007) who define volatility as the changing of trading prices experienced throughout a trading day and state that volatility does not represent a bias for up or down price movement, but merely a fluctuation over a period of time. The degree of this fluctuation they argue can vary whether an asset's price trend is bullish or advancing, bearish or declining, or staying the same. Knight (1921) too recognised the importance of differentiating between risk and uncertainty. Knight understood risk to refer to a scenario where known probabilities were attached to the occurrence of a future event, where a future event was considered to be uncertain if the likelihood of its occurrence was unknown. Similarly, Eeckhoudt and Schlesinger (2005) defined uncertainty as a scenario where several possible outcomes are associated with an event, but it is impossible to assign probabilities to these possible events. Risk, in contrast, allows probabilities to be assigned to different outcomes.

The simplest models of price volatility are based on historical price ranges. Range-based volatility forecasts were introduced by Mandelbrot (1971), with Parkinson (1980) also arguing range-based volatility to be more efficient than models based on classic returns.

In chapter two, the effectiveness of price limits is evaluated by investigating the relationship between price limits, price variability (volatility) and trading activity (volume) and this chapter

makes use of range-based volatility estimates. This chapter sources data from Bloomberg for the opening, closing, high and low prices for each of the March, May, July, September and December delivery contracts. Consistent with similar studies, the maturity week data is removed to remove any maturity bias. The price volatility for this chapter is calculated by using four measures of volatility: the trading hour volatility – calculated using opening and closing prices; non-trading hour volatility – calculated using closing and opening prices; market direction volatility – calculated using closing prices and a high low range using the high and low prices.

In contrast, for chapters three, four and five which look respectively at the effects of uncertainty on investor expectations, speculative ratios, and volatility transmission and connectedness, the thesis makes use of closing prices for the active contracts for maize futures to estimate volatility using GARCH models. Autoregressive conditional heteroskedasticity (ARCH) models were designed to model conditional variances. These models were introduced by Engle (1982) and generalised as GARCH by Bollerslev (1986) and Taylor (1986). This thesis makes use of the GARCH (1,1) model, which is found to be the better fit when comparing the Akaike information criterion with other estimated GARCH extensions. Although several volatility models exist for financial analyses, the GARCH models are more appropriate when variance changes over time, and have been found to be superior at forecasting when compared with historical volatility models (Akgiray, 1989).

In addition, for these three chapters the rolling front-month (active/continuous) contract is used. The front-month refers to the month closest to maturity and each rolling front-month series uses the contract with the highest volume and open interest. Booth and Ciner (1997) argue that these contracts are the most liquid and contain more information. Continuous contracts

therefore allow researchers to go back several years in order to identify extreme moves in particular futures contracts. Active contracts are artificial contracts created by combining the most liquid portions of the actual expiry month contracts together to get a longer view of commodity price patterns. Actual contracts for each expiry month generally have a shorter life with little activity during the early portion of the contract. Active contracts were therefore the most appropriate for these three chapters and as a further motivation, have also been employed in all the studies cited in each of these chapters.

Other important data variables that are used in this thesis pertain to the trading activity variables, trading volume and open interest. Trading volume refers to the total number of completed contracts that have traded on a given trading day. Open interest refers to the total number of outstanding contracts that have yet to be completed.

An important aspect of volatility is its relation to liquidity variables such as trading volume and open interest (Martinez & Tse, 2008). Trading volume has frequently been employed as a measure for the rate of information arrival (Sutcliffe, 2006). Following the sequential information model of Copeland (1976) and the mixture of distribution hypothesis (MDH) of Clark (1973), trading volume is viewed as a proxy for new information. These price volatility and volume theories predict a positive relationship between daily volume and volatility.

In chapter two trading volume is calculated for each of the futures contracts concerned and this data is sourced from Bloomberg. The role of the trading volume variable in chapter two is to proxy for liquidity in the market, so that liquidity in the presence of price limits can be examined.

In chapter four however, trading volume and open interest data is used to construct speculative and hedging ratios in order to test for the presence of speculative activity in the market, as well as to examine its relationship with price volatility. In this chapter therefore, trading volume is used to proxy for speculative day traders who do not carry over their positions to the next trading day. While, open interest reflects hedging positions, as it is assumed that those market participants holding these positions have a long-term and sincere interest in trading the underlying asset. This data is also sourced from Bloomberg at a daily frequency.

According to Mougoue and Aggarwal (2011), open interest can be used as a proxy for dispersion of beliefs and is therefore also an important determinant of volume. In their study of stock index futures, Bessembinder and Seguin (1993) argued that the effects of volume on volatility depends on whether volume generates changes in open interest by illustrating that trading volume has a significantly positive effect on volatility, while open interest has a negative effect. Ripple and Moosa (2009) also found trading volume and open interest to be significant determinants of volatility when they investigated crude oil futures.

1.2 OVERVIEW OF THE THESIS

Chapter One sets the stage for this thesis, providing a comprehensive introduction and overview of the research. It presents the context, significance, and objectives of the study, establishing a foundation for the subsequent chapters. Chapter Two delves into an examination of the effectiveness of price limits in the South African white maize futures market. By analysing historical data and market behaviour, this chapter assesses the impact of price limits on curbing volatility, market liquidity, and price discovery. It investigates whether the existing price limit mechanisms effectively mitigate excessive price fluctuations. Chapter Three

explores the effects of uncertainty on investor expectations and price volatility in the South African white maize futures market by employing technical analysis and making use of three South African volatility indices. Chapter Four focuses on speculative ratios and their relationship with price volatility in the South African white maize futures market. Through an analysis of trading activity in the form of open interest and volume, this chapter examines the presence and impact of speculative trading activity on price volatility. It explores whether excessive speculation contributes to increased volatility and evaluates the significance of speculative ratios in understanding market dynamics. Chapter Five broadens the scope to encompass volatility spillover and dynamic connectedness in maize futures among major exporters. It investigates the extent to which price volatility in the South African white maize futures market is influenced by volatility spillovers from other major maize-exporting countries. Chapter Six concludes the thesis by summarizing the key findings, implications, and contributions of the research. It also highlights the limitations of the study and proposes areas for future research and further exploration. This chapter offers valuable insights into risk management, market regulation, and strategies for participants in the maize futures market.

CHAPTER TWO: THE EFFECTIVENESS OF PRICE LIMITS IN THE SOUTH AFRICAN WHITE MAIZE FUTURES MARKET

Abstract of Chapter Two

Futures markets perform two essential functions by creating a platform for price discovery as well as permitting low cost hedging of risk. Some futures markets impose limits on the amount futures prices can change within a single trading day to prevent the market from overreacting. While the objective of price limits may be to dampen volatility, many argue that they are instead self-fulfilling, create a "magnetic effect" and amplify volatility. This magnetic or gravitation effect causes trading volume and price variability to increase as market participants panic and advance the execution of their trades. This chapter empirically investigates the effectiveness of price limits using daily data for 40 white maize futures contracts over the period December 2009 to December 2017. Four issues predominant in the circuit breaker literature are examined: the volatility spillover hypothesis, the delayed price discovery hypothesis, the liquidity interference hypothesis and the magnetic or gravitation effect hypothesis. Most of the empirical evidence presented in this chapter indicates that for white maize futures, price limits may be ineffective.

2.1 Introduction

Futures markets perform two important functions, namely, price discovery and price risk management with reference to a given commodity (Easwaran & Ramasundaram, 2008). Price discovery is the dynamic process through which market prices incorporate new information (Yan & Zivot, 2010) and is the process of determining the price of a commodity based on demand and supply changes. As new supply and demand developments occur, expectations change, and as new and more accurate information becomes available, futures prices may increase or decrease. The process of price discovery is therefore a continuous one` (Garbade & Silver, 1983). According to Hazell, Jaramillo and Williamson (1990), price transparency is vital for efficient price discovery as it assures that all market participants have access to the same information at exactly the same time. Efficient price discovery in futures markets also benefit several market participants (Easwaran & Ramasundaram, 2008). It benefits producers as it provides them with an idea of possible spot prices for commodities so that they can decide between various competing commodities. It enables consumers to forecast commodity spot prices to better inform their decisions. Furthermore, exporters also benefit from forecasting possible spot prices which helps them to realistically quote prices as well as to secure export contracts in competitive markets.

The risk management function of futures markets allows the transfer of risk from hedgers, who have long-term perspectives of the markets, to speculators, who have a more immediate view of the market. Keynes (1930) referred to this as the risk transfer hypothesis that asserts that speculative participants in the commodity futures market earn a risk premium as compensation for absorbing the hedger's risk. There exists a clear dichotomy that operates between hedging and speculation. According to Tomek and Peterson (2001) hedging is the application of off-setting the price risk inherent in any commodity spot market position by taking an equal but

opposite position in the corresponding commodity futures market. Hedging can therefore be seen as a risk-reducing initiative as it attempts to protect against losses that may be incurred from adverse price changes in the underlying security. Speculation, on the other hand, is a risk-augmenting exercise as it attempts to profit from price volatility. Working (1953) has been credited as the first to note that speculation and hedging in commodity markets are intricately intertwined. He asserted that speculation is limited to the overall hedging volume and more importantly, that speculators provide the liquidity necessary for hedging to take place. Fisher (1930) and Friedman (1953) also shared the opinion that profitable speculation exerts a stabilising influence on price, as speculators are informed traders equipped to capitalise on mispricings. Friedman in particular asserted that speculators who practice 'information theory arbitrage' should be thought of as expert researchers who work aggressively to narrow the price-value gap. This view was further reiterated by Labys and Granger (1970), Peck (1980, 1985) and Leuthold (1983) who were all concerned that there was a the lack of speculation needed to meet hedging demand.

The debate on the role of the commodity speculator has been longstanding and widespread. Hart (1977) evaluated this debate from the perspective of economists and non-economists. According to Hart, non-economists view speculation as socially undesirable as they believe that speculation increases uncertainty about the future by creating disturbances and fluctuations in the economy. Further, they believe that by engaging in speculative activity, traders who exert influence in the market are able to profit at the expense of smaller traders who instead trade for hedging purposes. Hart (1977) contrasts this with the view of economists who he argues regard speculation as socially beneficial. Economists believe that speculators earn profits by correctly predicting economic trends and that their trading stabilises the path of the economy by accelerating the transition of the economy from one long-run equilibrium to another. Much of

the recent literature has reignited the debate on the role of speculation and whether it has a destabilising effect on futures markets, distorts prices and causes unnecessary and excessive price volatility. In the last two decades the commodity futures market has grown to unprecedented levels, as it has become attractive to financial investors and fund managers. It was estimated that passive investment in commodities grew more than tenfold from $20bn in 2002 to over $250bn at the end of 2008 (Basu & Gavin, 2011). Long-only commodity index funds were glamorised for allowing investors to capture substantial risk premiums while reducing portfolio risk through relatively small investments (Gorton & Rouwenhorst, 2006). This dramatic surge in commodity index fund investments became known as the financialisation of commodity markets (Domanski & Heath, 2007). Financialisation has been defined by Hujo and Lupo (2022) as the increasing role of finance, its institutions and practitioners, in the operations of the global economy and the subsequent influence on global value chains and transnational commodity trade. Cheng and Xiong (2014) outlined the impact of financialisation through a critical review of how financial investors affected risk sharing and information discovery in commodity markets. They argued that as hedgers are typically on the short side of futures markets, they need to offer positive risk premia in order to attract speculators to complete their contracts and take the long side. However, speculators (financial investors) may need to unwind their long positions if prices in other markets unexpectedly falls. This in turn transmits price volatility to other commodity markets. Financialisation therefore affects risk sharing in commodity markets through the dual roles of financial investors. Firstly, as providers of liquidity to hedgers when trading to accommodate hedging demand. Secondly, as consumes of liquidity from hedgers when trading to meet their own needs. Financialisation also affects information discovery in commodity markets as noise brought on by financial investors (speculators) trading in futures markets leads to changes in the commodity demand of final-goods, consequently increasing price volatility (Cheng & Xiong, 2014). Much of the

uncertainty stems from the fact that producers cannot differentiate if futures prices move because of changes in global economic fundamentals, or because of financial investor trading (speculation).

Several practitioners, academics and policymakers blamed financialisation for the increase in volatility and price fluctuations observed in commodities in the early 2000s. This excessive price volatility, especially in agricultural commodities, had serious implications for food security. Unprecedented levels of rising food prices were observed, reversing a four-decade long trend of declining food prices. According to Maros and Martin (2008) lower-income households spend up to 75% of their income on food and are therefore the most vulnerable to volatility in food prices. To this end, several governments and non-profit organisations aggressively advocated for a change in the regulation of futures markets which would restrict speculative trading and market manipulation. Masters and White (2008) recommended the re-establishment of speculative position limits for all speculators in commodity futures markets as well as the elimination of, or at least severe restriction on, commodity index investment by financial speculators. What followed was the implementation of regulatory tools to confine speculative trading activity. Many market participants voiced their concerns that the new regulatory changes were unnecessary and that the global surge in energy and food prices were in fact a result of fundamental supply and demand factors that pushed prices higher (Sanders & Irwin, 2008). Nevertheless, several exchanges, including the Johannesburg Stock Exchange (JSE), implemented circuit breakers to constrain market manipulation and curb the volatility linked to speculation.

From Cheng & Xiong's (2014) first argument it is clear that one of the most important aspects of futures markets that is affected by financialisation, and the response to financialisation in

the form of regulatory tools like position and price limits, is liquidity. Frank (1992) defines a liquid futures market as one where traders move in and out of their positions with ease. This ensures that short position holders can always find long position holders to complete their contracts and *vice versa*. Frank (1992) also importantly points out that liquidity feeds on itself in the sense that if a futures market is liquid, then traders will enter the market more freely because they are confident that they can close out their positions rapidly and easily if they need to. The large number of buyers and sellers in the futures market therefore not only ensures liquidity but according to Jones, Kaul and Lipson (1994) also results in efficient price discovery. In contrast, illiquid or thin markets prevent market participants from easily closing out their positions. This in turn also prevents traders from entering such a futures market in the first place, thereby aggravating the liquidity problem.

According to Evans and Mahoney (1997), circuit breakers are used by exchanges for the purpose of limiting both market volatility and panic trading through trading halts, positions limits and price limits. Trading halts represent a break in the trading process, position limits constrain the number of contracts any one market participant can hold, and price limits require all trading prices to be within a certain range. For the scope of this chapter, only trading limits are investigated. Anderson (1984) contends that the purpose of daily trading limits is to prevent both excessive price swings as well as significant price changes from deviating too far from its mean. Price limits are designed to control volatility by establishing price constraints and by providing time for rational reassessment during times of panic trading (Kim & Rhee, 1997). Unlike trading halts, price limits do not prevent trading entirely, but instead set a ceiling and a floor within which price movements can occur during a trading day.

Critics of price limits have outlined at least four important issues. These are most notably referred to in the literature as: the volatility spillover hypothesis, which tests if price limits result in higher volatility levels on subsequent trading days; the delayed price discovery hypothesis, which tests if price limits prevent futures prices from efficiently reaching their equilibrium level; the liquidity interference hypothesis, which tests if price limits impair liquidity and cause increased trading on post- limit days; and lastly, the 'magnetic' or 'gravitational' effect hypothesis, which claims that trading limits accelerate prices toward their limits prematurely.

This chapter tests all four of these hypotheses by examining daily data for South African white maize futures contracts for the delivery months of March, May, July, September and December over the period 2010 to 2017.

While maize may be consumed as second-cycle produce in developed countries in the form of meat, dairy and eggs, it is the most important grain crop in South Africa, being both the major feed grain and the staple food for the majority of the population. White maize is also the largest and most liquid agricultural commodity futures contract traded on the South African Futures Exchange (SAFEX) and is the focus of this chapter. Between 2014 and 2016 the South African agricultural sector was burdened with the worst drought recorded in 104 years, creating panic and uncertainty in local markets and increasing food prices to record levels (Walt, 2016). As this chapter will show, this period was also characterised by a high frequency of price limit hits in white maize futures contracts. Price limits are designed to be triggered only under unusual circumstances, making the observed surge in occurrences the perfect environment to evaluate its effectiveness.

Even though price limits are implemented in more than two-thirds of organised markets in the world (Hall & Kofman, 2001), research into their efficiency is scarce, with most papers focusing on stock markets. Brennan (1986) states that due to the institutional structure of futures markets (particularly its daily settlement mechanism), they are more appropriate than stock markets to test the efficiency of circuit breakers.

2.2 Literature Review

According to Moser (1990) the first use of price limits can be dated back to the Dojima exchange in Japan during the 18th century. Rice markets at the time were described as deteriorating and characterised by excessive volatility. Price limits were imposed so that settlements in the futures contract for rice could not deviate by more than a fixed amount, otherwise contracts were closed out or delivered. Although price limits were formalised in 1925 at the Chicago Board of Trade (CBOT), brought on by grain price volatility, it was only after the 1987 stock market crash that the use of price limits became popular (Ma, Rao & Sears, 1989).

Kim and Yang (2004) provide three benefits for using price limits in futures markets. First, price limits help to prevent large movements in prices arising from panic and speculation. Second, price limits reduce the daily liability of market participants arising from the cost of portfolio adjustment. Lastly, price limits provide brokers and clients with additional consultation time during periods of market turbulence.

The intended purpose of price limits is to reduce short-term volatility by delaying price changes. However, whether price limits in fact achieve this purpose depends on the cause of

the volatility. According to Harris (1997), if an order imbalance originating from uninformed traders is the cause of volatility, price limits may be beneficial. This is because price limits will improve market performance by allowing traders to be better informed prior to executing their trades. If new fundamental information however is the cause of the volatility, then the price limit will simply delay the inevitable and excessive price volatility and increased trading activity will be observed on subsequent trading days.

The implementation of price limits has been met with much concern and criticism. At the forefront of the debate is the argument that these limits can cause excessive price volatility and distort trading activity. Empirical evidence evaluating the use of price limits has been mixed, with some studies showing that price limits do indeed calm overreaction, while others have proved that they cause overreaction instead.

Advocates of circuit breakers argue that trading limits provide a cooling-off period by allowing traders time to absorb new information before trading (Khoury & Jones, 1983). In his study on the U.S. futures market, Brennan (1986) also supported the use of price limits, as he rationalised that limits serve as substitutes to margin requirements and therefore reduce the total cost of trading for market participants. The use of price limits was also advocated by Ma, Rao, and Sears (1989a, 1989b) who found that price limits prevented the overreaction of futures markets. They argued that any deviations observed from the true equilibrium price is temporary and will dissipate with time. Most of the studies in the literature to date however have not found any positive benefits from the implementation of price limits in futures markets.

Opponents of circuit breakers assert that trading limits undermine the risk management function of futures markets and infringe on the efficient, free-market system of price setting

(Kodres & O'Brien, 1994). In addition, some opponents argue that trading limits impede the price discovery process of futures markets as the price of the restricted asset is not observable to market participants when the price limit is binding (Lee, Ready & Seguin, 1994). Trading limits can also create what many market participants term the "magnetic effect" (Hieronymus, 1971; Cantor, 1989) which causes trading volume and price variability to increase as market participants anticipate an impending trading limit and advance the execution of their trades. Some advocates note that trading limits can discourage unreasonable prices that result from excessive speculation because the limits provide a cooling off period that gives traders time to absorb new information (Khoury & Jones, 1983). Brennan (1986) provides a convincing argument for the rationale for price limits in the U.S. futures market, arguing that the limits serve as a substitute to margin requirements to reduce the total cost of trading for market participants. He found theoretically that the price limits are partial substitutes with the calls for markup whose cost is exorbitant. Brennan (1986) concluded that the price limits reduce the total transaction costs and reduce the risk of defects in contracts. Proponents further argue that trading limits may lessen credit risks and curtail detrimental trading strategies by explicitly recognising that markets have a limited capacity to absorb enormous one-sided order flow (Brady Commission, 1988). Thus, it is possible that daily price limits can either calm overreaction or cause it.

According to Yeh and Yang (2013) the debate on price limit effectiveness rests on the assumptions made about traders' rationality. If traders are presumed to be irrational with a tendency to overreact to new information, as found by Tversky and Kahneman (1974), then price limits will be beneficial to the market and its participants. Alternatively, if traders are believed to be adequately rational with the competence to process new information efficiently, then price limits will result in several negative effects. These negative effects have been defined

in the literature as: the volatility spillover hypothesis, the delayed price discovery hypothesis, the liquidity interference hypothesis and the magnetic or gravitation effect hypothesis.

The volatility spillover hypothesis asserts that price limits increase volatility on subsequent trading days, as limits prevent immediate corrections in order imbalances (Fama, 1989). According to Fama (1989) if the price discovery process is disrupted, then the underlying volatility will increase as a result. Lehman (1989) also suggested that rather than reducing volatility, price limits cause volatility to spread out over a longer period. This hypothesis was supported by Kuhn, Jurserk, and Locke (1991) who found that circuit breakers failed to moderate volatility during the 1989 U.S. mini-crash. Kim and Rhee (1997) also found support for this hypothesis when they analysed price limits on the Tokyo Stock Exchange from 1989 to 1992 and found that limits do not decrease volatility, but instead spread volatility out over a longer period.

The second problem often cited with price limits is a delay in price discovery. This hypothesis was proposed by Fama (1989) and tests if limits prevent prices from reacting to new information as well as from reaching equilibrium. According to Kim and Rhee (1997), trading limits interfere with the price discovery process and cause a lag in assets reaching their true price equilibrium, as trading is constrained. Many studies that investigated the volatility spillover hypothesis also tested for a delay in the price discovery process. Support for this hypothesis was found by, but not limited to, Fama (1989), Lehman (1989) and Kim and Rhee (1997). In another study, Yeh and Yang (2013) constructed an artificially simulated stock market composed of rational and heterogeneous traders in order to investigate if price limits generated negative effects on the market. They found evidence in support of the price discovery

hypothesis. Specifically, they found that price limits distort traders' expectations about prices and inhibit their ability to reach the true fundamental value of assets.

Next is the liquidity interference hypothesis. This problem too was also outlined by Fama (1989) and suggests that price limits interrupt continuous trading which impairs market liquidity and causes trading volume to be higher on post-limit days. Lehmann (1989) found that imbalances in demand and supply in trading caused prices to reach their limits, transferring additional trading activity onto subsequent days. He also argued that price limits induce prices to reach their limits more quickly, as only impatient investors will trade at unfavourable prices, whereas patient investors will defer trading until prices have reached their equilibrium levels. For both sets of investors, the trading volume will be higher on subsequent trading days.

Lastly, the magnetic or gravitation effect suggests that traders panic in anticipation of a price limit, which causes them to overreact. Their overreaction leads to panic trading which causes the markets to reach their limits prematurely. Miller (1989) was among the first theorists of the magnetic effect as he argued that trade barriers can induce a flurry of fear-fuelled trades in the direction of the barrier as traders become anxious that they may not be able to close out their open positions. Lehmann (1989) too examined the magnetic effect and suggested that order imbalances and the consequent decline in trading encourages prices to reach their limits more quickly. McMillan (1990) examined market breaks on the S&P 500 during October 1987 and found strong patterns of runs in prices prior to limit hits, supporting the magnetic effect. Subrahmanyam (1994) found that price variability, market liquidity, trading volume and the probability of price limits increased in the period prior to the limit hit because of suboptimal order submissions. According to Arak and Cook (1997) behaviour by both noise traders and day traders can produce a magnetic effect. For instance, if noise traders assume an upward

price trend and are anxious about a new upper limit equilibrium, they will trade before the price limit is triggered. Using high-frequency data from the Taiwan Stock Exchange, Cho, Russell, Tiao, and Tsay (2003) found strong evidence of stock prices accelerating towards their upper bound, in support of the magnet effect. Arak and Cook (1997) however did not find evidence of the magnet effect when they investigated Treasury bond futures contracts. Abad and Pascual (2007) also rejected the magnetic effect as they found that prices on the Spanish Stock Exchange reversed when the price limit was approached.

Most of the literature on price limits to date have examined stock markets, with a few exceptions examining futures markets. Evans and Mahoney (1997) evaluated the effectiveness of price limits by investigating its effect on exchange traded volume using intraday data. Their analysis focused on cotton futures on the New York Cotton Exchange (NYCE) for just over 20 trading days in September 1995. They concluded that price limits were effective in limiting the volume of futures contracts traded. In another futures market study, Park (2000) examined daily futures prices for four agricultural commodities over the period 1986 to 1998 to observe what happens to volatility on post-limit trading days. His results revealed that although price limits were correlated with volatility, changes in volatility were more likely caused by demand and supply imbalances than by price limits.

More recently, He and Serra (2022) examined the lean hog and live cattle futures markets which had experienced significantly heightened price volatility and frequent limit moves following the Porcine Epidemic virus in 2014, the U.S.-China trade war in 2018, the African Swine Fever in 2019 as well as cyclical demand and supply shocks. Their paper tested if price limits resolve uncertainty and facilitate liquidity provision and also if price limits affect trading to the extent that a spillover is seen in corresponding limit-free option markets. They used intraday futures

data for the period 2014 to 2019 and found that price limits neither reduced price volatility nor did they improve liquidity in the lean hog and live cattle futures markets. Instead, price limits were found to exacerbated the uncertainty that preceded the limit move which in turn lead to increased price volatility and less liquidity following the limit move. The authors therefore concluded that instead of allowing futures markets to cool off, price limits instead adversely affects market quality, impairs liquidity and worsens excessive price volatility.

2.3 Data

The objective of this chapter is to investigate the relationship between price limits, price volatility and trading activity (volume) in the South African white maize futures market. In so doing, the effectiveness of price limits can be evaluated. If price limits are effective in reducing speculative trading, then a simultaneous decrease in both volatility and volume will be observed when the limits are in effect.

The JSE Commodity Derivatives Market provides a platform for price discovery and risk management for the grains market in South and southern Africa. The JSE introduced price limits to prevent market manipulation. These price limits were updated on 8 November 2007 and implemented in the market on 30 November 2007. SAFEX agreed in principal that price limits should represent approximately 2.5% of the value of the underlying commodity. The price limits on white maize for trading days examined between December 2010 and February 2016 were R80 per ton (with extended limits of R100 per ton). From March 2016 to December 2017 the price limits on white maize was R100 per ton (with an extended limit of R150 per ton). Currently, daily price limits for white maize are set at R130 per ton (with extended limits of R195 per ton).

Daily data for the volume, opening, closing, high and low prices for each of the March, May, July, September and December delivery contracts between 2010 and 2017 were collected from Bloomberg. Consistent with other studies in the literature, the maturity week data was removed from the futures series to remove the maturity bias (when the underlying contract approached maturity, data from the next contract was selected).

The price limit range is based on the previous day's closing price and is re-established each day. To identify days where price limits were in effect, the high and low prices for each day were matched with their previous day's closing price, plus the price limit. Similar to Kim and Rhee (1997), upward limits for each contract are reached when $H_t \geq C_{t-1} + LIMIT_t$, where H_t represents day t's high price, C_{t-1} represents the previous day's closing price, and $LIMIT_t$ is the maximum limit up price movement for each trading day, t. Similarly, downward limits are reached when $L_t \leq C_{t-1} – LIMITt$, where L_t represents trading day t's low price and $LIMIT_t$, is the maximum limit down price movement allowed for each trading day, t.

Economists classify two types of volatility: fundamental and transitory (Kim, Liu, & Yang, 2013). Fundamental volatility takes place when there is uncertainty about underlying assets, while transitory volatility is caused by the trading process. Kim *et al.*,, (2013) point out that market regulators are more concerned with reducing transitory volatility than its fundamental counterpart. According to Garman and Klass (1980) as well as Parkinson (1980), volatility measures based on daily high and low prices capture transitory volatility better than volatility measures based on daily closing prices. Furthermore, Grossman (1988) identifies close-to-close returns as a measure of market direction volatility. For the sake of completeness, and in line with other studies in this literature, this chapter includes the following measures of

volatility: trading-hour volatility/ open-to-close returns (measured by $\ln(C_t/O_t)$), non-trading hour volatility/ close-to-open returns (measured by $\ln(O_t/C_{t-1})$), market direction volatility/ close-to-close returns (measured by $\ln(C_t/C_{t-1})$), and the high/low range volatility/ high/low returns (measured by $\ln(H_t/L_t)$).

Table 2.1 provides descriptive statistics for the entire sample, the price limits sample (trading days when the limits were in effect) and the no-hits sample (trading days when the limits were not in effect).

Table 2.2 provides a summary of the number of price limit days in effect for each of the 40 contracts. The contracts with the highest number of hits coincided with the time when uncertainty and panic were rife among farmers and traders as a result of the drought between 2014 and 2016. For the March delivery contracts, 2017 had the highest percentage of trading days in limit (20.14%) with 26 upper limits and 30 downward limits. This was followed by the 2016 contract which had 13.16% of its trading days in limit, with 19 upper limits and 16 downward limits. For the May contract, 2016 was the highest with 9% of trading days in limit, 27 upper limits and 14 downward limits. For July, September and December, the contracts with the highest number of limits all occurred in 2015 and 2016. After the March 2017 contract, the contract with the highest number of trading days in limit was March 2016 at 20% (with 23 limit ups and 25 limit downs).

Table 2.1: Descriptive Statistics

Entire Sample

	Open	**Close**	**High**	**Low**	**Volume**	***open-to-close-returns***	***trading-hour volatility***	***close-to-open returns***	***non-trading hour volatility***	***close-to-close returns***	***close-to-close volatility***	***high/low returns***	***high/low range volatility***	**%Δ *in trading activity***	**Volatility $_{t+1}$**
Mean	2430	2430	2453	2406	1946	0,02%	0,02%	-0,01%	0,03%	0.06%	0.04%	1.8%	0.05%	-0,07%	0.04%
Median	2225	2227	2244	2208	1806	0,00%	0,00%	0,00%	0,00%	0,00%	0.01%	1.6%	0.03%	-1,20%	0.01%
Maximum	5320	5296	5376	5236	8341	6,12%	0,39%	6,36%	13.84%	8,60%	14.8%	11.35%	1.3%	282,00%	14.78%
Minimum	1008	1019	1026	996	61	-6,28%	0,00%	-37,20%	0,00%	-38,40%	0,00%	0,00%	0,00%	-327,00%	0%

Limits Sample

	Open	**Close**	**High**	**Low**	**Volume**	***open-to-close-returns***	***trading-hour volatility***	***close-to-open returns***	***non-trading hour volatility***	***close-to-close returns***	***close-to-close volatility***	***high/low returns***	***high/low range volatility***	**%Δ *in trading activity***	**Volatility $_{t+1}$**
Mean	3361	3359	3403	3318	2267	-0,06%	0.04%	0.04%	0.07%	0.02%	0.149%	2.64%	0.099%	3.6%	0.1%
Median	3250	3230	3284	3200	2074	0,00%	0.03%	0,00%	0.01%	1.01%	0.065%	2.36%	0.06%	4.3%	0.02%
Maximum	5320	5296	5376	5236	7133	5.89%	0.39%	5.31%	13.84%	8.65%	14.8%	11.35%	1.3%	282,00%	14.78%
Minimum	1093	1101	1108	1010	122	-6,28%	0,00%	-37,20%	0,00%	-38,40%	0,00%	0,00%	0,00%	-327,00%	0,00%

No-hits sample

	Open	**Close**	**High**	**Low**	**Volume**	***open-to-close-returns***	***trading-hour volatility***	***close-to-open returns***	***non-trading hour volatility***	***close-to-close returns***	***close-to-close volatility***	***high/low returns***	***high/low range volatility***	**%Δ *in trading activity***	**Volatility $_{t+1}$**
Mean	2249	2249	2268	2229	1883	0.04%	0.01%	-0,02%	0,02%	0.04%	0.02%	1.73%	0.038%	-0,80%	0.028%
Median	2129	2126	2145	2110	1773	0,00%	0,00%	0,00%	0.04%	0,00%	0.075%	1.54%	0.03%	-1,80%	0.09%
Maximum	5150	5106	5152	5085	8341	6.12%	0.38%	6.36%	1.86%	6.36%	0,50%	7.91%	0.6%	176,00%	1.48%
Minimum	1008	1019	1026	996	61	-4,66%	0,00%	-13,65%	0,00%	-6,80%	0,00%	0,00%	0,00%	-257,00%	0,00%

Table 2.2: Summary of Price Limits								
	Mar-10	**Mar-11**	**Mar-12**	**Mar-13**	**Mar-14**	**Mar-15**	**Mar-16**	**Mar-17**
no. of tradings days *in limit*	4	2	10	4	22	25	50	32
no. of trading days *limit up*	0	1	4	1	16	17	33	8
no. of trading days *limit down*	4	1	6	3	6	8	17	24
	May-10	**May-11**	**May-12**	**May-13**	**May-14**	**May-15**	**May-16**	**May-17**
no. of tradings days *in limit*	0	2	4	3	1	4	18	3
no. of trading days *limit up*	0	1	3	2	0	0	8	3
no. of trading days *limit down*	0	1	1	1	1	4	10	0
	Jul-10	**Jul-11**	**Jul-12**	**Jul-13**	**Jul-14**	**Jul-15**	**Jul-16**	**Jul-17**
no. of tradings days *in limit*	1	2	7	2	1	13	12	2
no. of trading days *limit up*	0	1	7	1	0	11	5	2
no. of trading days *limit down*	1	1	0	1	1	2	7	0
	Sep-10	**Sep-11**	**Sep-12**	**Sep-13**	**Sep-14**	**Sep-15**	**Sep-16**	**Sep-17**
no. of tradings days *in limit*	0	1	6	0	0	9	19	0
no. of trading days *limit up*	0	1	3	0	0	4	8	0
no. of trading days *limit down*	0	0	3	0	0	5	11	0

	Dec-10	**Dec-11**	**Dec-12**	**Dec-13**	**Dec-14**	**Dec-15**	**Dec-16**	**Dec-17**
no. of tradings days *in limit*	1	7	6	0	0	14	32	0
no. of trading days *limit up*	1	6	3	0	0	10	18	0
no. of trading days *limit down*	0	1	3	0	0	4	14	0

2.4 Methodology

2.4.1 The volatility spillover hypothesis

A popular approach in the literature to measure daily volatility is to use the daily squared return. Andersen and Bollerslev (1998) showed that the daily squared return is an unbiased estimator of true volatility. To test the volatility spillover hypothesis, daily price volatility was measured by $V_t = (r_t)^2$, where rt represents close-to-close returns using trading day_{t-1} closing price and day_t closing prices for each trading day. If the post-limit days experienced greater daily volatility on average than the trading days after non-limit days, then this finding supports the volatility spillover hypothesis. Similar to Kim and Rhee (1997), observations of cluster limit days where limits were in effect for the second or third consecutive day were excluded in order to eliminate any high prelimit-day volatility bias from occurring.

2.4.2 The delayed price discovery hypothesis

In order to examine the impact of price limits on the price discovery process, two return series were constructed for each of the 40 contracts. The first series, $r(O_tC_t)$ represents open-to-close returns measured by $\ln(C_t/O_t)$, where C_t and O_t denote the closing and opening prices respectively on the day of the limit hit. The second series, $r(C_tO_{t+1})$ represents the close-to-

open returns measured by $\ln(O_{t+1}/C_t)$. The two series were used to assess whether white maize futures prices experienced more price continuations than reversals on limit days, as this would support the hypothesis that price limits delay the price discovery process. Nine outcomes can be observed where the first sign gives the return of the first series, and the second symbol is the return of the second series. Returns can be positive (+), negative (−) or zero (0). For limit up days, price continuations are denoted as [+, +] and [+,0], while price reversals are classified

as [+, −], [0, −], [−, +], [−,0] and [−, −]. Finally, return series [+,0] and [0,0] represent no change in prices. For limit down days, price continuations are denoted as [−,−] and [0, −], and price reversals as [−, +], [0, +], [+, −], [+,0] and [+, +]. Lastly, return series [−,0] and [0,0] represent no change in prices. Unlike with the volatility spillover test, consecutive limit days were not excluded for this analysis, as this would have underestimated the frequency of price continuations.

2.4.3 The liquidity interference hypothesis

If price limits interfere with liquidity, one would expect to find trading volume decreasing dramatically on limit-days and increasing exponentially on post-limit days. With increased trading on subsequent days, the consequence is that price limits prevent rational trading on limit days. Moser (1990) argues that price limits reduce access to markets, which further diminishes the ability of markets to resolve their liquidity requirements. A turnover ratio for trading activity was calculated as a percentage change from the preceding day as follows: $\ln(TV_t/TV_{t-1})$, where TV represents trading volume. In this analysis, consecutive limits days were excluded in line with the volatility spillover analysis.

2.4.3 The magnetic or gravitation effect hypothesis

Price limits can also create what is termed the magnetic effect (Hieronymus, 1971), which causes trading volume to increase as market participants anticipate an impending trading limit and advance the execution of their trades. Similar to the liquidity interference hypothesis, this effect tests for abnormal trading activity as a result of price limits. In contrast to the liquidity interference hypothesis however, support for the magnetic effect is found when the percentage change in trading activity increases dramatically on days when the limits are in effect and decreases sharply on subsequent trading days. The percentage change in the number of contracts traded on both limit-days as well as post-limit days were investigated.

2.5 Results

From Tables 2.1 and 2.2, and Figure 2.1 it is clear that the March 2016 contract was the most volatile during the sample period and experienced the highest number of price limit hits. This contract also had the highest average open, high and closing prices, while its average volume was not out of the ordinary relative to the number of contracts traded in the rest of the sample. The other two contracts which recorded a high number of trading days in limit were December 2016 and March 2017. It would appear therefore that the contracts that had trading activity constrained the most coincided when anxiety and panic regarding the drought were rife. It is impossible to know what the average prices in each of the contracts would have been, had price limits not been present; however, price limits were implemented during times when overreaction and panic trading would have naturally occurred. In order to evaluate the effectiveness of the price limits, however, the results need to illustrate whether volatility and volume increased or decreased when the limits were in effect.

2.5.1 The volatility spillover hypothesis

The objective of price limits is to moderate volatility and this test investigated if the average volatility on post-limit days was greater than the average volatility on normal-limit days. The results are summarised in Table 2.3. From the table, it can be seen that almost half of the contracts show evidence of volatility spillovers on post-limit days. Furthermore, while not reported, the daily volatility figures are largest for the trading days when the limits are in effect. If one examines the top 10 contracts with the highest number of limit hits, it can be seen that the two months with the highest frequency of limits, March and December 2016, did not experience volatility spillovers. For the contracts that experienced the largest number of limit occurrences, the price limits were effective in moderating volatility and did not result in volatility spillover. However, for the majority of the remaining frequently hit contracts (March 2014, March 2015, July 2015, July 2016, September 2016 and March 2017) evidence supporting the volatility spillover hypothesis is confirmed. This is reiterated by the Volatility $_{t+1}$ averages in Table 2.1. It is clear that the Limits sample exhibits volatility spillover with a daily average of 0.1%, while the No-hits sample is 0.028%. These findings are interpreted as evidence that price limits result in volatility spillovers on subsequent trading days. From Table 2.1 it is also clear that average volatility is higher for the Limits sample, than the No-hits sample, as can be seen from the respective figures: average trading hour volume is 0.04% against −0.02%, average non-trading hour volatility is 0.07% versus 0.02%, average market direction volatility is 0.15% against 0.02% and high/low range volatility is 0.099% against 0.038%. If price limits were effective, the average volatility in the Limits sample should have been lower than the average volatility in the No-hits sample. It is clear therefore that price limits, while implemented timeously to control trading activity, did not in fact manage to confine and reduce volatility.

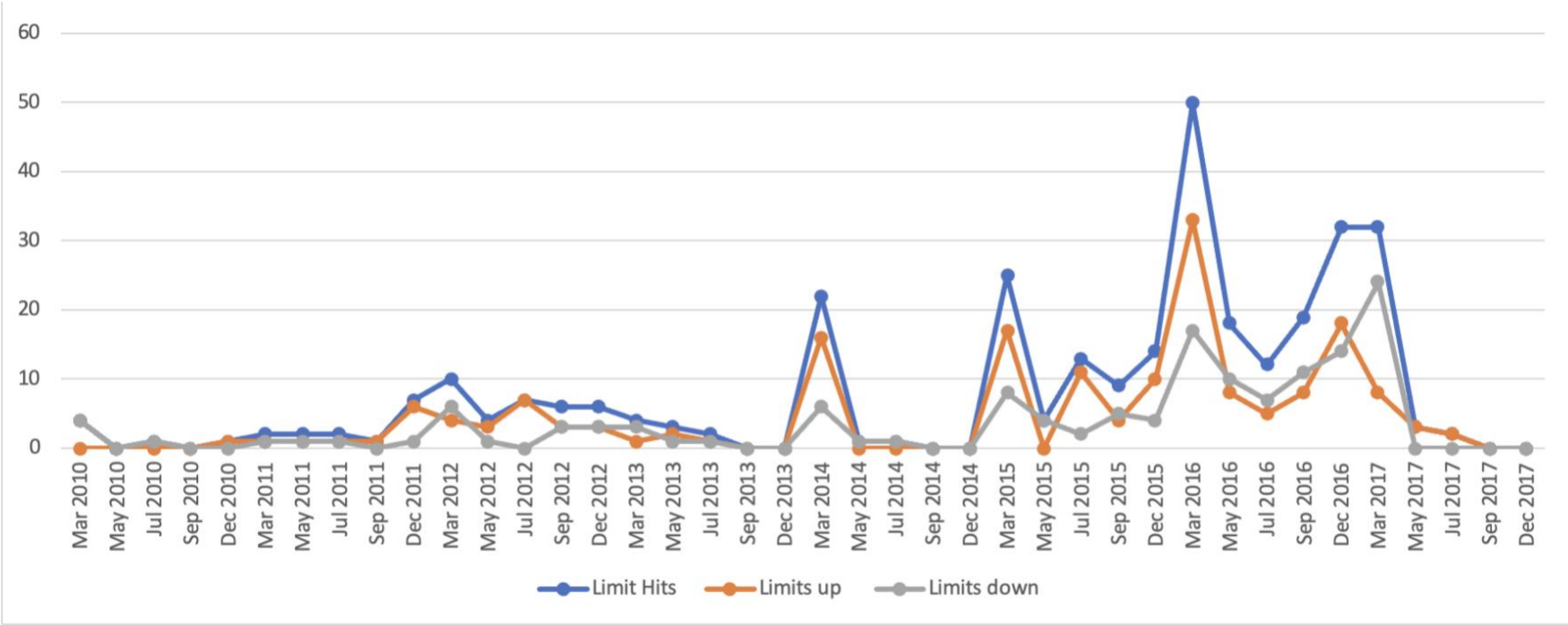


Figure 2.1 Summary of Price Limit Hits

Table 2.3: Volatility Spillover Hypothesis								
	Mar-10	**Mar-11**	**Mar-12**	**Mar-13**	**Mar-14**	**Mar-15**	**Mar-16**	**Mar-17**
Average daily volatility for postlimit days	0,009%	0,011%	0,020%	0,011%	0,012%	0,030%	0,002%	0,029%
Average daily volatility for post-normal days	0,041%	0,036%	0,019%	0,018%	0,011%	0,017%	0,007%	0,020%
	May-10	**May-11**	**May-12**	**May-13**	**May-14**	**May-15**	**May-16**	**May-17**
Average daily volatility for postlimit days	N/A	0,040%	0,005%	0,002%	0,016%	0,007%	0,006%	0,077%
Average daily volatility for post-normal days	N/A	0,027%	0,024%	0,037%	0,011%	0,011%	0,008%	0,028%
	Jul-10	**Jul-11**	**Jul-12**	**Jul-13**	**Jul-14**	**Jul-15**	**Jul-16**	**Jul-17**
Average daily volatility for postlimit days	0,003%	0,069%	0,010%	0,002%	0,003%	0,044%	0,011%	0,011%
Average daily volatility for post-normal days	0,026%	0,017%	0,031%	0,033%	0,014%	0,008%	0,010%	0,027%
	Sep-10	**Sep-11**	**Sep-12**	**Sep-13**	**Sep-14**	**Sep-15**	**Sep-16**	**Sep-17**
Average daily volatility for postlimit days	N/A	0,005%	0,017%	N/A	N/A	0,012%	0,012%	N/A
Average daily volatility for post-normal days	N/A	0,017%	0,014%	N/A	N/A	0,012%	0,011%	N/A
	Dec-10	**Dec-11**	**Dec-12**	**Dec-13**	**Dec-14**	**Dec-15**	**Dec-16**	**Dec-17**
Average daily volatility for postlimit days	0,048%	0,015%	0,017%	N/A	N/A	0,005%	0,009%	N/A
Average daily volatility for post-normal days	0,038%	0,009%	0,012%	N/A	N/A	0,011%	0,019%	N/A

Table 2.3.1 - Volatility Spillover Hypothesis			
Underlying Contract	Limit Hits	Ave daily volatility – post limit days	Ave daily volatility - post-normal days
Mar-16	50	0,002%	0,007%
Dec-16	32	0,009%	0,019%
Mar-17	32	0,029%	0,020%
Mar-15	25	0,030%	0,017%
Mar-14	22	0,012%	0,011%
Sep-16	19	0,012%	0,011%
May-16	18	0,006%	0,008%
Dec-15	14	0,005%	0,011%
Jul-15	13	0,044%	0,008%
Jul-16	12	0,011%	0,010%
Mar-12	10	0,020%	0,019%

2.5.2 The delayed price discovery hypothesis

The trading and non-trading volatilities were examined for the trading days where the limits were in effect. A higher occurrence of continuations over reversals and changes would indicate support for the delayed price discovery hypothesis. The results are reported in Table 2.4. If one examines the price continuations relative to the reversals and no changes for the top 10 contracts with the highest limits in effect, continuations outperformed reversals for each of those contracts. It is clear therefore that price limits delayed price discovery in the white maize futures contracts examined. Price continuations indicated that price limits prevented rational and informed trading, as price reversals should be observed instead in the context of erratic and over-reactive behaviour (Ma *et al*.,1989a).

Table 2.4: Price Discovery Hypothesis - Price Continuations and Reversals								
	Mar-10	**Mar-11**	**Mar-12**	**Mar-13**	**Mar-14**	**Mar-15**	**Mar-16**	**Mar-17**
Upward Price Movements								
Continuation	-	-	1	-	0,67	0,7	0,67	0,63
Reversal	-	1	-	0,5	0,33	0,18	0,27	0,25
No change	-	-	-	0,5	-	0,12	0,06	0,12
Downward Price Movements								
Continuation	0,5	-	0,83	0,33	0,57	0,75	0,59	0,79
Reversal	0,25	-	-	0,67	-	0,125	0,29	0,21
No change	0,25	1	0,17	-	0,43	0,125	0,11	-
	May-10	**May-11**	**May-12**	**May-13**	**May-14**	**May-15**	**May-16**	**May-17**
Upward Price Movements								
Continuation	-	1	0,33	0,5	1	-	0,57	0,33
Reversal	-	-	0,67	-	-	-	0,29	0,67
No change	-	-	-	0,5	-	-	0,14	-
Downward Price Movements								
Continuation	-	-	1	-	0,2	0,75	0,6	-
Reversal	-	1	-	1	0,4	0,25	0,3	-
No change	-	-	-	-	0,4	-	0,1	-
	Jul-10	**Jul-11**	**Jul-12**	**Jul-13**	**Jul-14**	**Jul-15**	**Jul-16**	**Jul-17**
Upward Price Movements								
Continuation	-	1	0,57	-	-	0,45	0,8	0,5
Reversal	-	-	0,43	1	-	0,27	0,2	-
No change	-	-	-	-	-	0,27	-	0,5

Downward Price Movements								
Continuation	1	-	-	-	1	1	0,29	-
Reversal	0	1	-	1	-	-	0,29	-
No change	0	-	-	-	-	-	0,42	-
	Sep-10	**Sep-11**	**Sep-12**	**Sep-13**	**Sep-14**	**Sep-15**	**Sep-16**	**Sep-17**
Upward Price Movements								
Continuation	-	-	0,5	-	-	0,5	0,5	-
Reversal	-	1	0,5	-	-	0,25	0,25	-
No change	-	-	-	-	-	0,25	0,25	-
Downward Price Movements								-
Continuation	-	-	0,67	-	-	0,4	0,45	-
Reversal	-	-	0,33	-	-	0,6	0,18	-
No change	-	-	-	-	-	-	0,36	-
	Dec-10	**Dec-11**	**Dec-12**	**Dec-13**	**Dec-14**	**Dec-15**	**Dec-16**	**Dec-17**
Upward Price Movements								
Continuation	1	0,17	1	-	-	0,6	0,67	-
Reversal	-	0,83	0	-	-	0,3	0,22	-
No change	-	-	0	-	-	0,1	0,11	-
Downward Price Movements								
Continuation	-	-	0,67	-	-	0,5	0,57	-
Reversal	-	1	0,33	-	-	0,25	0,29	-
No change	-	-	-	-	-	0,25	0,14	-

2.5.3 The liquidity interference hypothesis

Table 2.5 presents the day-to-day trading activity changes and shows an overall pattern of significant volume decreases on limit-days with increases on subsequent trading days. According to Lehmann (1989) increased trading activity is observed on the days following the limit-days because of order imbalances for liquidity. This result can therefore be interpreted as market participants delaying their trading to post-limit days to obtain their preferred pricing and positions. One of the intended objectives of price limits is to reduce trading activity, evidence of which would be seen in a decrease in the percentage change in volume. This reduction is trading volume can be seen in most of the 40 contracts examined. This decrease however was followed by dramatic increases in the percentage change in trading volume on the subsequent days following the days in limit. It is clear therefore that price limits impaired liquidity in white maize futures contracts, as the fall in trading activity when limits were in effect were intensely reversed once the limits were lifted.

2.5.4 The magnet or gravitation effect hypothesis

Table 2.6 provides a summary of the trading behaviour resulting from the implementation of price limits. Several of the limit-days experience uncharacteristically high increases in the number of contracts traded. This increase in trading activity is then followed by a sharp (in some instances) decline during the next trading day. It should be reiterated that these extractions do not include consecutive limit days. These results support the magnetic effect and show that instead of facilitating a cooling-off period, price limits instead are self-fulfilling and cause disturbances in trading activity which induce price limit hits.

Table 2.5 : Liquidity Interference Hypothesis							
Trade Date	**Underlying Contract**	**%△ in volume on limit day**	**%△ in volume on post limit day**	**Trade Date**	**Underlying Contract**	**%△ in volume on limit day**	**%△ in volume on post limit day**
2011/02/23	MAR 2011	-177	132	2012/06/26	JUL 2012	-53	49
2012/02/03	MAR 2012	-42	127	2012/07/09	JUL 2012	-97	42
2014/02/17	MAR 2014	-11	53	2012/07/19	JUL 2012	-107	69
2015/01/14	MAR 2015	-57	76	2015/05/27	JUL 2015	-21	60
2015/01/19	MAR 2015	-30	103	2016/05/30	JUL 2016	-13	30
2016/02/11	MAR 2016	-57	60	2016/06/01	JUL 2016	-27	34
2016/02/22	MAR 2016	-15	72	2016/06/13	JUL 2016	-4	62
2017/01/25	MAR 2017	-89	106	2016/07/12	JUL 2016	-16	11
2017/02/06	MAR 2017	-123	69	2012/07/23	SEP 2012	-8	37
2017/02/20	MAR 2017	-22	39	2012/08/10	SEP 2012	-31	22
2011/04/29	MAY 2011	-64	47	2015/07/23	SEP 2015	-53	56
2013/03/11	MAY 2013	-63	90	2016/07/20	SEP 2016	-13	18
2015/03/02	MAY 2015	-239	126	2011/10/03	DEC 2011	-43	49
2016/03/07	MAY 2016	-25	32	2011/10/12	DEC 2011	-58	46
2016/04/11	MAY 2016	-20	64	2011/10/21	DEC 2011	-63	39
2016/05/05	MAY 2016	-7	56	2011/12/07	DEC 2011	-29	129
2016/05/10	MAY 2016	-26	34	2011/12/09	DEC 2011	-44	63
2016/05/20	MAY 2016	-9	55	2012/10/01	DEC 2012	-327	282
				2012/10/15	DEC 2012	-21	30
				2015/11/06	DEC 2015	-36	49
				2015/11/27	DEC 2015	-80	31
				2016/09/26	DEC 2016	-140	93
				2016/10/11	DEC 2016	-36	11

Table 2.6 : The Magnetic Effect Hypothesis							
Trade Date	**Underlying Contract**	**%△ in volume on limit day**	**%△ in volume on post limit day**	**Trade Date**	**Underlying Contract**	**%△ in volume on limit day**	**%△ in volume on post limit day**
2010/01/04	MAR 2010	139	-6	2010/07/09	JUL 2010	60	-42
2010/01/13	MAR 2010	86	-39	2011/07/13	JUL 2011	107	-23
2012/01/13	MAR 2012	76	-54	2012/07/03	JUL 2012	67	-21
2012/02/21	MAR 2012	98	-24	2015/06/09	JUL 2015	72	-52
2012/02/29	MAR 2012	37	-136	2015/05/23	JUL 2016	55	-36
2012/12/27	MAR 2013	81	-64	2016/05/26	JUL 2016	29	-27
2014/02/07	MAR 2014	70	-37	2017/06/30	JUL 2017	42	-41
2014/12/08	MAR 2015	44	-27	2015/07/03	SEP 2015	88	-55
2015/12/03	MAR 2016	37	-95	2015/08/07	SEP 2015	34	-14
2016/02/18	MAR 2016	24	-23	2010/10/11	DEC 2010	131	-100
2016/02/24	MAR 2016	15	-69	2011/09/22	DEC 2011	98	-20
2016/02/26	MAR 2016	88	-2	2015/10/05	DEC 2015	88	-37
2016/12/20	MAR 2017	93	-19	2015/10/28	DEC 2015	54	-19
2012/03/07	MAY 2012	130	-2	2015/11/11	DEC 2015	64	-68
2013/03/14	MAY 2013	90	-33	2016/12/06	DEC 2016	73	-12
2014/04/08	MAY 2014	72	-16				
2015/03/12	MAY 2015	41	-58				
2016/03/30	MAY 2016	12	-45				
2016/04/01	MAY 2016	25	-44				
2017/03/31	MAY 2017	68	-19				
2017/04/04	MAY 2017	37	-14				

If one compares the daily volume for the Limits sample in Table 2.1, the mean is 2 267 contracts, while for the No-hits sample the daily mean for volume is 1 883. If price limits were effective in moderating volatility through limiting trading activity, a lower daily average in the number of contracts traded would have been observed for the Limits sample. It is clear therefore that price limits failed in reducing volatility and volume, its two intended objectives.

2.6 Conclusion

The debate surrounding the use and implementation of price limits has been longstanding, with little attention given to evaluating its effectiveness in grain futures markets. The objective of this chapter was to evaluate the effectiveness of price limits in the South African white maize futures market. The behaviour of price variability and trading activity was investigated by testing four common issues in the circuit breaker literature. Although it is impossible to determine what the trading volume and volatility would have been in the absence of price limits, several of the trading days examined supported each of the hypotheses to some extent, indicating that for white maize futures, price limits are on average ineffective.

Despite the market structure improvements of futures trading from pit to electronic platforms, the fundamental purpose of futures markets to manage risk and provide market liquidity should remain its primary objectives. Price limits have been implemented on SAFEX to improve and restore confidence in the markets. These efforts however must be balanced against ensuring that such limits do not have adverse effects on the price discovery and hedging capabilities of futures markets. Confidence cannot be enhanced by measures that impair liquidity, distort efficiency and pressurise traders to utilise markets that are less transparent and unregulated. As so eloquently put by Moser (1990, p. 5), ‘the imposition of price limits, an apparent impediment

to the price discovery purpose of futures exchanges, coincides with threats to the independence of the exchanges.'

Given the results and the large number of position limits observed in this chapter, this thesis recommends that the JSE consider the possibility of a dynamic price limit (based on a percentage price change) instead of the current static price limit (which is a rand-based value per ton). This percentage change should be tied to the value of the underlying commodity. Not only will this be consistent with other global futures exchanges, but it will also avoid large consecutive limit hits occurring unnecessarily. For instance, the high number of limits observed in March 2016 occurred predominantly before 1 March 2016 (when the price limit increased from R80/ton to R100/ton).

In terms of recommendations for future research, this thesis recommends the use of high frequency data, such as the intraday data used by He and Serra (2022). Due to data constraints, intraday data could not be used in this chapter. Future research in this field would benefit from employing intraday data, especially when testing for the magnetic effect. Distinct from the volatility, spillover, delayed price discovery and liquidity interference hypotheses, the magnetic effect is best tested in the period immediately before the price limit hit. With the use of intraday data, trading irregularities would more appropriately capture the gravitational feature of the magnetic effect.

This thesis also recommends that the South African futures market adopt the weekly Commitment of Traders report that is currently available for U.S. commodity futures trading. The split of open interest positions between commercial (hedgers) and non-commercial (speculators) traders is currently unavailable for SAFEX contracts. Making this data available

would allow the necessity of circuit breakers to be empirically investigated, an important prerequisite to testing their effectiveness. If one can empirically corroborate that excess-speculative trading positions are indeed the cause behind excessive price volatility, this would validate the need for trading limits.

CHAPTER THREE: THE EFFECTS OF UNCERTAINTY ON INVESTOR EXPECTATIONS AND PRICE VOLATILITY IN THE SOUTH AFRICAN WHITE MAIZE FUTURES MARKET

Abstract of Chapter Three

Given the tumultuous and rapidly changing nature of financial markets, volatility indices often influence the trading behaviour of market participants, as they identify market patterns, predict market risk and gauge market sentiment. This chapter examines the effects of uncertainty on the expectations of South African white maize futures traders as well as on price volatility at a daily level. Uncertainty effects are measured using three volatility indices: the SAVI Top 40, the SAVI Dollar and the SAVI White Maize. Investor expectations in the South African white maize futures market are proxied by three momentum indicators, the moving average convergence divergence (MACD), the relative strength index (RSI) and the rate of change (ROC). Volatility is estimated using a fitted GARCH (1,1) model of South African white maize futures closing prices. A time-varying vector autoregressive (VAR) framework is used to examine the reactions of each of the three technical indicators to shocks from each of the three volatility indices. The results confirm that changes in uncertainty influence the expectations of South African white maize futures momentum traders; and that these resulting trades influence price movements, resulting in increased volatility.

3.1 Introduction

Futures markets facilitate price discovery and risk management for two distinct types of market participants, namely, hedgers and speculators. Hedgers and speculators are often distinguished by their intention to trade (Working, 1953) and the length of their investment (Cornell, 1981). Hedgers are identified as the commercial participants in a futures contract and are often the farmers, food producers and end-users, with a sincere and long-term interest in trading the underlying asset. Speculators in contrast, are defined as non-commercial traders who, although provide critical market liquidity, are seen merely as day traders, participating predominantly to make a profit. Volatility in commodity futures prices, particularly in agricultural markets, has witnessed unprecedented and increasing levels in recent decades with prices peaking in 2007-2008 and again in 2010-2011 (Bohl, Siklos & Wellenreuther, 2018). Many academics and practitioners have attributed these volatility levels not to changes in fundamental supply and demand factors, but to the increased participation in these markets by non-commercial, speculative traders. According to Bobenrieth and Wright (2009), the global food product price increases observed between 2006 and 2008 triggered widespread concern over the volatility experienced in agricultural commodity markets. Several reports claimed that grain prices had been drastically inflated by manipulative financial speculation.

The debate surrounding the financialisation of commodities, documented by Masters (2008) as the abnormally large inflow of investment capital into commodity futures markets, has continued over the last decade. However, there is still no conclusive evidence on the impact of speculative trading on price volatility. Haase, Zimmerman and Zimmerman (2016) reviewed the findings of 100 empirical studies that examined the impact of speculation on commodity futures markets, spanning multiple sample periods across several international markets. They concluded that most studies did not find a systematic speculative impact; and where studies did

find speculative effects, they predominantly identified reinforcing price effects and not effects on returns and volatility.

Despite the obscurity surrounding the effects of speculative trading on price volatility, the makeup of market participants has indeed evolved in recent years with an increasing number of speculative traders now present across commodity futures markets. According to Czudaj (2019b) the excessive involvement of these institutional investors and speculative traders has strongly affected the behaviour of commodity markets, including the co-movement of commodity prices with other assets. Czudaj (2019a) further argues that if these investors' expectations are affected by uncertainty, this uncertainty is capable of significant futures price movements and consequently, increased price volatility. This argument is supported by Coiboin and Gorodnichenko (2015) who state that the investigation of the effects of uncertainty on investor expectations is plausible under the rational expectation's model and the presence of information rigidities, which are more pronounced during periods of uncertainty. Information rigidity refers to information frictions under the sticky information model of Mankiw and Reis (2002), whereas under the noisy information model of Sims (2003), it refers to the limited ability of economic agents to process new information from noisy signals.

An additional consequence of the financialisation of commodities and the growth of commodity index investments has been the rise in popularity of technical analysis in commodity futures markets (Han, Yang & Zhou, 2013). Technical analysis is the use of historical data such as past prices and trading volume to forecast futures price movements (Zhu & Zhou, 2005). Technical analysis indicators are designed to reveal changes in the strength, direction, momentum and duration of a trend in an asset's price (Drake & Downs, 2003). These indicators, established by professional traders, have successfully demonstrated their ability to

predict recent trends and momentum in financial markets. Technical analysis indicators have also proven to be superior to traditional autoregressive (fractionally) integrated moving average (AR(F)IMA) models in predicting trends and momentum in financial markets (Han *et al.*, 2013). Yin, Yang and Su (2017) examined the financialisation and structural co-movement of 26 commodities selected across energy futures, metals futures, agricultural futures, industrial futures and livestock futures over the period January 1991 to December 2014. They found that technical analysis indicators exhibit statistically and economically significant in-sample and out-of-sample forecasts of the co-movement of commodity markets, confirming them as suitable predictors of commodity markets. Technical analysis indicators, therefore, provide a reasonable proxy for expectations of commodity futures traders at a daily level (Czudaj, 2019a).

According to Yin and Han (2014), the most important aspect of volatility in commodity returns is in fact volatility of uncertainty and not necessarily uncertainty itself. While uncertainty in commodity futures markets may be measured and defined by several sources, studies examining the role of uncertainty on investor expectations have primarily used the VIX. The VIX is a volatility index developed in 1993 by the Chicago Board of Options Exchange (CBOE) used to measure U.S. stock market volatility. Volatility indices are often employed in market timing studies as they are known to gauge investor fear and market sentiment with their forward-looking capabilities and are available at a daily frequency.

This chapter examines the effects of uncertainty on investor expectations and volatility in the South African white maize futures market. Uncertainty effects are measured using three volatility indices, the South African Volatility Index (SAVI) Top 40, the SAVI Dollar and the SAVI White Maize. Investor expectations are proxied using three momentum indicators – the

moving average convergence divergence (MACD), the relative strength index (RSI) and the rate of change (ROC). It should be noted that while it may be a potential avenue for future research, a comparison of the buying and selling signals of each of the indicators is beyond the scope of this chapter. These indicators have been selected to proxy for investor expectations as they are frequently employed in practice to detect changes in trends and momentum. Momentum traders buy and sell according to prevailing price trends. Therefore, if uncertainty shocks result in momentum traders shifting the directions of their trade from a change in expectations; this would consequently lead to larger price changes and increased volatility. If uncertainty, as measured by volatility indices, is found to alter investor expectations, then market participants would be able to pre-empt changes in price volatility simply by observing changes in volatility indices. This increased price volatility would result from market participants changing or reversing their existing positions in white maize futures contracts to reflect revised expectations. Volatility indices, such as the VIX and SAVI, assist in determining whether there is over-confidence or fear in financial markets. When investor sentiment lies on either end of the spectrum, the market is inclined to reverse. The effects of volatility are also investigated with the volatility of South African white maize futures estimated by fitting a GARCH (1,1) model.

It is assumed that forward-looking investors adjust their expectations to changes in the level of uncertainty on a day-by-day basis motivating for the use of daily data. The sample period was limited by the availability of data for all three of the SAVI indices which confined the sample from 25 September 2013 to 31 December 2019. In order to examine the transmission of uncertainty and the dynamic shifts in investor expectations, a time-varying structural vector autoregression (VAR) was applied following Primiceri (2005). The results confirm that South African white maize futures traders update and change their expectations during periods of

uncertainty at the daily level. The results also show the strong reactions to volatility from shocks of each of the volatility indices. This chapter highlights the importance of trading activity in examining price volatility in the South African white maize futures market while also highlighting the strong positive influence of the SAVI indices on price volatility in the South African white maize futures market.

3.2 Literature Review

Van der Vyver and van Zyl (1989) were among the first to document not only the interdependent relationship between the futures market and the physical maize market in South Africa, but also the ability of the futures market to alleviate some of the price risks involved. The determinants of grain price volatility, specifically in an emerging market like South Africa, has therefore continued to be an imperative area of research. This is reiterated by Louw *et al.,* (2010) who argued that price variability is a crucial component of the grain farmer's planning as it impacts his profitability. Therefore, any knowledge surrounding price volatility and the factors affecting it benefit derivative instrument users and aids in the management of price risk. Research investigating price volatility in the South African maize futures market have been recorded by Geyser and Cutts (2007), Auret and Schmitt (2008), Monk et al.,, (2010) and Sayed and Auret (2018, 2019, 2020), among others. Each of these studies, however, assessed the determinants and factors influencing prices from a fundamental supply and demand and/or economic perspective only. Studies by Fisher and Statman (2000), Baker and Wurgler (2006) and Bandopadhyaya and Jones (2008) have shown non-economic factors, such as investor sentiment (or expectations), to be viable determinants and influencers of asset prices. Baek, Bandopadhyaya and Du (2005) found that shifts in investor expectations may explain short-term movements in asset prices better than any other set of fundamental factors.

Given the consequences of unexpected uncertainty in financial markets and the importance of modelling and predicting volatility, several volatility indices have been developed in recent years. Volatility indices are now available on all major global stock indices as well as on several commodities, with each index constructed using prices of standard European options (Alexander, Kapraun & Korovilas, 2015). The VIX, an important indicator of investor sentiment, commonly referred to as the "investor fear gauge", was the first implied volatility index constructed (Whaley, 2000). It was originally based on the S&P100 index before the Chicago Board Options Exchange (CBOE) redefined the calculation methodology in 2003 to instead use prices of synthetic 30-day options on the S&P500 index. The VIX calculation methodology was again updated in 2014 to include highly liquid weekly options to more appropriately match 30-day constant volatility.

The SAVI indices were modelled on the VIX and although they are not tradeable products, are used as forward-looking daily predictions of market volatility for the next three months (JSE, 2020). The SAVI Top 40 was launched in 2007 with the SAVI Dollar and SAVI White Maize launched in 2009 and 2013, respectively. Each of these three indices provides a measure of market sentiment relating to the local equity, currency and white maize markets respectively. This is among the first studies to explicitly examine the effects of the SAVI Top 40, the SAVI Dollar and the SAVI White Maize on the South African white maize futures market.

The objective of this chapter is to examine the effects of uncertainty, proxied by forward-looking volatility indices, on investor expectations, proxied by momentum indicators. This chapter is influenced by the methodology and rationale of Czudaj (2019a, 2019b).

In Czudaj (2019a), the author examined the effects of different dimensions of uncertainty on expectations of West Texas Intermediate (WTI) crude oil futures traded on the New York Mercantile Exchange (NYMEX) over the period January 1990 to August 2018. The expectations of momentum traders at a daily level were examined to provide insights on the surge and burst of crude oil prices observed since 2007. They were proxied by two conventional technical analysis indicators – the moving average convergence divergence (MACD) and the relative strength index (RSI). The two sources of uncertainty were the CBOE volatility index of the S&P500 (VIX) as well as the economic policy uncertainty (EPU) index suggested by Baker, Bloom and Davis (2016). Wavelet techniques were used to decompose crude oil futures prices into different frequencies accounting for investor sentiment at various horizons. Wavelet decomposition is advantageous as it allows the differentiations between various horizons with short-run components being related to speculative trading, and long-run components being related to long-term supply and demand. The results revealed that the reaction to uncertainty differed across frequencies. High frequencies were found to exhibit short-lived reactions to uncertainty, while low frequencies showed a persistent reaction to uncertainty shocks.

Czudaj (2019b) extended the study on uncertainty and momentum trading by investigating the role of different sources of uncertainty on agricultural futures markets. Daily data on futures prices of first nearby contacts for ICE Coffee, CBOT Corn, CBOT Soybean Oil, CBOT Soybeans, ICE Sugar and CBOT Wheat were examined for the period January 2005 to December 2014. Similar to the previous study, the two sources of uncertainty employed were the VIX and newspaper-based Economic Policy Uncertainty (EPU). The two technical indicators used were the MACD and RSI. The results favoured a time-dependent uncertainty effect on expectations of daily momentum traders in agricultural futures markets. This finding

was confirmed by the direct effect of both uncertainty sources on the volatility of the agricultural futures markets investigated.

This chapter extends the studies of Czudaj (2019a, 2019b) by incorporating three volatility indices, distinct to the South African market, i.e., the SAVI Top 40, the SAVI Dollar and the SAVI White Maize. The expectations of momentum traders are proxied by the MACD and RSI similar to earlier studies, however, a third indicator, the Rate of Change (ROC) is also included. The ROC is known as a pure momentum oscillator and is therefore expected to react faster and stronger to uncertainty shocks. This chapter also contributes to emerging commodity market literature as it examines the South African white maize futures for which there is limited research, as well as to research in the area of behavioural finance in futures markets, which is also limited at best.

3.3 Data

The objective of this chapter is to examine the effects of uncertainty on investor expectations in the South African white maize futures market using technical analysis indicators to proxy for momentum trading. Daily data for the SAVI Top 40 data is available from 2007 as mentioned above. Unfortunately, daily data for SAVI Dollar and SAVI White maize is only available from September 25, 2013. The daily data sample for this chapter, therefore, covers the sample period 25 September 2013 to 31 December 2019. SAVI indices data, as well as daily closing price data for white maize futures listed on SAFEX, was obtained from Bloomberg. The rolling front-month (active month) contract was used for South African white maize futures. The front-month refers to the month closest to maturity and each rolling front-month series uses the contract with the highest volume and open interest. Front-month contracts

have the closest expiration date for a futures contract, while contracts with later expiration dates are referred to as back-month contracts.

3.3.1 Measuring uncertainty effects

Uncertainty effects are measured using three South African volatility indices, namely the SAVI Top 40, the SAVI Dollar and the SAVI White Maize, each of which enables investors to gauge fear and market sentiment relating to the local equity, currency, and white maize markets respectively. Similar studies such as Czudaj (2019a, 2019b) measured uncertainty effects using the Chicago Board Options Exchange (CBOE) volatility index of the S&P 500, known as the VIX. The VIX relates to stock market volatility, reflecting a conventional measure of risk and uncertainty in equity markets. Comparable to the VIX, the SAVI provides a fear gauge for investors in the South African market, the SAVI Top 40, SAVI Dollar and SAVI White Maize are defined according to the JSE (2020). The SAVI Top 40 is a forecast of equity market risk in South Africa and is calculated using implied volatilities obtained daily from specific JSE Top 40 options. The SAVI Dollar represents a forecast of the 90-day implied volatility of the rand against the dollar. The SAVI White Maize is a forward-looking index that forecasts daily predictions of market volatility in 90-days' time. It enables maize producers, investors and other market participants to gauge volatility and sentiment relating to the local white maize market. According to Louw *et al.*, (2010), the SAVI white maize serves as a transparent volatility indicator. It measures the implicit volatility of the white maize contract, representing the market's expectation of how white maize prices are likely to move. While the rationale for including SAVI White Maize as a measure of uncertainty may be clear, the inclusion of the SAVI Top 40 and SAVI Dollar requires additional support. Geyser and Cutts (2007) investigated the fundamental factors determining the price of maize futures on the South African Futures Exchange (SAFEX) and outlined three. First, global supply and demand as

reflected in the Chicago Board of Trade (CBOT) price of corn. Second, South African demand, supply and stock levels of maize. Lastly, the Rand-Dollar Exchange rates due to its impact on import and export parity. The inclusion of SAVI Top 40 and SAVI Dollar is further supported by Sayed and Auret (2020), who examined volatility transmission in the South African white maize futures market over the period February 1999 to August 2018. The authors found significant volatility spillovers and high time-varying conditional correlations between the JSE Top 40 futures and Rand/Dollar futures with the South African white maize futures contracts. This supports the possibility that changes in the SAVI Top 40 and SAVI Dollar could also pre-empt South African white maize futures momentum traders to alter their expectations.

3.3.2 Measuring investor expectations through technical analysis indicators

Momentum indicators are frequently employed in practice to measure the velocity at which prices change. This chapter makes use of these trend-following and counter-trend indicators to approximate the expectations of South African white maize futures traders at a daily level. Momentum investing, popularised by the works of Jegadeesh and Titman (1993) amongst others, involves a strategy to exploit the persistence of an existing market trend. Momentum investing is based on technical indicators that dictate market entry and exit points and attempts to identify not only the direction of the trend but changes in the trend as well. Similar to Czudaj (2019a, 2019b), this chapter uses the momentum indicators, the moving average convergence divergence (MACD) and the relative strength index (RSI) to proxy for investor expectations; while also including a third momentum indicator, the rate of change (ROC).

3.3.2.1 The Moving Average Convergence Divergence (MACD)

The MACD is a responsive, trend indicator that rapidly reacts to recent price information (Drake and Downs, 2003). It is based on two exponential moving averages (EMA), with the

conventional parameters being a 12-period EMA and a 26-period EMA (Murphy, 1999). The EMA uses the factor K=2/*(k+1)* for a chosen parameter *k*, with P_t representing the closing price of South African white maize futures on trading day, *t*:

$$EMA_{k,t} = K\left(P_t - EMA_{k,t-1}\right) + EMA_{k,t-1,} \quad (1)$$

The MACD line is defined as the difference between a long-run EMA and a short-run EMA:

$$MACD_{s,l,t} = EMA_{s,t} - EMA_{l,t} \quad with\ l > s \geq 1 \quad (2)$$

where *s* and *l* are 12 and 26 days respectively. The MACD line crossing 0 is often interpreted as a sign that momentum is changing, and a new trend is emerging. The MACD line, however, is criticised for overweighting recent price information. An alternative is to, therefore, apply the Signal line, which is a 9-period EMA of the MACD line:

$$Signal_{k_t} = K\left(MACD_{s,l,t} - Signal_{k_{t-1}}\right) + Signal_{k,t-1} \quad (3)$$

When the MACD line crosses above the Signal line it is known as a bullish crossover and a buy signal is generated as the trend is seen as taking its momentum in an upward direction. While a bearish crossover is observed when the MACD line crosses below the Signal line and a sell signal is generated. These signal line crossovers, however, do not indicate the duration or amplitude of a trend. A MACD histogram is therefore applied which is the difference between the MACD line and the Signal line:

$$Hist_{s,l,k,t=}\ MACD_{s,l,t} - Signal_{k_t} \quad (4)$$

If the histogram is above the zero line, it implies an upward trend, with strong bullish momentum indicated by large positive values, and if the histogram is below the zero line, it implies a downward trend, indicated by large negative values. The MACD histogram has not only been found to be a reliable forecast of commodity prices but is also an effective tool for confirming short-term trading opportunities. This chapter uses the MACD histogram in Equation (4) as a proxy for investor expectations. The MACD histogram has however also been criticised for not being able to identify extremes in trends and momentum and for identifying changes in trends and momentum with a delay. Two additional momentum indicators are therefore also applied, the Relative Strength Index (RSI) and the Rate of Change (ROC). The Closing prices of South African white maize futures, the MACD line, the Signal line and the MACD Histogram are shown in Figure 3.1.

3.3.2.2 The Relative Strength Index (RSI)

The RSI is a bounded counter-trend indicator which fluctuates between 0 and 100, with 70 representing the overbought level and 30 representing the oversold level. It is based on the average level of the up- and down- closing prices of South African white maize futures over the last 14 days (k=14). The RSI is the second proxy for investor expectations used in this chapter and is defined as:

$$RSI_{k,t} = 100 * \frac{G_{k,t}}{G_{k,t} + L_{k,t}}, \tag{5}$$

where $G_{k,t}$ and $L_{k,t}$ represent the average gain and loss at time, t respectively, by exponential smoothing over the last 14 days. The RSI together with the overbought line at 70 and oversold line at 30 are shown in Figure 3.2.

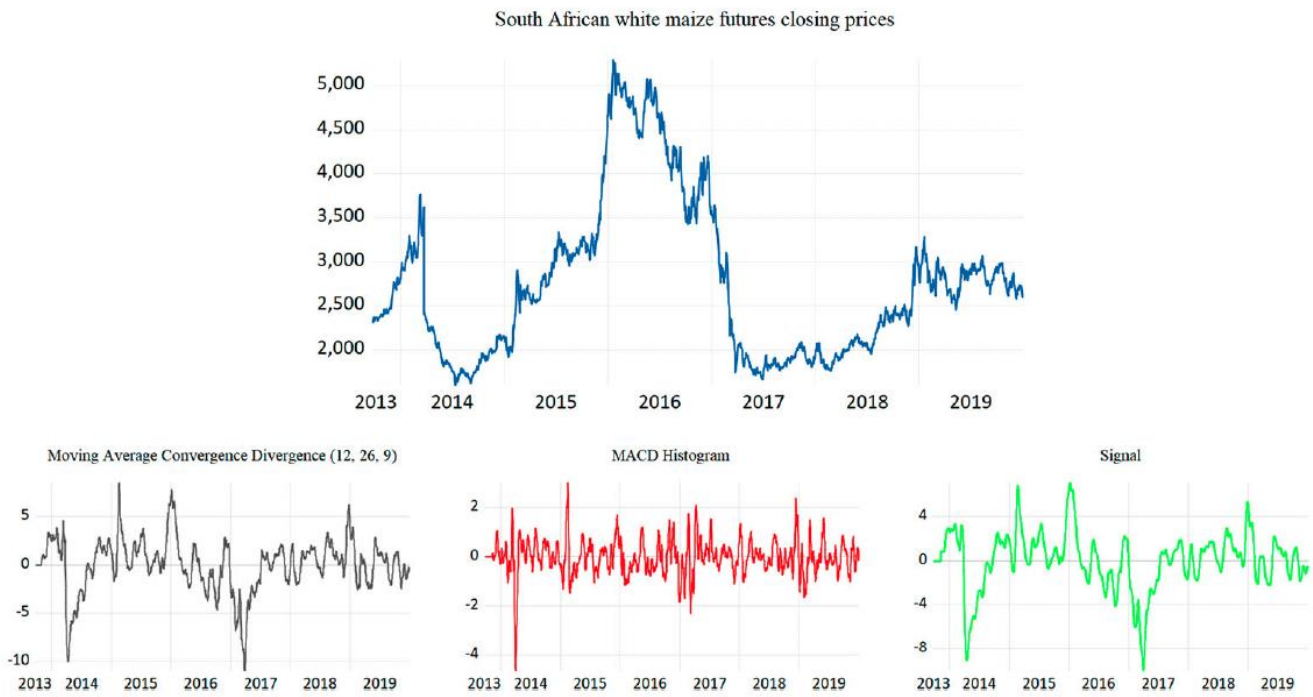


Figure 3.1: South African white maize futures closing prices and the moving average convergence divergence (MACD) indicator

The upper panel shows the daily closing prices. The bottom panel shows the MACD line according to equation (2) and is displayed on the extreme left. The signal line is derived from equation (3) and is shown in the bottom middle panel. Lastly, the MACD histogram is derived from equation (3) and is shown in the bottom panel on the extreme right. The MACD histogram is the response variable used in the time-varying impulse response functions.

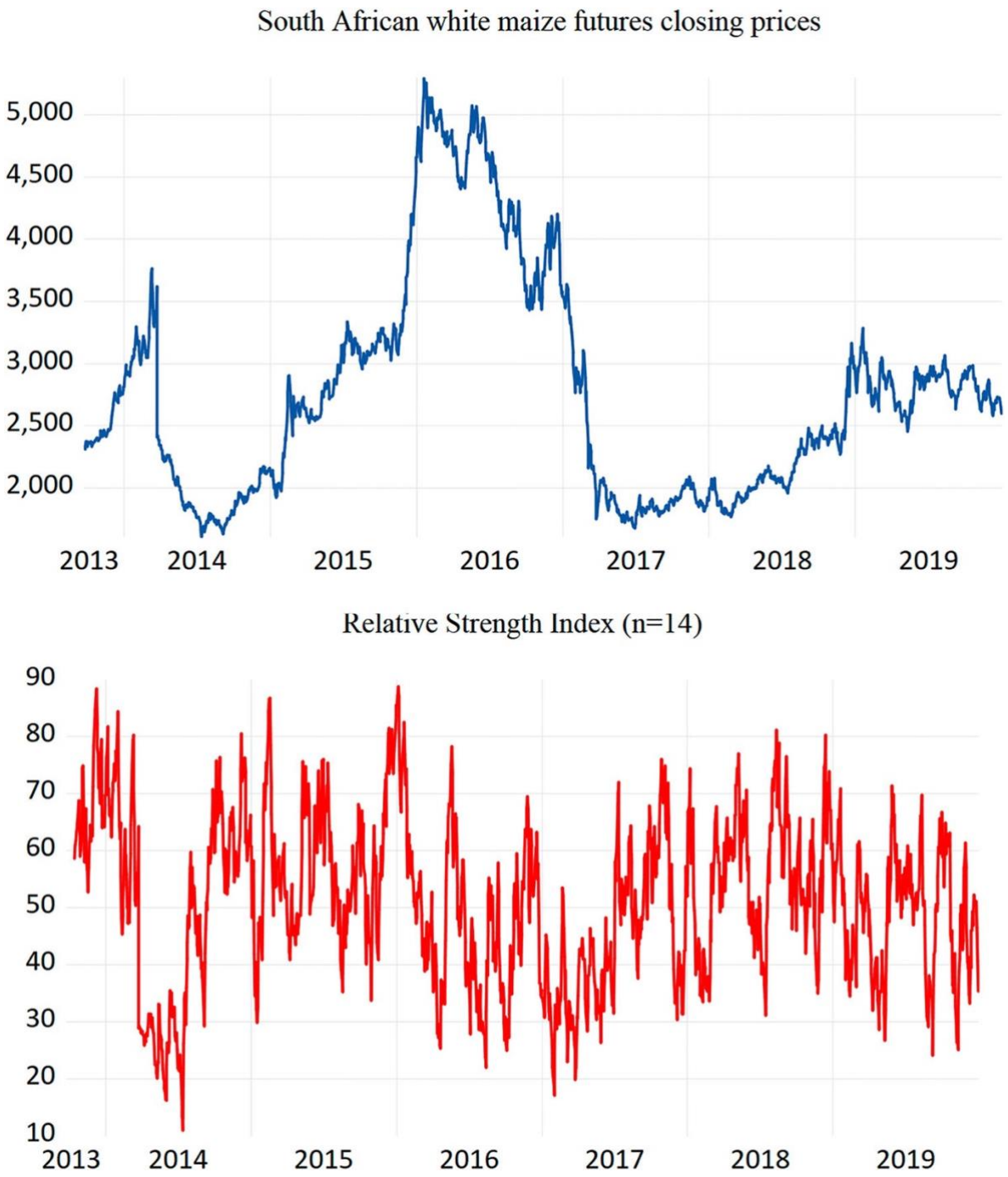


Figure 3.2: South African white maize futures closing prices and the relative strength index (RSI) indicator. The upper panel displays the daily closing prices of South African white maize futures. The bottom panel shows the relative strength index (RSI) according to equation (5).

3.3.2.3 The Rate of Change (ROC)

The ROC is a pure momentum oscillator that indicates velocity as it measures the strength of price momentum from one period to the next. This indicator is unbounded above zero with positive values indicating upward buying pressure (bullish momentum) and negative values below zero indicating selling pressure (bearish momentum). The ROC is the third proxy used for investor expectations and is defined as:

$$ROC_{n,t} = (P_t - P_{t-n}/P_{t-n}) * 100, \quad (6)$$

where P_t is the closing price of South African white maize futures at time *t*, and P_{t-n} is the closing price of South African white maize futures *n* periods before time, *t* where *n*=12. The value of n often varies between 12, 25 and 200. Short-term traders however typically use the smallest number, i.e., 12. As this chapter focuses on changing investor expectations, specifically for short-term traders, n = 12 has been selected. The ROC is shown in Figure 3.3.

3.3.3 Measuring volatility

The secondary objective of this chapter is to examine the effects of uncertainty on the volatility of South African white maize futures returns. Daily returns are calculated as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \quad (7)$$

where P_t is the daily closing price of South African white maize futures on trading day, *t.* Augmented Dickey-Fuller (ADF) (1979) unit-root tests are conducted on the levels of the daily returns data. This tests the null hypothesis that the return series has a unit root (is integrated of order 1) against the alternative hypothesis that it is I (0) or stationary.

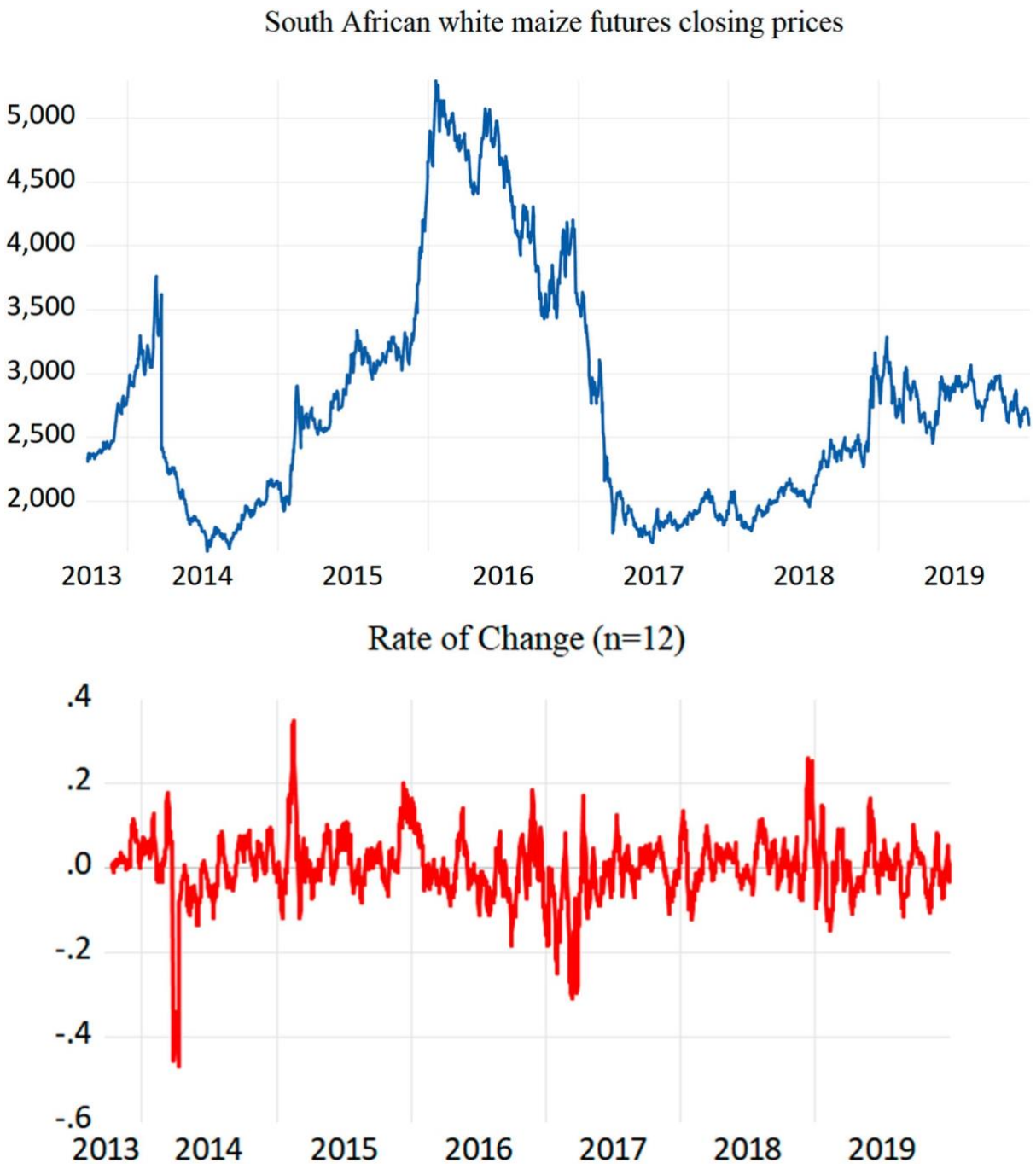


Figure 3.3: South African white maize futures closing prices and the rate of change (ROC) indicator. The upper panel displays the daily closing prices of South African white maize futures. The bottom panel shows the rate of change (ROC) according to equation (6).

Table 3.1 : Descriptive Statistics of uncertainty measures, trading indicators and South African white maize futures (SAWMF) prices and returns								
	Mean	Median	Max	Min	Standard deviation	Skewness	Kurtosis	Jarque-Bera
SAVI Top 40	18,1842	17.89000	25.64000	11.88000	2.795817	0.300635	2.443173	45.72357***
SAVI Dollar	15.78200	15.48500	24.24000	9.630000	2.779744	0.146900	2.464330	25.41281***
SAVI White Maize	29.30603	28.60000	52.50000	16.70000	6.081537	0.882837	3.980875	277.7611***
MACD Histogram	-0.003421	-0.022157	3.026155	-4.586147	0.730152	-0.564258	8.252620	1926.643***
RSI	51.06388	51.61873	88.77064	10.89472	14.34316	-0.004482	2.478716	18.14381***
ROC	0.000829	0.001999	0.348623	-0.471109	0.078338	-0.964006	9.319296	2913.686***
SAWMF Prices	2765,3600	2650,5000	5296,0000	1611,0000	889,2070	1,0050	3,2581	279,6102***
SAWMF Returns	0,0000	0,0000	0,1042	-0,4068	0,0204	-4,9254	101,2244	663477,3***
*** denotes significance at the 1% level								

Table 3.2: GARCH (1,1) Model - Estimated coefficients and diagnostics														
ω	Std. error	α	Std. error	p-value	β	Std. error	Persistence	AIC	BIC	SBC	WLB	WLB2	SB	AP*Gof*
60,8544	17,21023***	0,2300	0,03097***	0,0000	0.76898	0,026849***	0,9990	10,3730	10,3960	10,3730	0,8331	0,5816	2,0027***	58,34***
*** denotes statistical significance at the 1% level														

The return series calculated in equation (7) is tested and found to be stationary at the 1% level of significance. The descriptive statistics of daily returns and the uncertainty measures are shown in Table 3.1. The kurtosis results show a presence of leptokurtosis for white maize futures returns and SAVI Top 40, which are above 3, indicating the presence of extreme movements. The Jarque-Bera statistics reject the null hypothesis that the return series are normally distributed at the 1% level. Lastly, the means and medians of white maize futures returns are zero. Although volatility is not directly observable, it can be estimated from measures related to the first and second moments of returns, such as daily squared returns and absolute returns. Figure 3.4 plots the time-series of returns, returns squared and absolute returns for South African white maize futures listed on SAFEX. The figure shows time-varying conditional volatility in returns as well as volatility clustering. This motivates for the use of a GARCH model which will more accurately capture the conditional variance and account for the volatility clustering observed (Bollerslev, 1986).

The volatility of South African white maize futures can be modelled as:

$$r_t = \sigma_t \epsilon_t, \tag{9}$$

where σ_t is the time-varying volatility and ϵ_t is an *i.i.d.* random error that is independent of σ_t. To model σ_t a simple GARCH (1,1) model is fitted, with the conventional parameter restrictions:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{10}$$

Table 3.2 shows the parameter estimates for the fitted GARCH (1,1) model. The estimated coefficients are all significant at the 1% level. The fitted time series of the standard deviation of the model is used to proxy for volatility in the South African white maize futures market and is shown in Figure 3.5. The GARCH (1,1) model was the most appropriate as the fitted time series of the standard deviation of the model was the best fit according to the Akaike Information Criterion (AIC). In addition, the GARCH (1,1) model is relatively parsimonious compared to higher-order GARCH models, making it computationally efficient and less prone to overfitting (Pilbeam & Langeland, 2015).

3.4 Methodology

Similar to Czudaj (2019a, 2019b), this chapter employs the time-varying vector autoregressive (VAR) model proposed by Primiceri (2005) to examine the reaction of momentum traders in the South African white maize futures market to uncertainty shocks. The time-varying VAR model has become increasingly popular in macroeconomics literature as it has been found show superior forecasting performance when compared with the standard VAR models (D'Agostino, Gambetti & Giannone , 2009). This approach allows changes over time in both the coefficients and the variance-covariance matrix. The data is therefore left to determine if the time-variation is due to changes in the magnitude of the shock – the impulse, or to changes in the transmission mechanism – the response. The time-varying VAR model is specified as:

$$Y_t = B_{0,t} + B_{1,t} Y_{t-1} + \cdots + B_{p,t} Y_{t-p} + A_t^{-1} \Sigma_t \epsilon_t, \quad (11)$$

where Y_t is a vector including one uncertainty measure (SAVI Top 40, SAVI Dollar or SAVI White Maize) or one momentum indicator ($Hist_{12,26,9,t}$, $RSI_{14,t}$ or $ROC_{12,t}$), p denotes the lag

length of the VAR model selected through minimising the Akaike Information Criterion (AIC), A_t is a time-varying lower triangular matrix with ones on the main diagonal, Σ_t is a diagonal matrix with positive elements, ϵ_t is an error term distributed as $N(0,i=I_2)$ and $\{B_{j,t}\}^{p}_{j=0}$ are time-varying coefficient matrices.

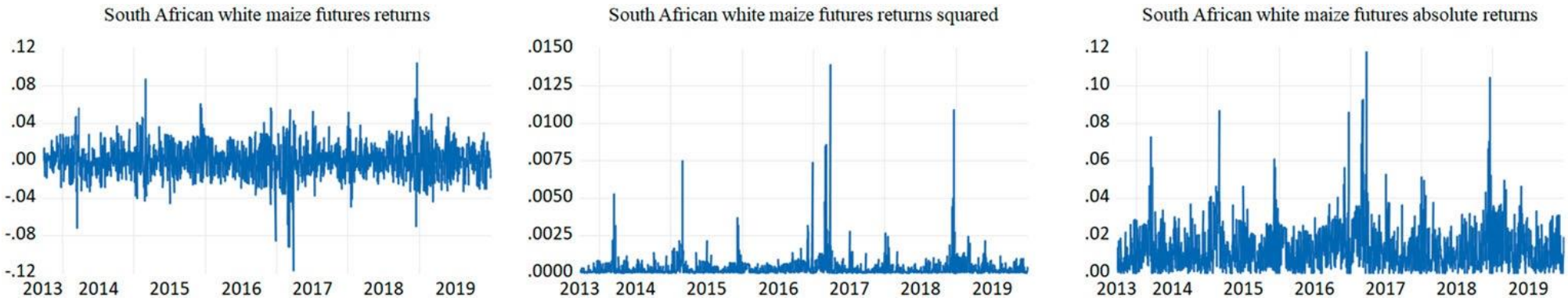


Figure 3. 4. **Time-series plots of the return series for white maize.**

The figure shows the returns, returns squared and absolute returns for South African white maize futures listed on SAFEX for the period 25 September 2013 to 31 December 2019. The returns have been calculated according to equation (7).

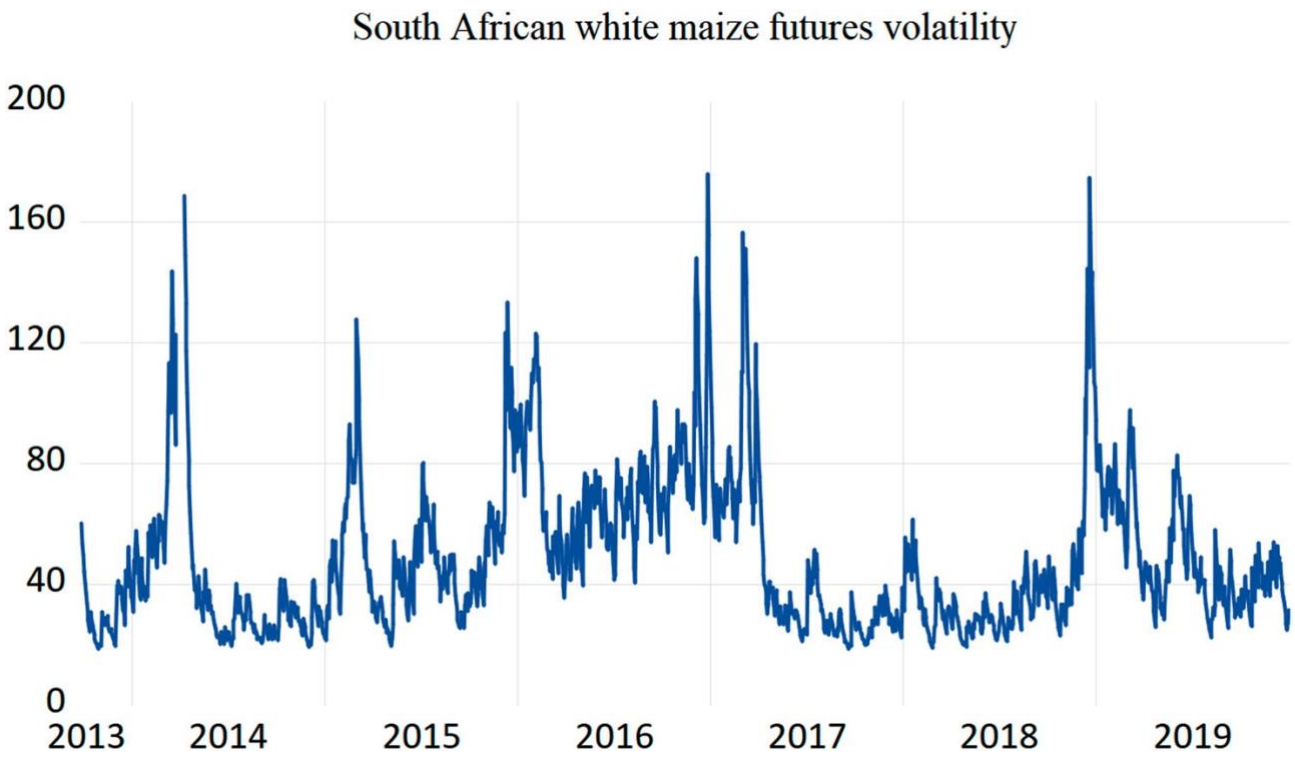


Figure 3.5. **South African white maize futures volatility**.
The figure shows the return volatility of the South African white maize futures market for the period 25 September 2013 to 31 December 2019. The volatility is proxied by the standard deviation of the fitted GARCH (1,1) model according to equation (10).

3.5 Results

In order to examine the effects of uncertainty on moment trading in the South African white maize futures market, time-varying impulse response functions are analysed. A one-unit shock of uncertainty proxied by (SAVI Top 40, SAVI Dollar or SAVI White Maize) on each of the momentum indicators (MACD histogram, RSI and ROC) are presented in Figures 3.6 to 3.8. A one-unit shock of uncertainty proxied by (SAVI Top 40, SAVI Dollar or SAVI White Maize) on the price volatility of South African white maize futures is shown in Figure 3.9. Each of the plots confirm that the effects of uncertainty on momentum trading and volatility in the South African white maize futures market are time-varying and significant. Investors in this market, therefore, incorporate changes in uncertainty when forming expectations regarding their trading behaviour.

Figures 3.6.1, 3.7.1 and 3.8.1 show the mean time-varying impulse responses of each of the technical indicators (MACD histogram, RSI and ROC) to a one-unit shock in the SAVI Top 40. The SAVI Top 40 is a fear gauge of the local equity market and in each of the plots with the indicators illustrates a negative reaction. The degree of this negative reaction, however, is different for each indicator. The RSI has the strongest negative reaction seen at the first period (n=1) of -0.1, this reaction to the SAVI Top 40 shock then converges to zero by the eighth period (n=8), and then becomes positive. The MACD histogram has the second strongest negative reaction to a one-unit shock from the SAVI Top 40, which reaches its peak at n=7 and then becomes slightly less negative. The ROC has the weakest negative reaction when the impulse variable is the SAVI Top 40 at -0.001 which peaks at n=1 and then dissipates to zero by n=12.

The SAVI Dollar has a similar result as can be seen from figures 3.6.2, 3.7.2 and 3.8.2. The mean time-varying impulse responses of the MACD histogram, the RSI and ROC to a one-unit shock from the SAVI Dollar are all negative. Once again, the RSI has the strongest negative reaction which peaks at n=1, followed by the MACD histogram which peaks only at n=5 and then the ROC has the weakest negative reaction which also peaks at n=1.

Finally, the results of a one-unit shock from the SAVI White Maize onto the technical indicators can be seen in figures 3.6.3, 3.7.3 and 3.8.3. Contrary to the SAVI Top 40 and SAVI Dollar, the reactions of the MACD histogram, RSI and ROC are all positive. Once again, the RSI has the strongest reaction which peaks at n=1 and then converges to zero by n=7, before becoming positive. The MACD histogram has the second strongest positive reaction only peaking at n=2 before converging to zero at n=7 and becoming negative thereafter.

The results of figures 3.6 to 3.8 illustrate a negative reaction of the MACD histogram, RSI and ROC to an uncertainty shock from either the SAVI Top 40 or the SAVI Dollar. This implies that momentum traders revise their expectations towards a bearish momentum period and would, therefore, be in favour of a selling signal for South African white maize futures. Similarly, a positive reaction of the MACD histogram, RSI and ROC to an uncertainty shock from the SAVI White maize leads momentum traders to revise their expectations to a bullish momentum period in favour of a buying signal for South African white maize futures. The higher the SAVI index, the higher the expected uncertainty and the higher the fear sentiment. This would lead investors to alter their expectations to a buy signal as they would anticipate white maize futures prices to increase in the near future.

Figures 3.9.1, 3.9.2 and 3.9.3 show the time-varying impulse response functions of price volatility in the South African white maize futures market to a one-unit shock from the SAVI Top 40, SAVI Dollar and SAVI White Maize. Each of the reactions is positive, i.e. a shock from each of the uncertainty measures leads to an increase in volatility. An impulse in SAVI White Maize leads to the most positive response in price volatility, followed by the SAVI Top 40 and SAVI Dollar, with each of the plots showing the positive reactions increasing over time.

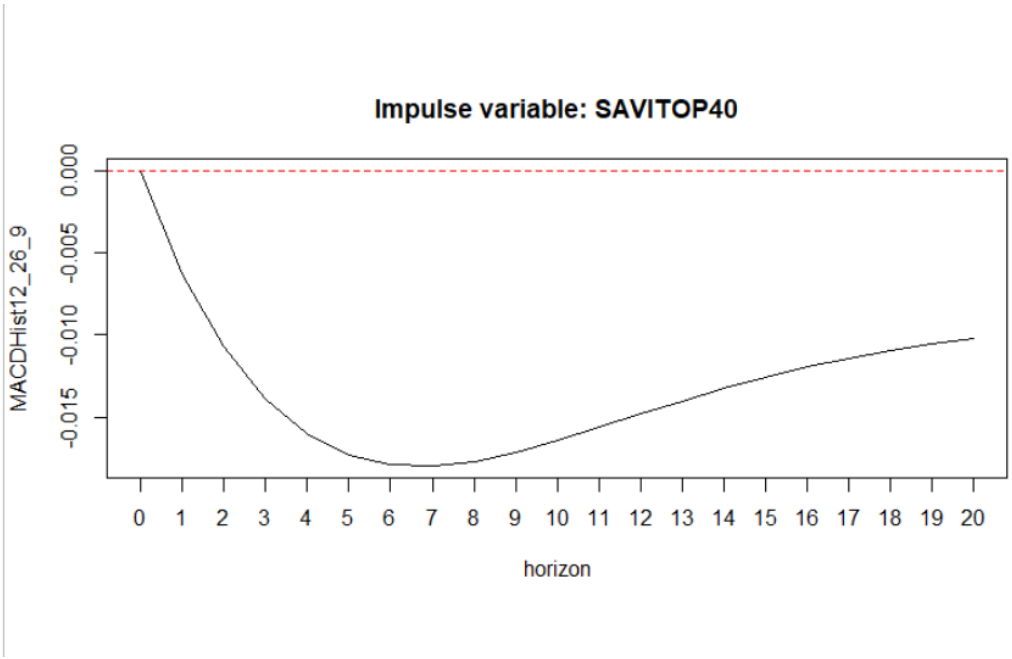


Figure 3.6.1: Time-varying Impulse Response Functions of the MACD Histogram from a one-unit shock in the SAVI Top 40.
The plot represents the mean time-varying impulse response function over every time period. It shows the response to the MACD Histogram by a one-unit shock in the SAVI Top 40.

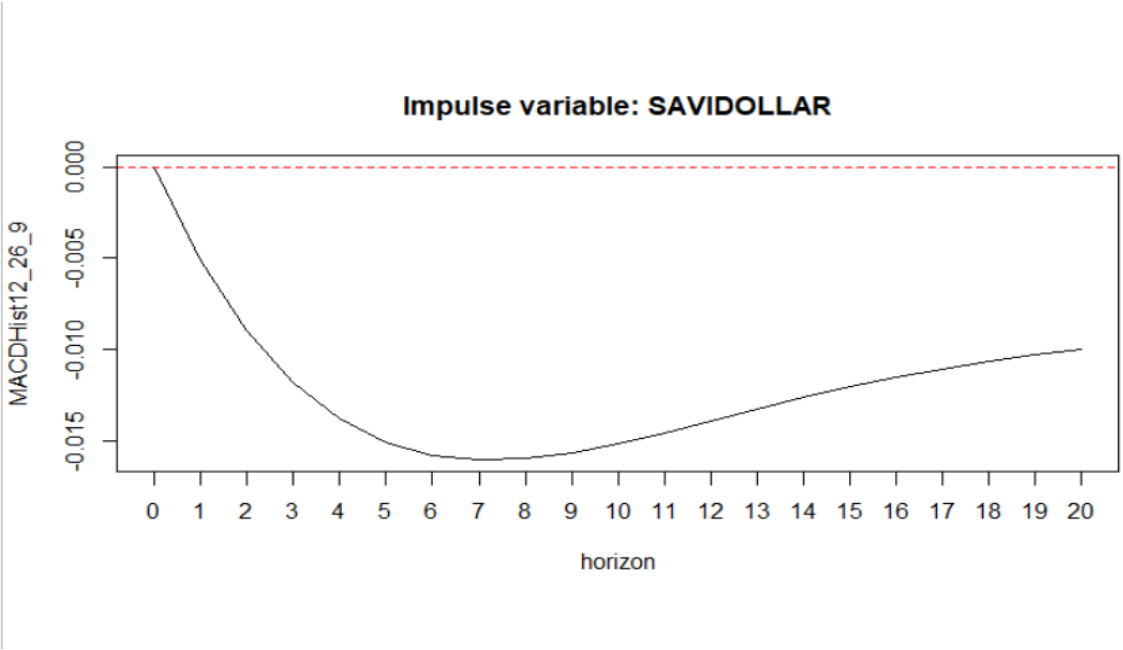


Figure 3.6.2: Time-varying Impulse Response Functions of the MACD Histogram from a one-unit shock in the SAVI Dollar
The plot represents the mean time-varying impulse response function over every time period. It shows the response to the MACD Histogram by a one-unit shock in the SAVI Dollar

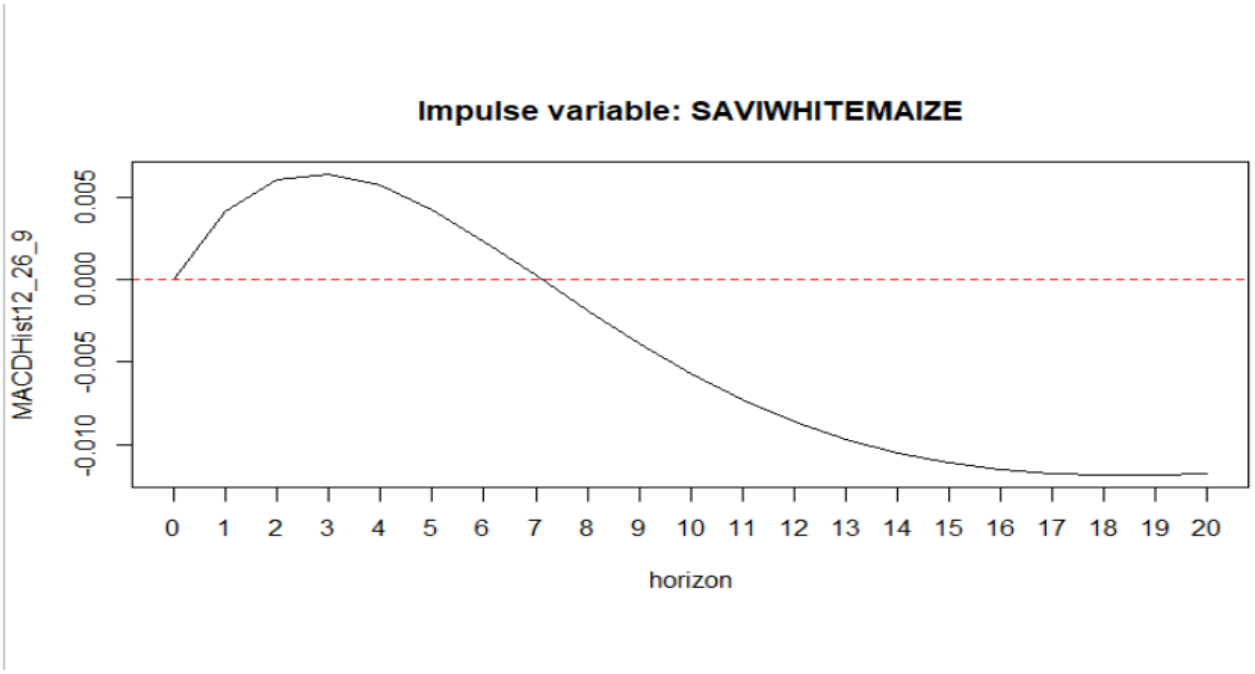


Figure 3.6.3: Time-varying Impulse Response Functions of the MACD Histogram from a one-unit shock in the SAVI White Maize

The plot represents the mean time-varying impulse response function over every time period. It shows the response to the MACD Histogram by a one-unit shock in the SAVI White Maize.

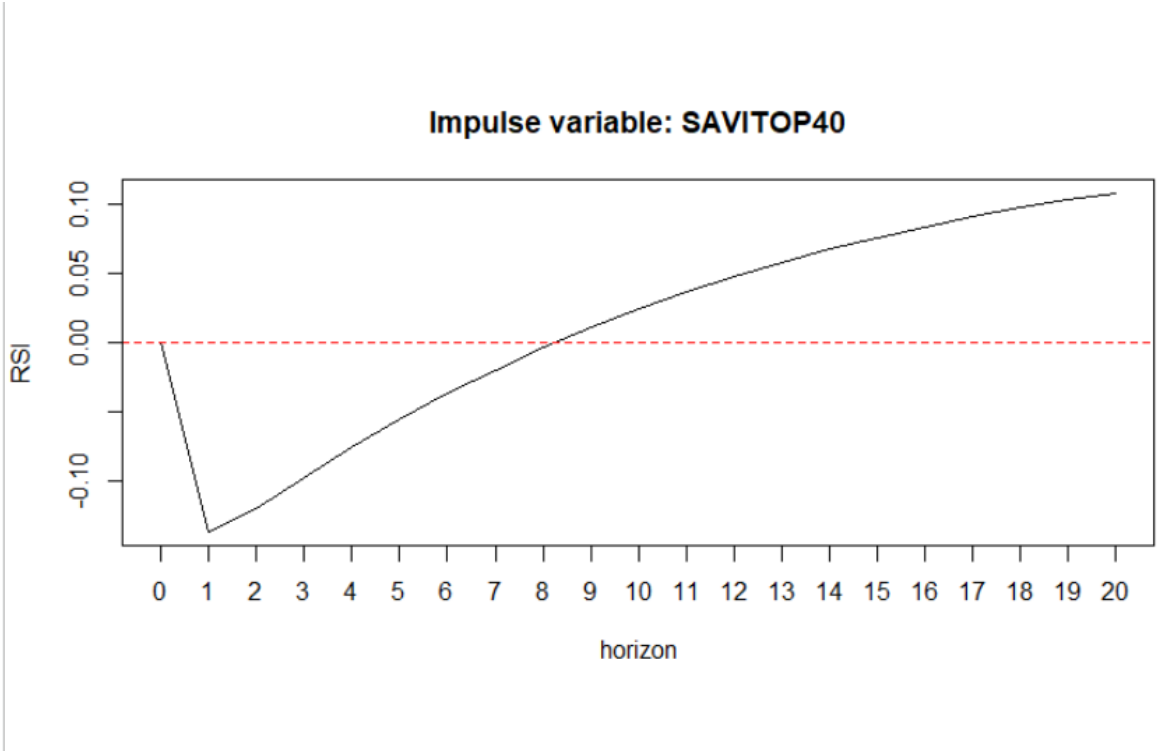


Figure 3.7.1: Time-varying Impulse Response Function of the RSI from a one-unit shock in the SAVI Top 40.
The plot represents the mean time-varying impulse response function over every time period. It shows the response to the RSI by a one-unit shock in the SAVI Top 40.

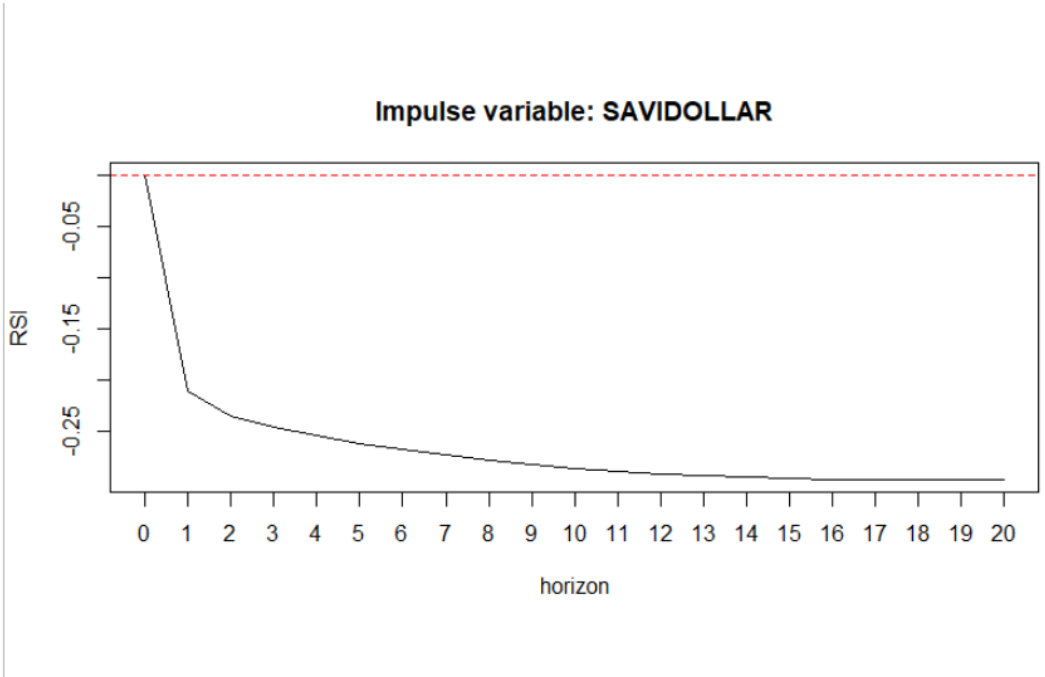


Figure 3.7.2: Time-varying Impulse Response Functions of the RSI from a one-unit shock in the SAVI Dollar.
The plot represents the mean time-varying impulse response function over every time period. It shows the response to the RSI by a one-unit shock in the SAVI Dollar.

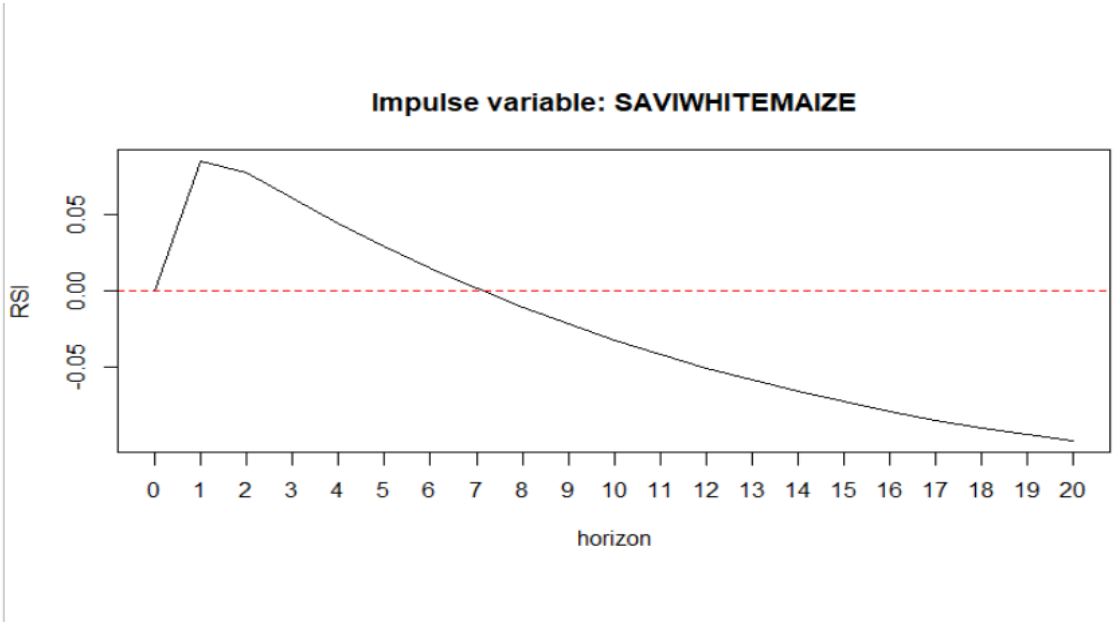


Figure 3.7.3: Time-varying Impulse Response Function of the RSI from a one-unit shock in the SAVI White Maize

The plot represents the mean time-varying impulse response function over every time period. It shows the response to the RSI by a one-unit shock in the SAVI White Maize.

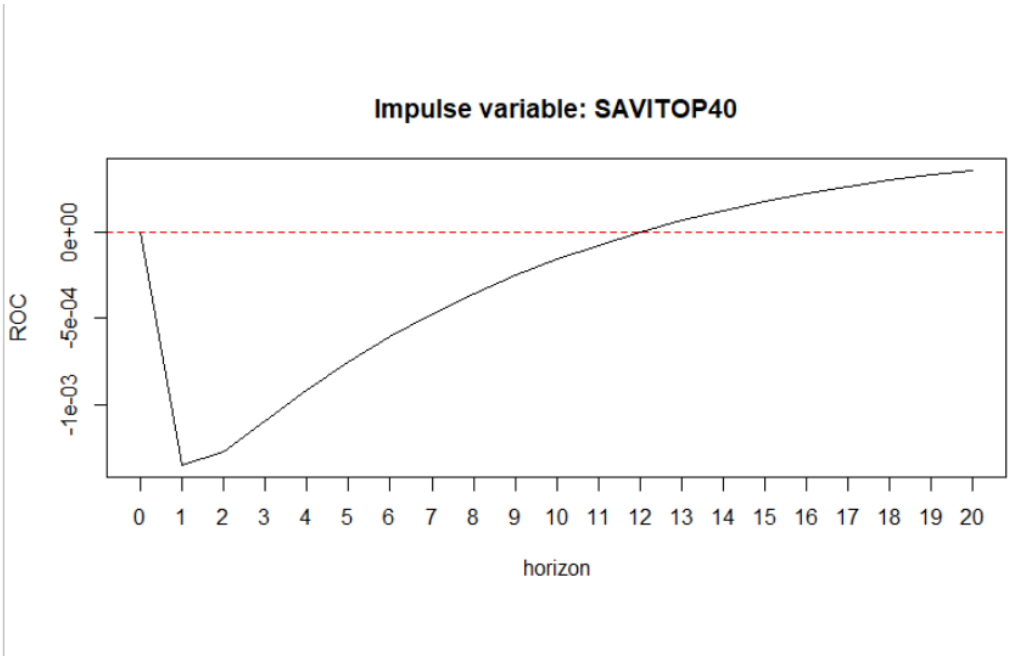


Figure 3.8.1: Time-varying Impulse Response Function of the ROC from a one-unit shock in the SAVI Top 40.

The plot represents the mean time-varying impulse response function over every time period. It shows the response to the ROC by a one-unit shock in the SAVI Top 40.

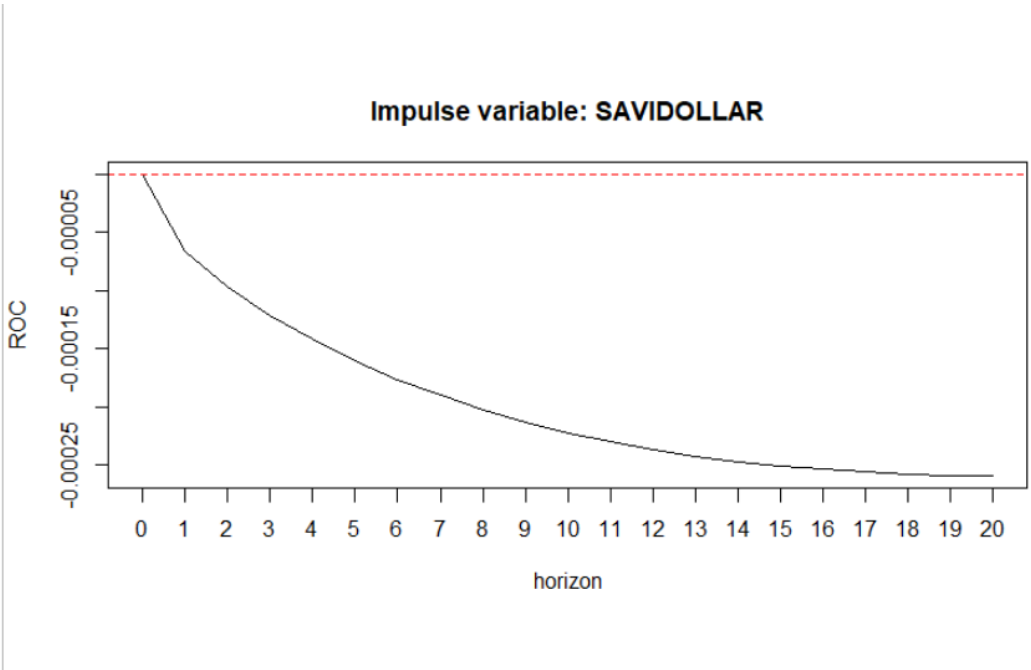


Figure 3.8.2: Time-varying Impulse Response Function of the ROC from a one-unit shock in the SAVI Dollar.

The plot represents the mean time-varying impulse response function over every time period. It shows the response to the ROC by a one-unit shock in the SAVI Dollar.

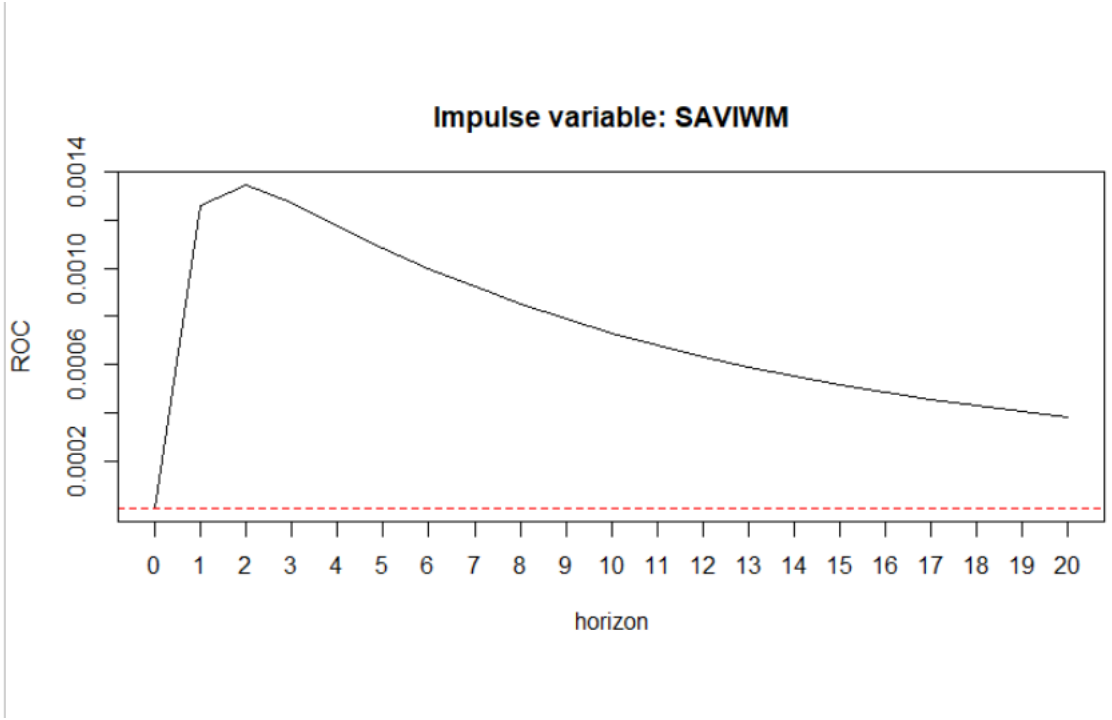


Figure 3.8.3: Time-varying Impulse Response Function of the ROC from a one-unit shock in the SAVI White Maize.
The plot represents the mean time-varying impulse response function over every time period. It shows the response to the ROC by a one-unit shock in the SAVI White Maize.

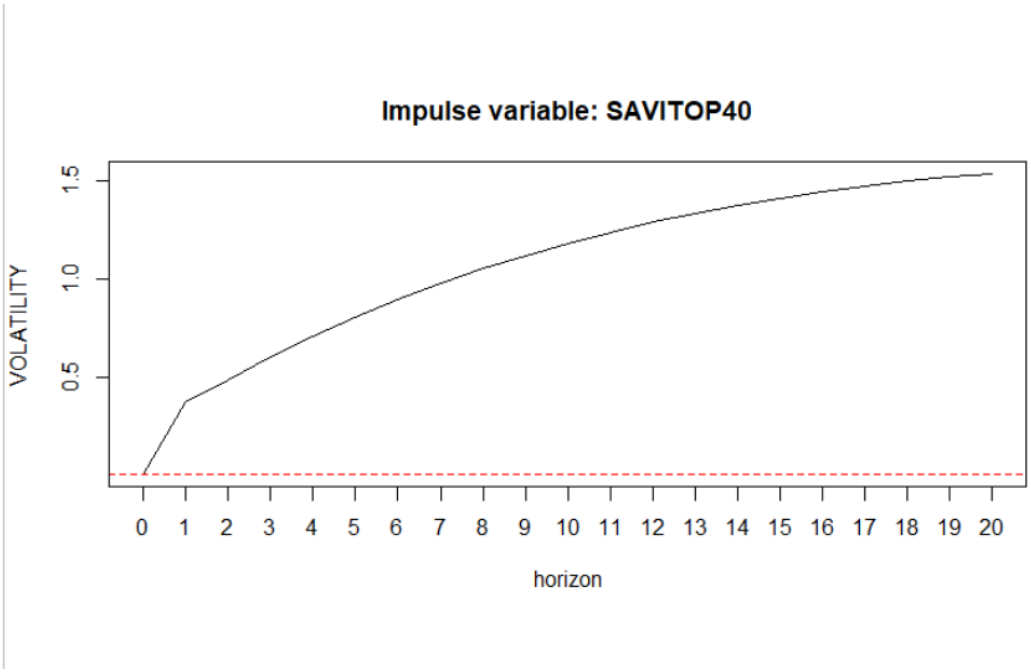


Figure 3.9.1: Time-varying Impulse Response Function of Volatility in South African white maize futures from a one-unit shock of the SAVI Top 40. The plots in each panel represent the mean time-varying impulse response function over every time period. It shows the response to the volatility of white maize futures by a one-unit shock in the SAVI Top 40

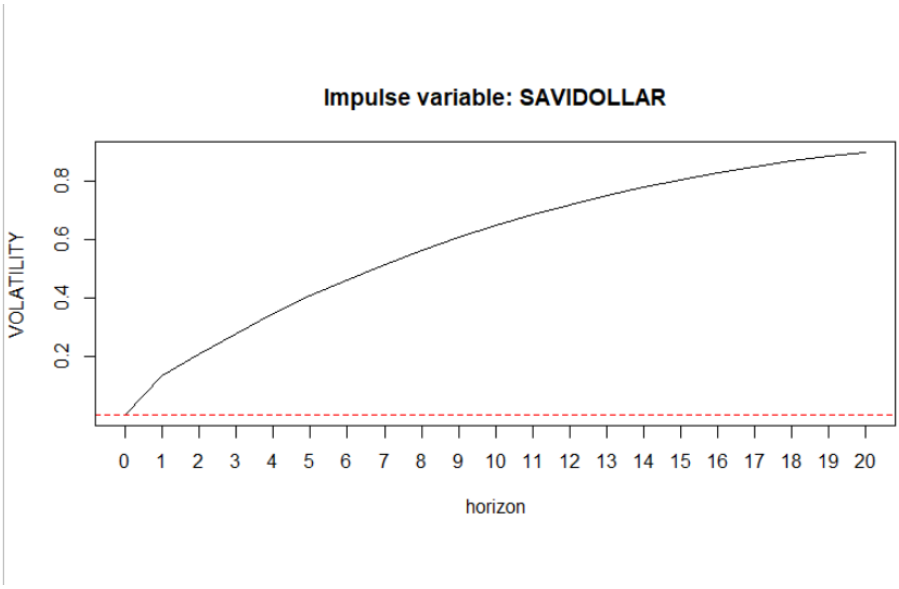


Figure 3.9.2: Time-varying Impulse Response Function of Volatility in South African white maize futures from a one-unit shock of the SAVI Dollar. The plots in each panel represent the mean time-varying impulse response function over every time period. It shows the response to the volatility of white maize futures by a one-unit shock in the SAVI Dollar.

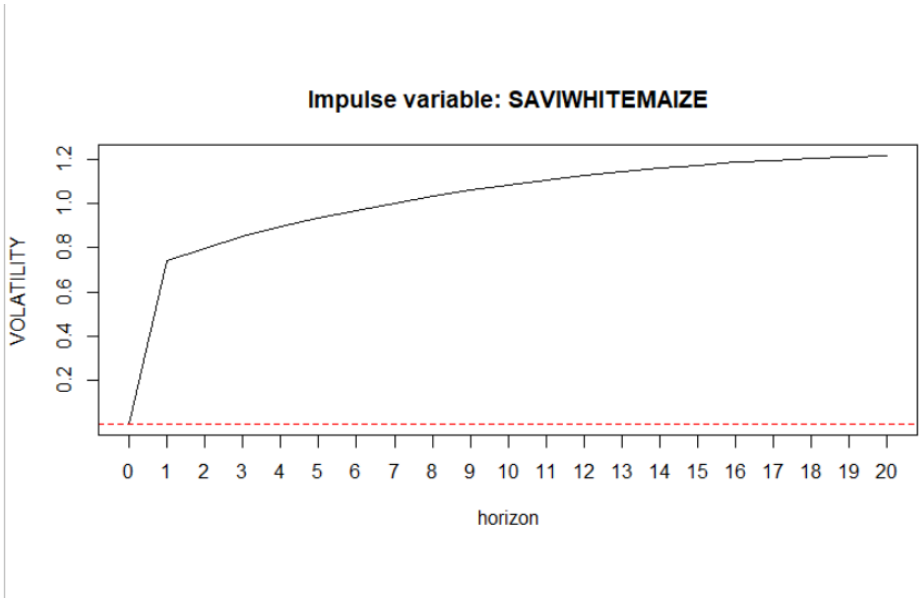


Figure 3.9.3: Time-varying Impulse Response Function of Volatility in South African white maize futures from a one-unit shock of the SAVI White Maize. The plots in each panel represent the mean time-varying impulse response function over every time period. It shows the response to the volatility of white maize futures by a one-unit shock in the SAVI White Maize.

3.6 Conclusion

The objective of this chapter was to examine the effects of uncertainty on investor expectations and price volatility in the South African white maize futures market. Using daily data over the period September 25, 2013, to December 31, 2019, the impact of uncertainty on momentum traders was investigated. Uncertainty was proxied by three volatility indices, the SAVI op 40, the SAVI Dollar and the SAVI White Maize. Investor expectations were proxied using three momentum indicators, the MACD histogram, the RSI and the ROC.

The SAVI Top 40 and SAVI Dollar were found to have negative effects of the expectations of momentum traders. Alternatively, the SAVI White maize was found to have positive effects. From the technical indicators used, the RSI was found to react the fastest to uncertainty shocks,

followed by the ROC and the MACD Histogram. Uncertainty shocks were found to have positive effects on the volatility of South African white maize futures, with SAVI White Maize having the largest positive reaction, followed by the SAVI Top 40 and SAVI Dollar. A dynamic VAR framework was employed which accounted for daily changes in the coefficients and variance-covariance matrix of the model.

The results of this chapter imply that traders update and alter their expectations during periods of uncertainty at the daily level. These findings are indicative of the importance of trading activity and behaviour in the determinants of price volatility in the South African white maize futures market. The results also have implications for policymakers regarding the regulations of agricultural futures and contributes to the body of knowledge concerning the long contested debate surrounding price (de)stabilisation by speculative trading. It is often argued that speculators are not only short-term traders but are also the most informed traders in the market. This is supported by Kang, Rouwenhorst and Tang (2014) who showed that speculators are short-term momentum traders and that their propensity to trade is higher than that of hedgers, who they argue trade like contrarians. Market sentiment indices like the VIX and SAVI can therefore be used by both hedgers and speculators to respectively forecast and pre-empt price changes in commodity futures markets. The results of this chapter also suggest that price volatility in the South African white maize futures market is not merely a result of changes in fundamental supply and demand factors. Instead, the behaviour and expectations of daily traders, who are arguably the speculators in the market, also contribute to changes in price volatility as they attempt to reconcile current changes in uncertainty with future price movements.

The findings of this chapter highlight the significance of white maize, particularly for practitioners who utilise technical analysis to guide their buy and sell decisions. The SAVI White Maize exhibited positive effects on the expectations of momentum traders. In contrast, the SAVI Dollar and the SAVI Top 40 had negative effects on the expectations of momentum traders. This suggests that traders should pay close attention to maize market dynamics and incorporate these into their trading strategies. .Strategies that account for uncertainty and adapt to changing market conditions may help mitigate risks and improve trading outcomes. The results of this chapter also observed the reactivity of various technical indicators to uncertainty shocks as captured by the SAVI indices. The Relative Strength Index was found to react most quickly, followed by the Rate of Change and the Moving Average Convergence Divergence histogram. Practitioners relying on technical analysis should be aware of these differences in reactivity and adjust their trading strategies accordingly. The results also emphasised the influence of trading activity as a determinant of price volatility in the South African white maize futures market. Traders therefore actively update and adjust their expectations during periods of uncertainty, which in turn affects market volatility. Policymakers and market participants should recognise the role of trading activity in shaping price dynamics and consider the measures that promote informed and efficient trading practices.

CHAPTER FOUR: SPECULATIVE RATIOS AND PRICE VOLATILITY IN THE SOUTH AFRICAN WHITE MAIZE FUTURES MARKET

Abstract of Chapter Four

This chapter examines the relationship between trading activity and price volatility in white maize futures listed on the South African Futures Exchange (SAFEX) and investigates the impact of speculative activity on price volatility. Price volatility is estimated using a GARCH(1,1) model. Trading activity changes are observed by computing two negatively correlated ratios from daily trading volume and open interest. The dynamic relationship between volatility and trading activity is explored over the period April 2000 to May 2022 using a vector autoregressive framework. This chapter examines not only the Granger-causality between speculative and hedging ratios against price volatility, but also assesses their interactions through variance decompositions and impulse response functions. The first ratio, of volume to open interest, is used to capture speculative market activity; and the second, a ratio of the change in open interest to volume, is used to reflect the activity of hedgers. The results shed light on the effectiveness of targeting speculators for regulation in grain futures markets, while also contributing to the veracity of price limits in effectively moderating volatility.

4.1 Introduction

Poverty and hunger remain the two largest developmental challenges of our time (Gassner *et al*., 2019), as global food insecurity intensifies owing to increases in human conflict, adverse climatic changes, and commodity price volatility. According to a 2020 Global Report on Food Crises, an estimated 135 million people suffer from acute hunger as a result of man-made conflict, economic downturns and climate change, with this number expected to double following the COVID-19 pandemic (Health, 2020). Furthermore, an increase of 60% in global food demand is expected by 2050, with maize output required to increase up to four-fold to meet food self-sufficiency by this date (Ten Berge, Hijbeek, Van Loon, Rurinda, Tesfaye, Zingore & van Ittersum, 2019). Maize production is therefore critical for food security with 85% of maize produced consumed in eastern and southern Africa (Lee, Davenport, Shukla, Husak Funk, Harrison & Verdin, 2022). Maize is also important to the renewable energy sector as it is used to produce biofuels like ethanol. It is estimate that up to 40% of corn production in the U.S. is used for ethanol, with several critics arguing that this trend will subsequently create shortages for other uses of maize such as livestock feed in the U.S. or in food supplies in other countries (Shultz, 2008).

Two varieties of maize are produced, with yellow maize predominantly used for livestock feed and biofuels like ethanol; and white maize reserved for human consumption, especially in Africa and Central America (Ranum *et al*., 2014). In South Africa, maize is not only the largest locally produced field crop, but is also the staple food for majority of the population with white maize consumption exceeding 4 million tons on average annually (Sayed & Auret, 2020). South Africa is also the main emerging market for price discovery of maize in Africa, with white maize being the largest and most traded futures contract listed on the South African Futures Exchange (SAEFX). SAFEX is also the only exchange globally where white maize

futures contracts are traded, as all other maize futures contracts relate to the yellow maize variety instead.

The volume of white maize futures contracts traded on SAFEX over the last 20 years has surpassed 16 million (Sayed & Auret, 2019). According to a report by the United States Department of Agriculture on World Agricultural Supply and Demand Estimates (USDA), South Africa (together, with the US, Argentina, Brazil, Russia and Ukraine) is one of the leading exporters of maize globally, with exports of 3.8 million metric tons (mmt) (USDA Wasde, 2022).

Futures markets provide a platform for price discovery and risk management and caters for two opposing types of market participants: hedgers and speculators. Hedgers are identified as the commercial participants in a futures contract and are often the farmers, food producers and end-users, with a sincere interest in trading the underlying asset. Speculators in contrast, are defined as non-commercial traders who, although are providers of critical market liquidity, are seen merely as day traders, participating predominantly to make a profit (Auret & Sayed, 2020). These definitions are supported by Kilian and Murphy (2014), who provide a simple economic definition of speculation which states that anyone purchasing a commodity not for current consumption but for future use is a speculator from an economic point of view. Common to all speculative purchases is that the long-position holder anticipates rising prices. Speculative buying involves either buying a commodity for physical storage or buying a futures contract and either strategy allows one to take a position on the expected change in the price of a commodity. Speculation defined in this manner reflects sound economic sense and is an important aspect of a functioning commodities market. Given the link between spot and futures markets and the implications that agricultural derivatives have on food security, it is broadly

accepted that futures markets should primarily serve and act in the best interests of the commercial end-users, i.e. the hedgers.

The role and impact of speculators has long been contested. One school of thought maintains that speculators are necessary as they provide the liquidity needed to hedge the risks of commercial traders (Berg, 2011). The other doctrine paints them as villains, responsible for the unprecedented levels of rising food prices and associating them with market manipulation and futures markets squeezes. The financialisation hypothesis accuses speculators of artificially driving up commodity prices beyond levels supported by market fundamentals, subsequently increasing price volatility (Haase *et al*., 2016). This financialisation and the rapid growth of commodity index fund investments observed between 2004 to 2008 resulted in a significant surge in open interest (Domanski & Heath, 2007). These open interest positions were predominantly held by speculators with no commercial interest to produce or consume commodities. Several non-governmental organizations (NGOs) therefore accused speculators of contributing to the 2007-2011 global food crises by gambling on food prices via commodity derivative instruments (Chadwick, 2018).

What followed was the implementation of several regulatory tools on futures exchanges, tasked with curbing the influence of speculators in commodity markets and on prices. As outlined by Berdell and Choi (2018), in the U.S., the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 directed the Commodity Futures Trading Commission (CFTC) to impose position limits that would prevent individual traders from holding more than a specified number of futures contracts at a time. This, in turn would prevent excessive speculation and market manipulation. Furthermore, price limits, that would constrain the range of price volatility allowed in a specific futures contract over a single trading day, were also

imposed. The CFTC argued that limits on the size of speculative positions in futures markets are necessary because they protect futures markets from excessive speculation that can cause unreasonable or unwarranted price fluctuations (NAMC, 2009).

While the impact of the financialisation of commodities was not as intricately examined in South Africa as it was in the U.S., South Africa, and its maize market in particular, also observed unprecedented price spikes that raised concerns. Many academics and practitioners argued that concentrated market participants were irresponsibly taking out large speculative positions in order to corner the market and drive futures prices away from fundamentals. In response, South Africa also imposed position and price limits on SAFEX. However this was initially only done for white maize futures given its importance as a regional supplier of maize and its price discovery mechanism. On the 1st of July 2003, the Johannesburg Stock Exchange (JSE) instituted position limits for speculative positions on SAFEX-traded white maize futures contracts in order to prevent individual market participants from cornering the market (NAMC, 2009). And on the 30th of November 2007, the JSE implemented price limits[2] for white maize futures in order to constrain market manipulation and curb excess-volatility linked to speculation (Sayed and Auret, 2018).

Several academics and market participants voiced their concerns that the implementation of these regulatory tools was premature and unnecessary. They argued that the global surge in food prices were a result of fundamental supply and demand factors and that these regulatory tools ran the risk of countering liquidity and destabilizing price discovery mechanisms. Boyd, Harris and Li (2018) review existing literature and found that commodity index trading seldomly leads to price distortions. Specifically, they reviewed studies concerned with the

[2] Price limits are a regulatory tool intended to control volatility in a financial market.

impact of financialisation and the role of speculators in recent years. They found that while speculation and financialisation can theoretically destabilise commodity markets, the existing literature finds little evidence of destabilisation. Instead, research has shown that speculators provide the liquidity necessary for hedgers to manage their risk.

A similar finding was echoed more recently by Borgards and Czudaj (2022) who contribute to the empirical literature on speculation in agricultural futures markets by investigating speculative price dynamics on the basis of investor sentiment. Sourcing open interest data from the CFTC reports, Borgads and Czudaj (2022) examined 12 agricultural commodities, including corn, for the period March 2006 to December 2020. They find that long-short speculators have valuable information which they use to exploit short-term price movements. They therefore reject the argument that speculators manipulate commodity prices, and instead show that long-short speculators represent the trader group with the clearest investment intentions, entering directional trades based on valuable information. Fan, Mo and Zhang (2022) also examined if the increased presence of speculators observed in recent years was responsible for destabilising commodity markets in China. They found no evidence that increased speculation had caused higher volatilities, raised cross-market correlations, or distorted the market's association with economic fundamentals.

In South Africa, Sayed and Auret (2018) investigated the efficacy of price limits in white maize futures contracts by testing four distinct hypotheses over the period March 2010 to December 2017. Testing the volatility spillover hypothesis, the authors found evidence that price limits resulted in heightened volatility on the trading days following limits. For the delayed price discovery hypothesis, the results showed that price limits prevented rational and informed trading which kept futures prices from efficiently reaching their equilibrium. The authors also

found support for the liquidity interference hypothesis, as a sharp reduction in trading volume was observed when limits were in effect, followed by an intense reversal once they were lifted. Finally, support for the gravitation or magnetic effect was found. This showed that the anticipation of an impending price limit caused prices to accelerate towards their limit prematurely, proving price limits to be self-fulfilling and disruptive to trading activity. Overall, price limits were found to be ineffective for white maize futures in curbing excess-volatility, and instead amplified volatility and impaired liquidity. In their conclusion, the authors recommended that the South African futures market adopt the weekly COT reports available in the U.S., as this split in open interest data would allow the necessity of price limits to be empirically investigated, an important pre-requisite to testing its effectiveness.

Much of the uncertainty surrounding the role of speculation and whether it destabilises futures markets can therefore be resolved by defining excess-speculation. Working (1953) was the first to note that speculation and hedging in commodity markets are intricately intertwined. He argued that speculation is limited to the overall hedging volume. Working (1953; 1960) proposed a speculative index to measure excess-speculation. His 'T' index is based on the notion that a certain number of speculative positions is needed to balance the hedging positions of commercial traders as their long and short positions might not exactly offset each other[3]. The index has a minimum value of 1.00 when the level of speculation equals hedging need and a value above 1.00 when speculative positions exceed those of commercial traders (hedgers) – an indication of excess-speculation. According to Working (1953) therefore, speculators correct imbalances in futures markets by providing critical market liquidity to complete the contracts of commercial traders. Speculative activity only becomes destructive when there is a

[3] $T = \left\{1 + \frac{SS}{(HL+HS)} \middle| \text{if } HS \geq HL\right\} \left\{1 + \frac{SL}{(HL+HS)} \middle| \text{if } HS < HL\right\}$, where HS (HL) are hedgers (commercial) short (long) positions and SS (SL) are speculators' (non-commercial) short (long) positions.

surplus of net long positions being held by non-commercial traders. This surplus creates artificial demand in the market and in so doing wrongly pushes up the price of the futures contract, simultaneously increasing the price of the underlying commodity. This was reiterated by Robles, Torerom and von Braun (2009), who argued that excess-speculation in commodity futures markets not only increases futures prices, but through arbitrage opportunities, also increases spot prices above levels justified by supply and demand fundamentals.

The necessary data source required to compute Working's T-Index, and thus excess-speculation, are the Commitment of Traders (COT) reports obtainable from the CFTC. These reports are available on a weekly basis and split open interest data into long and short commercial (hedging) positions as well as long short non-commercial (speculative) positions. To date, the split of open interest data on SAFEX into commercial and non-commercial participants remains unavailable. Given the absence of this data, alternative methods to measure excess-speculation is required. Speculative and hedging ratios that make use of trading activity variables, such as trading volume and open interest, have been put forward to address this gap. According to Bohl *et al.*,, (2018) the rationale behind these ratios lie in the assumption that hedgers hold their positions for longer periods, whereas speculators mainly try to avoid holding their positions over night and can therefore be assumed to be day traders.

The objective of this chapter is to measure speculative and hedging ratios for the South African white maize futures market, given the absence of COT reports, while also analysing its impact on price volatility. This chapter makes use of daily trading volume, open interest and closing price data for South African white maize futures contracts over the period April 2000 to May 2022. In addition to measuring speculative and hedging activity, this chapter also investigates the relationship between speculative ratios and price volatility using a vector autoregressive

(VAR) framework, which explores not only Granger-causality between the variables, but also assesses their interactions through variance decomposition and impulse response functions. According to Lütkepohl (1990), VAR models are standard tools for economic analyses. They allow one to trace the responses in a system to an innovation in one of the variables, while also decomposing the forecast error variance in order to investigate the interrelationships within the system.

While most studies often employ volume and open interest data to proxy for liquidity and market depth respectively, this chapter uses volume and open interest to estimate speculative and hedging trading activity. The daily trading volume used in this chapter accounts for the portion of trading activity that has taken place in a specific contract over a specific trading day, while the daily open interest determines the number of outstanding contracts at the end of a specific trading day. Drawing from the argument of Working (1960) that only excess-speculation is detrimental to futures price volatility, the speculative ratio in this chapter highlights the dominance of speculative activity beyond that required to fully offset hedging demand (i.e. relative to open interest).

According to a report by Oxfam in 2011, markets in agricultural derivatives were designed to make food markets work more efficiently; and when they do, stakeholders all along the food chain benefit, from farmers to food processors to consumers (Herman, Kelly & Nash, 2011). Several studies have questioned the effectiveness of regulating agricultural futures markets by constraining trading activity through price limits and position limits in order to reduce price volatility. Despite the impact that regulation in agricultural futures markets has on food security, there is a paucity of research in this area, especially in emerging commodity futures contracts, like South African white maize. This chapter, while contributing to this gap, also

highlights the need for commitment of trader reports in emerging futures exchanges. Access to this data is vital to empirically assess the efficiency of futures markets in the presence of new policies and regulations.

A significant relationship between speculative activity and price volatility in the South African white maize futures market would justify the imposition of circuit breakers in agricultural futures markets. However, if excess-speculation is found to have an immaterial role in the influence of price volatility in South African white maize futures, this questions the use of price and position limits and whether they hinder the efficient functioning of the very markets they are entrusted to serve.

4.2 Literature Review

The rationale behind using trading activity variables to estimate and separate hedging and speculation stems from the ability to distinguish between traders based on their intention to trade as well as their holding period. Carret (1930) suggests that motive is the best way to distinguish investment from speculation. He linked the investor to the economics of the business, and the speculator to the price, defining their motives as the purchase or sale of commodities in expectation of profit. Market participants that trade with the intention of making a profit with no commercial interest in the underlying commodity are therefore seen as the speculators; while hedgers are believed to trade with the intention of managing their risk as they have a sincere commercial interest in the underlying commodity. With regards to using contract holding periods to distinguish between trader types, hedgers are believed to hold their contract positions for more than one day while speculators are believed to be day traders. This theory is supported by Cornell (1981) and Garcia, Leuthold and Zapata (1986), who observed

data for major agricultural commodities traded on the Chicago Board of Trade (CBOT) and found daily volume to range between 20 to 30% of open interest, while the daily change in open interest was often not more than 1 to 2% of total open interest. This observation illustrates that while contracts have a high daily turnover, the number of contracts in existence remains relatively the same. Speculators being defined as short-term or day traders is further supported by Borgards and Czudaj (2022).

Investigating the dynamics between price volatility, volume and open interest in futures markets sheds light on the price effects of speculation and hence on market regulation. Trading volume has often been used as a proxy for speculative activity (Rutledge, 1979) and speculators /day-traders (Kumar & Pandey, 2010); while open interest is an important indicator of futures trading activity and has been used as a proxy for hedger's opinions (Kamara, 1993), hedging demand (Chen, Cuny & Haugen, 1995), market depth (Bessembinder & Seguin, 1993) and hedgers (Kumar & Pandey, 2010).

Rutledge (1979) was among the first to proxy for speculation using trading volume. He argued that changes in daily trading volume is largely a measure of variations in speculation, as hedgers' positions only make up a small proportion of daily trading volume. In his study on the relationship between volume and price variability, Rutledge examined 136 different futures contracts for 13 commodities during the mid-1970s using causality tests developed by Sims (1972). He also argued that evidence of causality running from trading volume to price variability (volatility) would strongly the support the need for tighter controls and regulation on speculative trading. Rutledge found that trading volume represented primarily a response to, rather than a cause of, movements in price variability.

Similar to Rutledge (1979), Garcia *et al.,,* (1986) examined the lead-lag relationships between trading volume and price variability (volatility) for selected futures contracts of corn, wheat, soybeans, soybean oil and soybean meal. Contrary to Rutledge, however, was the authors' use of alternative measures of price variability for volatility and trading volume. While Rutledge (1979) measured volatility as the absolute value of the percentage change in daily closing prices, and volume as the number of trades in a day; Garcia *et al.,,* (1986) proposed four different measures for volatility and two for volume. Measures of price variability included the change in daily closing prices, the percentage change in daily closing prices, the daily price change – taken as high minus low as well as an adjusted price range. For volume, the number of trades in a day was used as well as a ratio examining daily volume relative to the level of open interest. According to Garcia *et al.,,* (1986) the total volume of contracts traded daily relative to the size of open positions at the end of the day reflected the relative importance of speculative behaviour. Their results found neither a discernible pattern between trading volume and price variability, nor between lead-lags and price trends.

Ap Gwilym, Buckle and Evans (2002) modified the speculative ratio of Garcia *et al.,,* (1986) by examining daily volume relative to the absolute change in open interest. The authors argued that the daily change in open interest more accurately reflect the activity of hedgers than simply the level of open interest. This adjusted open interest is further supported by Lucia and Pardo (2010) who outline the drawbacks of the speculative ratio of Garcia *et al.,,* (1986). According to Lucia and Pardo (2010), trading volume is a flow variable measured over a specific period, for instance, a trading day; whereas open interest is a stock variable measured at the end of a trading day. The ratio therefore relates a flow variable that refers to a specific trading day to a stock variable measured at the end of that same trading day, making it inadequate for following the speculative activity of traders over time. Lucia and Pardo (2010) acknowledged that the

ratio by ap Gwilym *et al.,,* (2002) was able to discriminate between day trades (short-term speculation) reflected in daily trading volume. However, they also criticised the ratio's lack of ability to distinguish between those days when the newly taken positions that were held overnight outnumbered the liquidation of old positions. To this end, Lucia and Pardo (2010) defined an additional speculative ratio as the change in open interest to volume. A positive number here indicates that the number of opened positions is greater than the number of liquidated positions with a negative number indicating the opposite.

The two ratios predominantly employed in the literature to measure speculative and hedging activity remain the two developed by Garcia *et al.,,* (1986) and Lucia and Pardo (2010) respectively. For instance, Lucia, Mansanet-Bataller and Pardon (2015) made use of these two ratios when they examined December futures contracts from the European Climate Exchange (ECX) of the Intercontinental Exchange Group (ICE) with deliveries between 2005 and 2020. Using the two measures combining volume and open interest data, they explored the relative importance of speculative versus hedging activities in the European carbon market and found high degrees of speculative behaviour.

In addition, Bohl *et al.,,* (2018) analysed the impact of speculative activity, proxied by these same two speculation and hedging ratios, in order investigate whether speculative activity in Chinese futures markets for agricultural commodities destabilised futures returns over the period 2003 to 2017. Their results showed that the amount of speculative activity in relation to hedging activity contained information about changes in futures volatility. Specifically, they found short-term speculation to have a statistically significant and positive impact on returns volatility. Their results using the hedging ratio were inconclusive however and did not confirm in the majority of cases the findings of the speculative ratio.

While most studies to date have used these speculative and hedging ratios in the equity, energy and currency futures markets (predominantly in the United States), this chapter employs these measures in an emerging agricultural futures market, specifically, for South African white maize futures.

No study to date has investigated speculation in South African white maize futures, despite it being the most liquid contract traded on SAFEX, and despite SAFEX employing price and position limits in grain futures contracts to curb excess-speculation. This chapter therefore contributes to the literature by estimating speculative and hedging ratios for South African white maize futures, as well as by assessing its impact on price volatility.

4.3 Data

The objective of this chapter is to empirically investigate the impact of speculative activity, as proxied by trading activity variables, on price volatility in South African white maize futures contracts listed on SAFEX. Data is obtained from Bloomberg and daily closing prices for the active contract, quoted in Rands/ton, are used to estimate returns and volatility. Daily trading volume and open interest for South African white maize futures contracts are used to estimate the speculative and hedging ratios. As outlined by Bohl *et al.*,, (2018), to investigate the effects of speculative activity on volatility, empirical analyses should be conducted on data with at least a daily frequency. The sample period in this chapter runs from 18 April 2000 to 18 May 2022 with a total of 5 550 observations.

4.3.1 Defining speculative and hedging ratios

The speculative ratio uses trading volume and open interest data as defined by Garcia et al.,, (1986) measuring the relative dominance of speculative activity in a contract analysed in comparison to the hedging activity. This ratio, if multiplied by 100 is interpreted as a percentage per trading day and is undetermined when volume and open interest are equal to zero. This volume to open interest ratio can take any positive real number, including zero and is defined as:

$$SpecRatio_t = \frac{TV_t}{OI_t} \quad , \tag{1}$$

The hedge ratio based on the different trading behaviour of speculators and hedgers is defined by Lucia and Pardo (2010). This ratio differs from the one above in equation (1) as it is a hedging ratio which gauges the relative dominance of hedging activity relative to speculative activity. This ratio is dimensionless with a positive number indicating that the number of open positions is greater than the number of liquidated positions, a negative number indicating that the number of liquidated positions is greater than the number of open positions and a number of zero indicating that the total number of open and closed positions are equal. Palao and Pardo (2012) further elaborate that a hedge ratio with a value close to either one or minus one indicates low speculative activity, while a value close to zero indicates relatively high speculative activity. The ratio is calculated as the daily change in open interest to daily trading volume and is defined as:

$$HedgeRatio_t = \frac{(OI_t - OI_{t-1})}{TV_t} \tag{2}$$

In each of the two ratios defined above, TV_t represents the trading volume for day *t* which captures all trades for a particular day executed during a specified trading day; and OI_t represents open interest for day *t* which describes all positions of that contract neither equalised

by an opposite futures positions nor fulfilled by the physical delivery of the commodity or by cash settlement.

4.3.2 Estimating volatility

Given the volatility clustering observed in Figure 4.2, which plots the daily returns from South African white maize futures closing prices; as well as the mean and median returns of 0 observed in Table 4.1, this chapter employs the GARCH model of Bollerslev (1986), similar to Chapter Three. Excess kurtosis is also observed in the returns as can be seen from Table 4.1, indicating that returns for South African white maize futures may be prone to extreme values on either side as its distribution is leptokurtic. To this end, a student's t-distribution was used when estimating the model. Similar to Chapter Three, the volatility of South African white maize futures is modelled as:

$$r_t = \sigma_t \epsilon_t, \tag{3}$$

where σ_t is the time-varying volatility and ϵ_t is an *i.i.d.* random error that is independent of $\sigma_{t..}$ A GARCH (1,1) model with the following conventional parameter restrictions are fitted to model $\sigma_{t.}$:

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{4}$$

Volatility in South African white maize futures contracts is measured using the fitted time-series of the standard deviation from this model and is plotted in Figure 4.3.

4.3.3 Preliminary data analysis

Table 4.1 displays descriptive statistics for the closing prices, returns, volatility estimated in equation (3), trading volume, open interest, the speculative ratio, estimated in equation (1) and, the hedging ratio, estimated in equation (2). The mean and median values for open interest are both higher than for trading volume at 8 051 and 6 153 respectively versus 1 402 and 1 0 67.

The mean closing price for South African white maize futures is shown as R2 020/ton with the maximum reaching R5 296/ton. Figure 4.1 plots the daily closing prices of South African white maize futures over the full sample period and shows that the maximum high values occurred over the 2014 – 2016 period. According to Walt (2016) the South African agricultural sector was burdened with the worst drought recorded in 104 years between 2014 and 2016. Furthermore, Sayed and Auret (2018) found that this period was also characterised by a high frequency of price limit hits in South African white maize futures contracts which is documented in detail in Chapter Two.

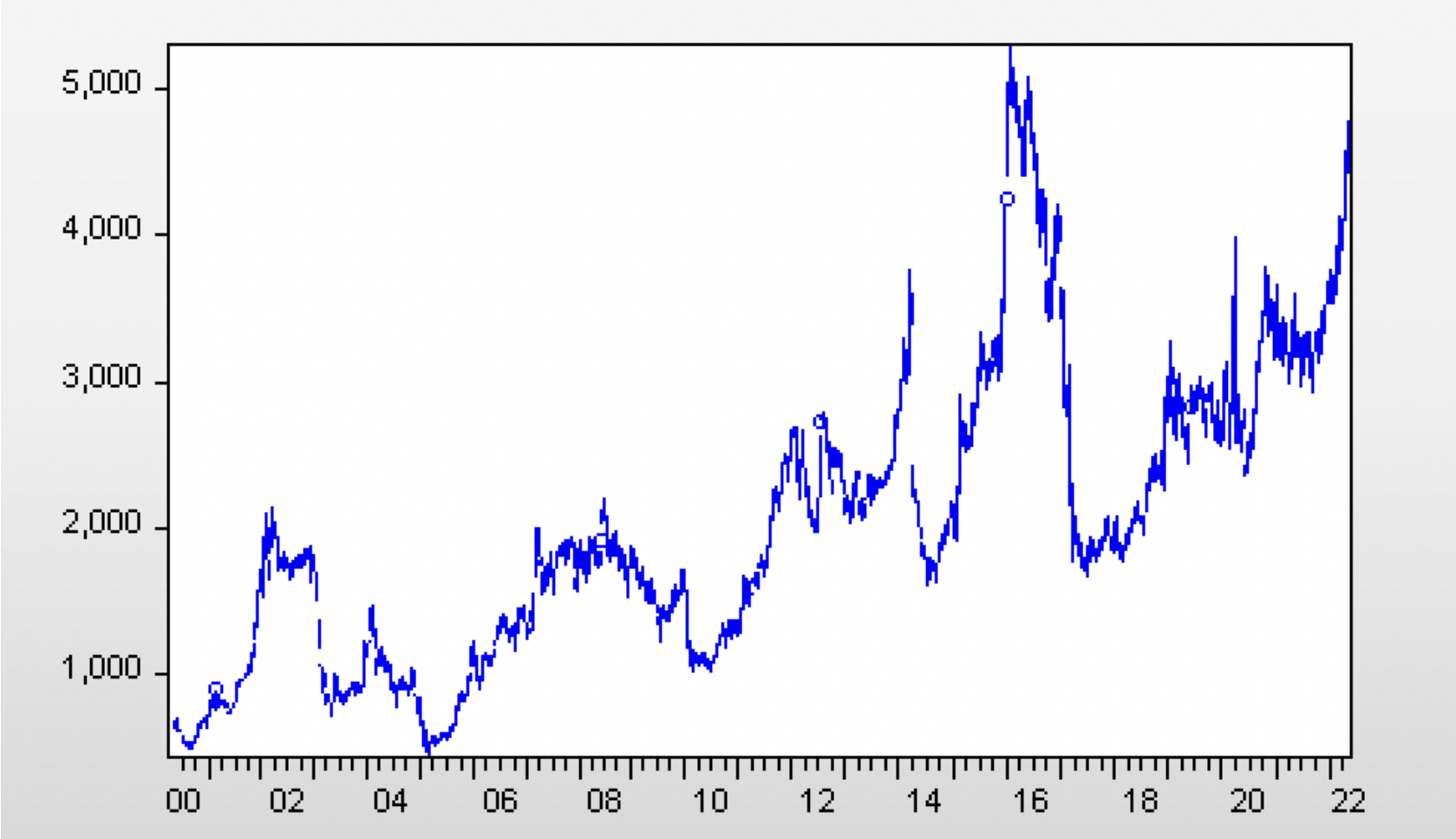


Figure 4.1 South African White Maize Futures Daily Closing Prices

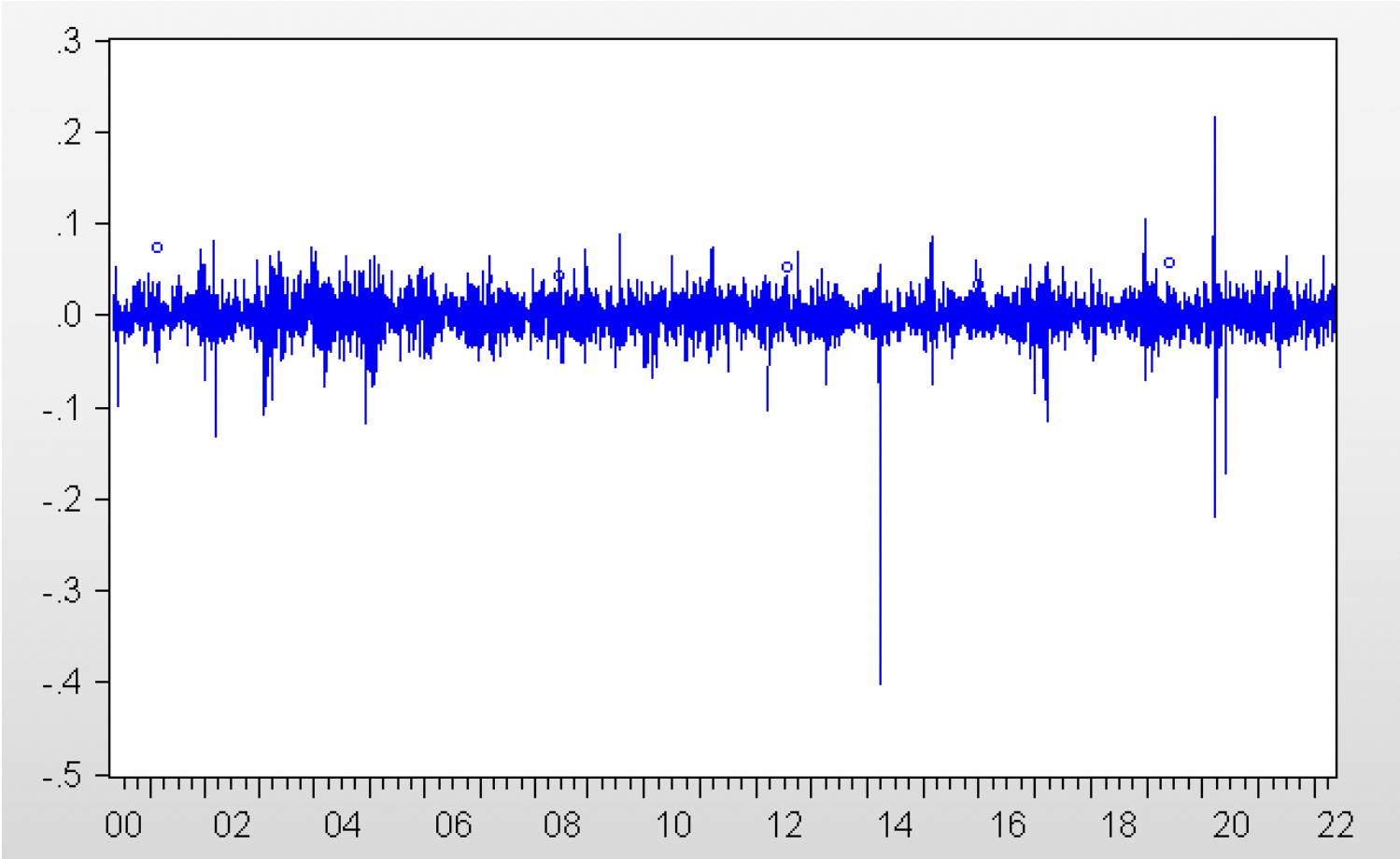


Figure 4.2 Daily Returns for South African White Maize Futures

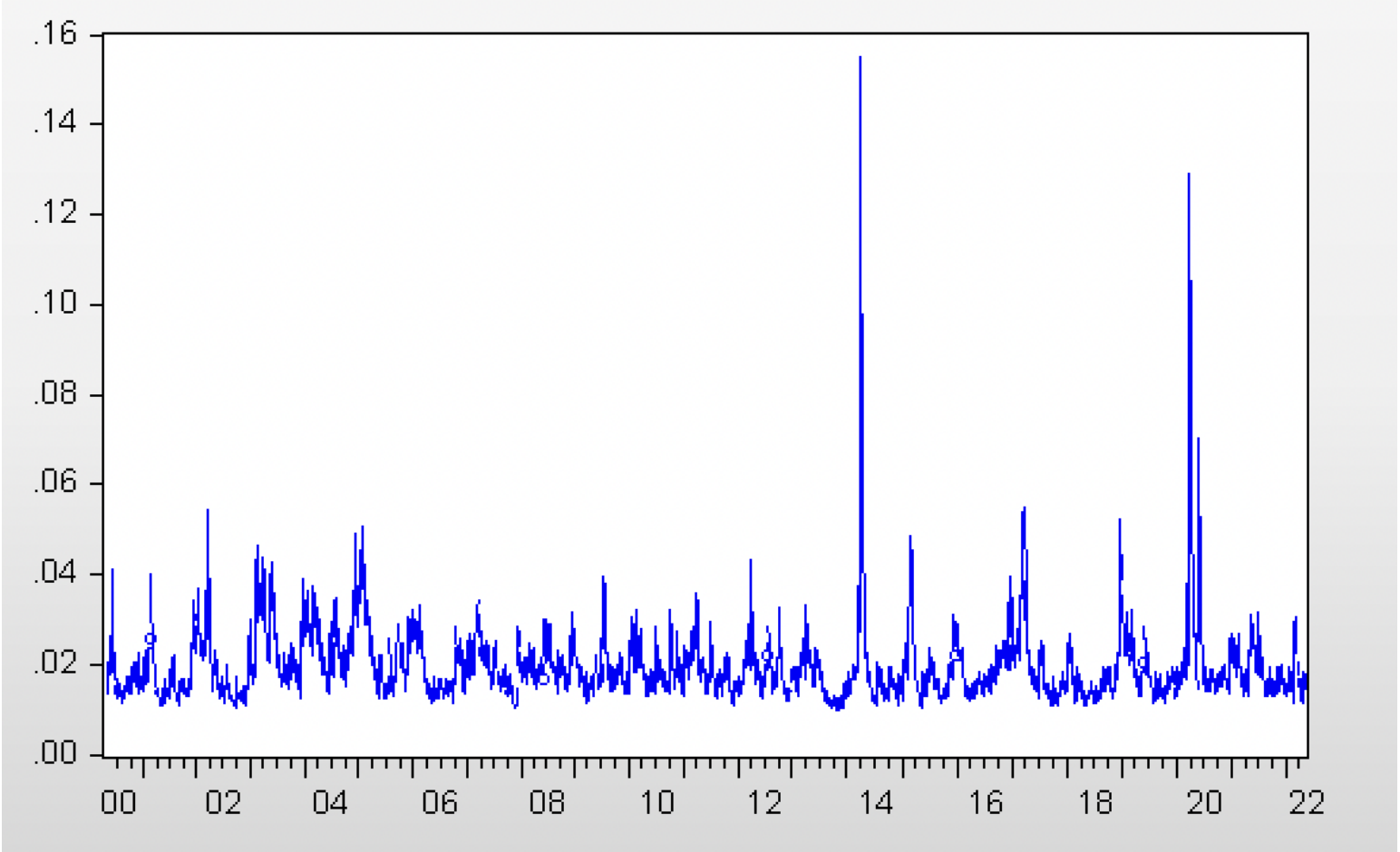


Figure 4.3 Volatility in the South African White Maize Futures Market

Table 4.1- Descriptive Statistics									
Variable	**Obs**	**Mean**	**Median**	**Max**	**Min**	**Std. dev.**	**Skewness**	**Kurtosis**	**Jarque-Bera**
Closing Price	5 550	2020.54	1853.50	5296.00	471.00	979.76	0.744	3.292	531.265***
Returns	5 550	0.00	0.00	0.22	-0.40	0.02	-1.765	37.821	283273.3***
Volatility	5 550	0.02	0.02	0.16	0.00	0.00	5.245	55.927	673244.4***
Trading Volume	5 550	1402.30	1067.00	23207.00	2.00	1289.00	3.776	41.200	350645.6***
Open Interest	5 550	8051.94	6153.50	24684.00	50.00	6295.257	0.522	1.993	487.624***
Spec. Ratio	5 550	0.322	0.168	7.550	0.00	0.711	23.783	998.416	0.000***
Hedge Ratio	5 550	-0.124	-0.08	1.00	-1.00	0.221	-0,606	5.328	1593.413***
Note: *** denotes significance at 1%.									

Table 4. 1 also shows that the mean, median and standard deviation of returns is zero. The daily mean and median of volatility is 2%, reaching a maximum of 16% in March 2014, when the effects of the drought at the time became apparent and increased volatility.

The speculative ratio is computed from equation 1 and measures the relative dominance of speculative activity relative to hedging activity, i.e., the excess-speculation in the South African white maize futures market. This ratio if multiplied by 100 can be interpreted as a percentage per trading day. Table 4.1 shows the mean and median of this ratio as 0.322 and 0.168 respectively. This illustrates that there is a positive presence of excess-speculation in the South African white maize futures market with a daily average of 32.2% of speculative activity relative to hedging activity. This can also be seen visually in Figure 4.4, which plots the speculative ratio.

The hedge ratio, although dimensionless, indicates low speculative activity for values close to either one or minus one and high speculative activity for values close to zero. Table 1 shows the mean hedge ratio as -0.124, with a median of -.08, implying high speculative activity as well. This ratio is plotted in Figure 4.5.

The preliminary analysis of the speculative and hedge ratios confirm a high speculative activity over the sample period and assert that excess-speculation is present in the South African white maize future market. Whether or not this excess-speculation can significantly explain or affect price volatility can only be confirmed through the vector autoregressive (VAR) methodology presented next.

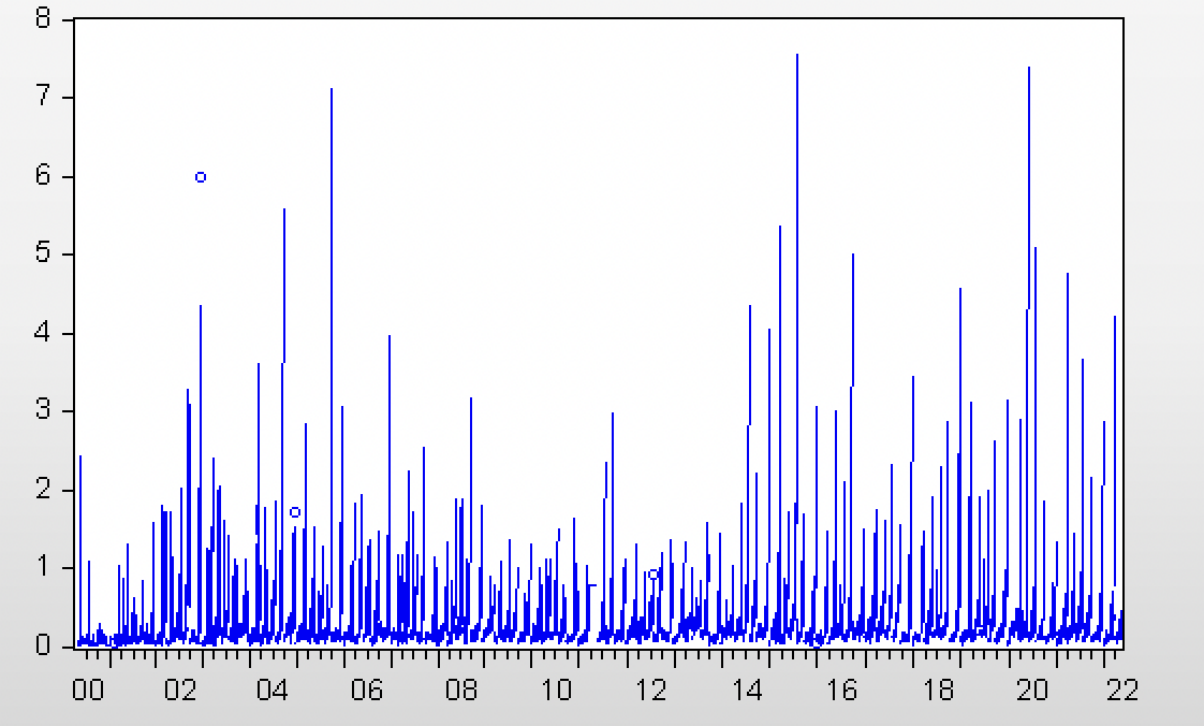


Figure 4.4 Speculative Ratio

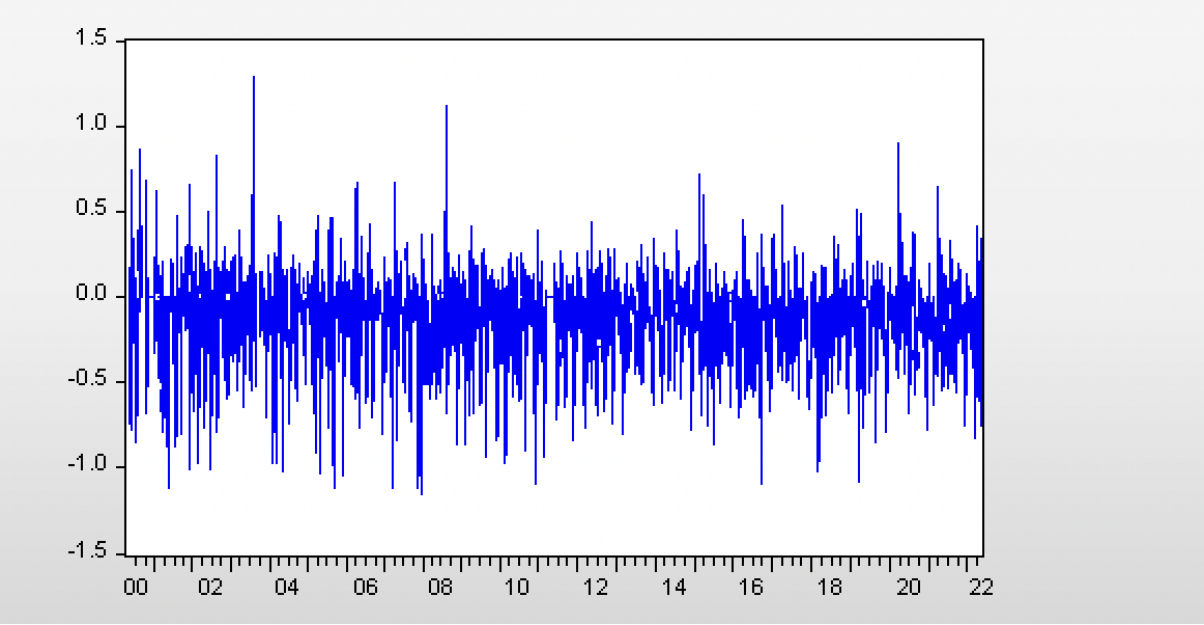


Figure 4.5 Hedging Ratio

4.4 Methodology

Assessing lead-lag relationships between speculative activity and price volatility helps clarify whether excess-speculation is driving volatility, or if instead amplified volatility is attracting and increasing speculative trading activity in the South African white maize futures market. Similar to Bohl *et al.*,, (2018), the dynamic relationship between price volatility and trading activity is investigated using the following vector autoregressive framework (VAR) framework:

$$\sigma_t^2 = a_{1,t} + \sum_{i=1}^{k} b_{1,t}\ \sigma^2{}_{t-i} + \sum_{i=1}^{k} c_{1,t}\ \mathrm{Ratio}^{\mathrm{Spec,Hedge}}{}_{t-i} + \varepsilon_t \quad (5)$$

$$\mathrm{Ratio}_t^{\mathrm{Spec,Hedge}} = a_{2,t} + \sum_{i=1}^{k} b_{2,t}\ \sigma^2{}_{t-i} + \sum_{i=1}^{k} c_{2,t}\ \mathrm{Ratio}^{\mathrm{Spec,Hedge}}{}_{t-i} + \vartheta_t, \quad (6)$$

where σ_t^2 is the estimate of volatility described in equation (4) above, $Ratio_t^{Spec}$ is the speculative ratio from equation (1) and, $Ratio_t^{Hedge}$ is the hedge ratio from equation (2). The residuals of the regression, which are assumed to be mutually independent and individually i.i.d. with zero mean and constant variance, are represented by ε_t and ϑ_t. The VAR framework is often used for forecasting systems of interrelated time-series as well as to assess the dynamic impact of random disturbances on the system of variables. Each of these variables are dependent on their own lagged values as well as on the lagged values of the corresponding variable.

This chapter examines lead-lag relationships through Granger (1969) causality tests, and through forecast error variance decompositions. According to Sims (1972, 1980), the statistical significance of economic variables as determined through Granger causality tests is not exhaustive, and should therefore be complemented with a generalised impulse response

analysis and forecast error variance decomposition. Sims (1980) argues that this produces additional insights beyond the Granger-causality tests, such as, the direction of the causal relationship as well as the strength of the causal relationship. Impulse response functions and variance decompositions are therefore also estimated and analysed.

Pesaran and Shin (1998) propose a generalized impulse response analysis and generalized forecast error variance decomposition (GFEVD) technique for unrestricted and cointegrated VAR models. Their revised technique does not require orthogonalisation of shocks and is invariant to the ordering of the variables in the VAR making it superior in exploring the interrelationships between economic variables like the ones defined in equations (1), (2) and (4).

Similar to Yang, Balyeat and Leatham (2005), let Z_t represent a vector including several economic variables. The vector Z_t can then be modelled as an infinite moving average process, such that:

$$Z_t = \sum_{i=0}^{\infty} C_i \varepsilon_{t-i}, t = 1,2, \dots, T \tag{7}$$

The GFEVD for the vector can then be defined as:

$$\theta_{ij}(n) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{n} \left(e_i' C_l \Sigma e_j\right)^2}{\sum_{l=0}^{n} \left(e_i' C_l \Sigma C_l' e_i\right)}, i, j = 1,2, \dots, m, \tag{8}$$

and reveals to what degree variation in a certain variable can be explained by shocks or innovations from other variables in the same system, thereby quantifying the relative importance one variable has in influencing another variable. In this chapter, the relative importance of speculative activity on returns volatility is assessed.

4.4.1 VAR estimation

The first step in specifying a VAR model is to choose the appropriate lag length. This chapter evaluates five different criteria in this regard, namely, Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and Hannan-Quinn Information Criteria (HQ) to determine the optimum lag lengths for the VAR model. The optimum lag length was determined by minimising the Schwarz Information Criteria (SIC). As daily data is used, the maximum lag length was set at 20 to represent a maximum of four trading weeks. The results for the optimal lag lengths of the VAR models for at least 10 lags are shown in Table 4.2. For both VAR frameworks, estimated in equation (6), i.e. volatility and the speculative ratio, and volatility and the hedge ratio, the optimum lag length was 3. To cater for the presence of residual serial correlation, Lagrange Multiplier (LM) tests are also conducted for a maximum of 3 lags. These results are displayed in Table 4.3. The VAR model for volatility and the speculative ratio shows no presence of serial correlation, while the VAR model for volatility and the hedge ratio shows no serial correlation at 3 lags.

4.4.2 Unit root tests

Granger-causality tests require that the variables used are stationary. As a pre-requisite therefore, unit-root tests are carried out in order to determine the order of integration. The augmented Dickey-Fuller (ADF) (1979) tests are conducted on the levels of the data in order to test the null hypothesis that a time-series, y_t has a unit root (is integrated of order 1) against the alternative hypothesis that it is I(0) or stationary. These results are displayed in Table 4.3,

and confirm that each series concerned (volatility, the speculative ratio and the hedge ratio) are stationary at the 1% level of significance.

Table 4.2 – VAR estimation

VAR estimation for model with Volatility and Spec. Ratio

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	12527.77	NA	3.70e-05	- 4.530114	-4.527721	4.529280
1	18886.59	12710.74	3.71e-06	- 6.828422	-6.821242	6.825918
2	19008.62	243.8374	3.56e-06	- 6.871109	-6.849142	6.866936*
3	19014.00	10.74676	3.56e-06	- 6.870608	-6.854854*	6.865766
4	19015.43	2.863364	3.55e-06*	- 6.871680*	-6.849139	6.863169
5	19018.71	6.548040	3.56e-06	- 6.870420	-6.844092	6.861239
6	19024.11	10.77159	3.560-06	- 6.870926	-6.839810	6.860076
7	19026.81	5.381897	3.56e-06	- 6.870455	-6.834553	6.857936
8	19029.22	4.812759	3.56e-06	- 6.869881	-6.829192	6.855693
9	19031.04	3.616286	3.560-06	- 6.869091	-6.823615	6.853233
10	19032.35	2.615874	3.57e-06	- 6.868119	-6.817856	6.850592

VAR estimation for model with Volatility and Hedge Ratio

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	19048.04	NA	3.54e-06	-6.875827	-6.873437	-6.874994
1	25538.56	12974.02	3.40e-07	-9.217532	-9.210363	-9.215032
2	25671.33	265.2957	3.25e-07	-9.264019	-9.252070	-9.259852
3	25729.25	115.6864	3.19e-07	-9.283483	-9.266754*	-9.277650
4	25742.80	27.06680	3.180-07	-9.286933	-9.265424	-9.279433*
5	25748.72	11.81578	3.17e-07	-9.287627	-9.261338	-9.278460
6	25760.00	22.50189*	3.16e-07*	-9.290253*	-9.259185	-9.279421
7	25763.54	7.065668	3.17e-07	-9.290088	-9.254241	-9.277589
8	25765.64	4.183680	3.17e-07	-9.289401	-9.248775	-9.275236
9	25768.32	5.341250	3.17e-07	-9.288925	-9.243518	-9.273093
10	25769.34	2.026750	3.178-07	-9.287848	-9.237662	-9.270349

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Source: Authors' calculation from research data

Table 4.3 – LM residual serial correlation tests

VAR model for Volatility and Spec. Ratio

Lags	**LM-Stat**	**Prob.**
1	2.61811	0.6236
2	2.817931	0.5887
3	4.663452	0.3236

VAR model for Volatility and Hedge Ratio

Lags	**LM-Stat**	**Prob.**
1	24.70611	0.0001
2	36.17377	0.0000
3	50.33682	0.1704

Table 4.4 – Unit Root Tests

	ADF tests with constant (level)	ADF tests with constant & trend
Volatility	-13.6082***	-13.6315***
Spec. Ratio	-36.7449***	-36.7545***
Hedge Ratio	-20.4112***	-20.9610***

Note: *** denotes significance at 1%.

4.4.3 Granger-causality tests

Granger-causality tests are used to test the lead-lag relationships between price volatility and the speculative and hedge ratios. Granger (1969) proposed a time-series based approach where *x* is a cause of *y* a cause of *y* if adding lagged valued of *x* improves the explanation of *y*. According to Gelper and Croux (2007) a time-series is said to Granger-cause another series if it has incremental predictive power when forecasting it. This test will therefore determine if speculative activity (in excess of hedging demand) causes price volatility in a forecasting sense. Granger-causality estimates a standard F-test and the null hypothesis is that the speculative ratio does not Granger-cause price volatility, and *vice versa* The hypothesis is rejected if coefficients of the lagged values are jointly significantly different from zero.

4.4.4 Variance decomposition

The variance decomposition is the next test that assists in interpreting the VAR model and is a widely used method for examining the relative effects of variables (Kim & Patel, 2017). Lütkepohl (2010) defines variance decomposition as a classical statistical method in multivariate analysis that uncovers relationships among a large set of variables. He further asserts that forecast error variance decomposition is effective for interpreting the relationships between variables described in VAR models. Variance decomposition measures the percentage of the forecast error of one endogenous variable that is explained by other variables, and is used to assess the relative importance of the speculative ratio and hedge ratio on price volatility.

4.4.5 Impulse response functions

Finally, impulse response functions are examined to test whether the causal relationships are positive or negative and to examine the interactions between the variables in the VAR system. This test simulates the impact of a shock to one variable in the system on the conditional forecast of another variable (Kumar & Pandey, 2010). Sims (1972, 1980) encourages the use of variance decomposition and impulse response functions to compliment the Granger-causality test, as he argues that it may be misleading to depend solely on the statistical significance of economic variables determined by Granger-causality. According to Pesaran & Shin (1998), an impulse response function measures the time profile effect of shocks at a given point in time on the (expected) futures values of variables in the system. They describe an impulse response as the outcome of a conceptual experiment in which the time profile of the effect of a hypothetical shock is compared with a base-line profile. Impulse response functions are therefore used to analyse the impact of a change in one variable (price volatility/speculative or hedge ratio) on another variable (speculative or hedge ratio/ price volatility).

4.5 Results

4.5.1 Granger-causality test results

Table 4.5 presents the results of the Granger-causality tests. Significant unidirectional causality, at the 1% level, is found from the speculative ratio to volatility. Therefore one can argue that the excess-speculation from trading activity does indeed affect volatility in the South African white maize futures market. Significant bidirectional, or feedback causality, is found between the hedge ratio and volatility.

4.5.2 Variance decomposition results

The variance decomposition results in Table 4.6 reiterate the independence of the speculative ratio relative to volatility that was observed with Granger-causality. Specifically, it shows that variations in the speculative ratio are produced almost entirely by its own lagged values, with volatility having at most a 0.07% role. Volatility on the other hand, has almost 3% of its forecast error variance explained by an exogenous shock in the speculative ratio. The variance of the hedge ratio is also almost entirely independent of volatility as can be seen in Table 4.4. At most, volatility explains 0.77% of its variance. The hedge ratio on the other hand, explains up to 0.34% of volatility's variance, which once again reiterates the results of the Granger-causality test, that the hedge ratio does indeed impact volatility.

Table 4.5 - Granger-causality tests

Null hypothesis	Obs.	Lags	F-Statistic	p-value
SpecRatio does not Granger-cause Volatility	5547	3	13.5060***	0.0000
Volatility does not Granger-cause SpecRatio			1.2869	0.2770
HedgeRatio does not Granger-cause Volatility	5547	3	2.0929 *	0.0989
Volatility does not Granger-cause HedgeRatio			5.4685***	0.0009

Note: F-Statistics for the Granger-causality tests for each variable within each of the VAR models is presented. The lag lengths are based on SIC. * denotes statistical significance at the 10% level. *** denotes statistical significance at the 1% level.

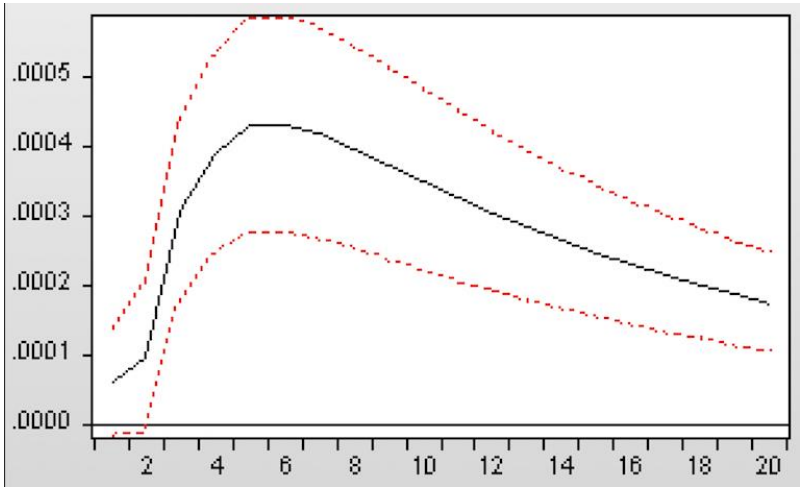
Table 4.6 - Variance Decomposition							
Explanatory variable	**Day**	**Speculative Ratio**	**Volatility**	**Explanatory variable**	**Day**	**Hedge Ratio**	**Volatility**
Volatility	1	0.05	99.95	Volatility	1	0.03	99.97
	5	1.25	98.75		5	0.05	99.95
	10	2.25	97.75		10	0.20	99.80
	15	2.57	97.43		15	0.30	99.70
	20	2.69	97.31		20	0.34	99.66
Speculative Ratio	1	100.00	0.00	Hedge Ratio	1	100.00	0.00
	5	99.96	0.04		5	99.76	0.24
	10	99.95	0.05		10	99.50	0.50
	15	99.94	0.06		15	99.32	0.68
	20	99.93	0.07		20	99.23	0.77

4.5.3 Impulse Response Function results

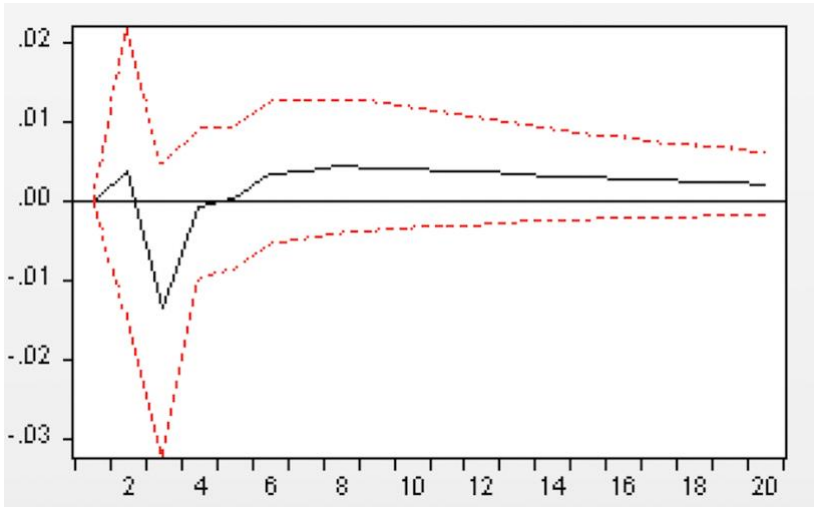
To confirm whether the causal relationships from the Granger-causality tests are positive or negative, the impulse response functions are examined next. These can be seen in Figures 4.6 and 4.7. Shocks are defined as one standard deviation and are regarded over a period of 20 trading days. From the top left graph of Figure 4.6 it is clear that a simulated shock in the speculative ratio has a positive and significant impact on volatility that persists for the full trading month. It should be noted however, that this impact, although positive, is quite small. A shock in volatility however does not have a significant impact on the speculative ratio, once again, reinforcing the results from the Granger-causality test. The response of volatility and the speculative ratio to innovations on itself are also positive and significant and in the case of volatility, persists for the full trading month.

Finally, figure 4.7 illustrates the impulse response functions of the VAR framework for the hedge ratio and volatility. The response of volatility to a shock in the hedge ratio is negligibly different from zero and not significant; while the response of the hedge ratio to an innovation in volatility is slightly positive and only significant for the first 2 days. Similarly, to the VAR framework for the speculative ratio and volatility, own innovations in volatility and the hedge ratio yield larger and more significant responses. It is clear therefore that most of the volatility observed in South African white maize futures is explained by its own lagged values, and that speculative activity in this market has a negligible, although positive and significant, impact.

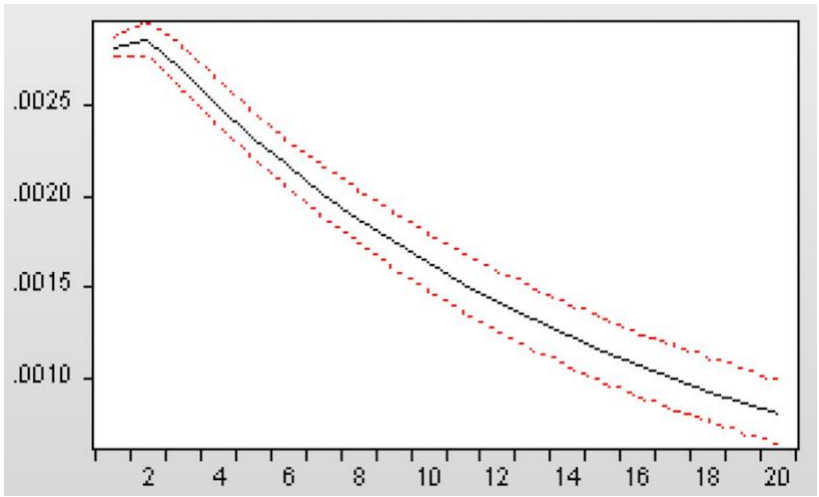
Response of Volatility to the Speculative Ratio



Response of the Speculative Ratio to Volatility



Response of Volatility to Volatility



Response of Speculative Ratio to Speculative Ratio

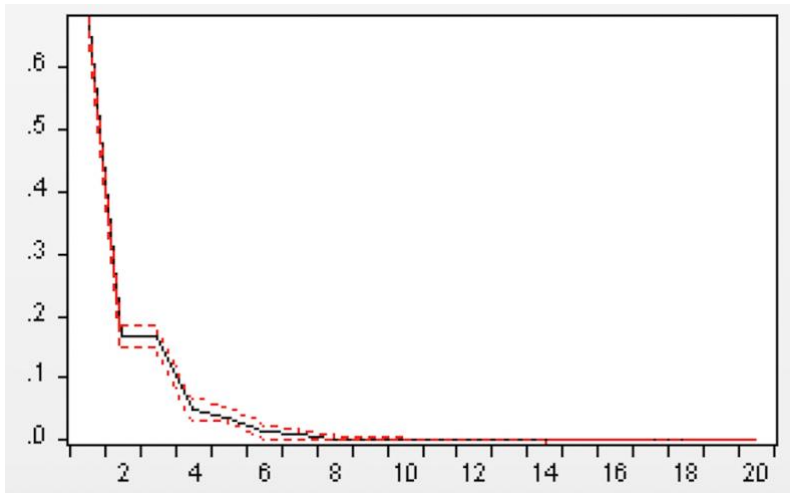


Figure 4.6 Impulse Response Functions (Speculative ratio and Volatility)

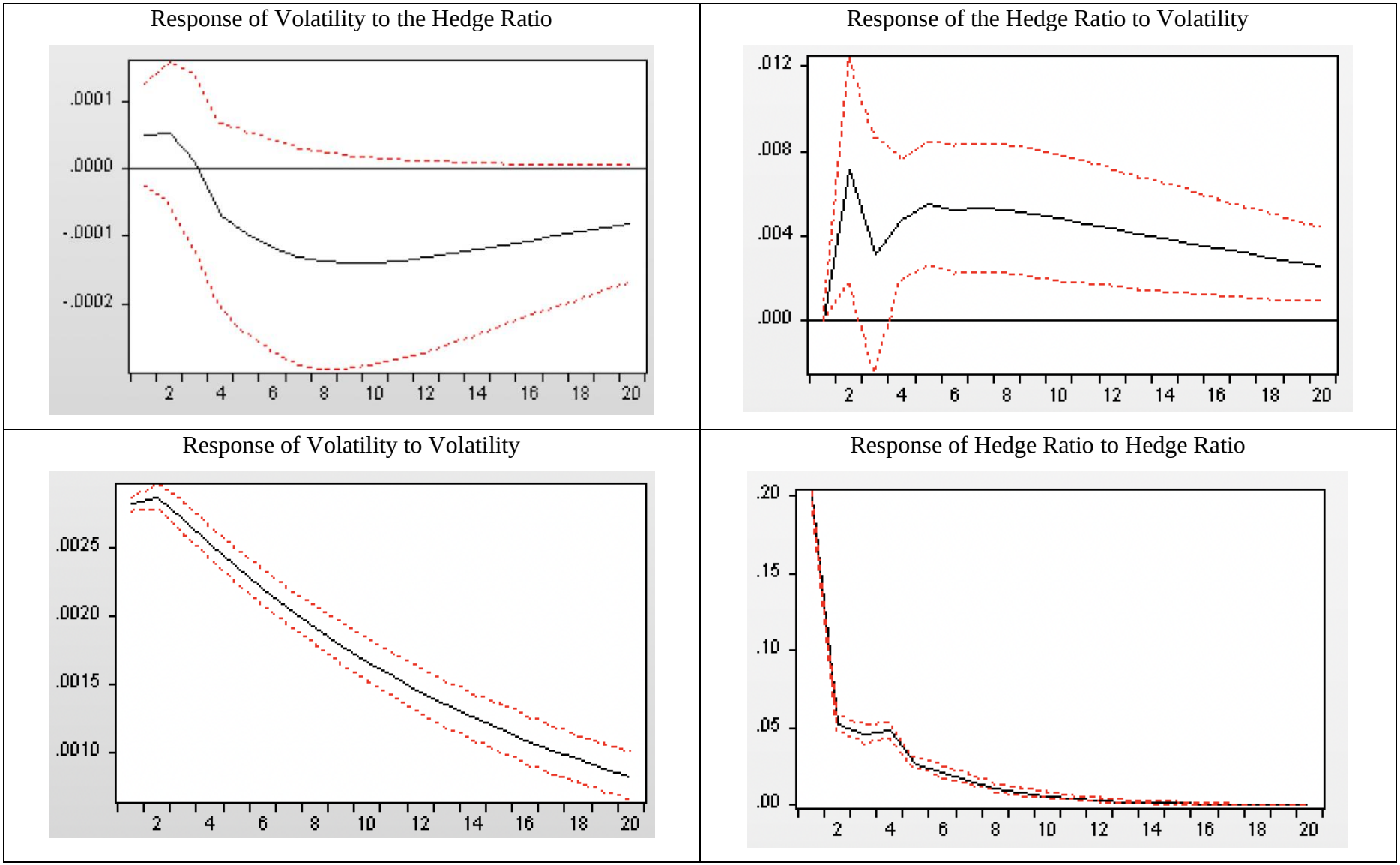


Figure 4.7 Impulse Response Functions (Hedge Ratio and Volatility)

4.6 Discussion of Results

Prior to the VAR analysis employed in this chapter, speculative and hedging ratios were computed to assess the overall level of speculative activity present in the South African white maize futures market. The mean of the speculative ratio reported in Table 4.1 was 0.322, representing a daily average of 32.2% of excess-speculation present in the South African white maize futures market. By comparison, Bohl et al.,, (2018) reported a mean of 0.48 on their speculative ratio for corn futures traded on the Dalian Commodity Exchange (DCE). Therefore, while still considerably high, the average daily level of excess-speculation in maize futures listed on SAFEX is smaller when compared with the level observed corn futures listed on DCE. Bohl et al.,, (2018) assert that Chinese agriculture futures markets are among the most fast paced and rapidly developing markets in the world, with trading behaviour discerned as highly speculative. The findings from this chapter therefore add to the argument that emerging agricultural futures markets exhibit high levels of speculative trading activity.

Earlier studies that proxy for speculation and hedging in futures markets, used trading volume and open interest alone, respectively (Rutledge (1979); Chen et al.,, (1995); Kumar and Pandey (2010)). The speculative ratio in this chapter however, measures the residual speculation in excess of that necessary to meet hedging demand. This chapter therefore does not test if all speculation is detrimental, but instead if excessive speculation influences price volatility. This distinction is important to reiterate when comparing the results of this chapter to the results of similar studies. The Granger-causality and impulse response function results confirm unidirectional causality from the speculative ratio to price volatility in SAFEX-traded white maize futures. These results contribute to the arguments of Working (1953) and Robles et al.,, (2009), who assert that only speculation in excess of hedging demand contributes to heightened

volatility. Speculators therefore remain an intrinsic part of futures markets necessary to maintain liquidity and efficiency.

In addition to contributing to the risk management function of futures markets, these results also contribute to their price discovery function. When futures speculation is accused of destabilising prices, the concern typically regards the spot price volatility of the underlying commodity. The spot and futures price are related together in what is known as the cost-of-carry model, which states that buying in the future at a price agreed upon today must be equivalent to buying at the current price and storing (carrying) the underlying asset until a future date (Dimpfl, Flad & Jung, 2017). In reviewing the examination of futures and spot prices, Tonin, Viera, de Sousa Fragoso and Martines Filho (2020) outline the dispute that futures prices destabilise spot markets through speculation. According to the variance decomposition results in Section 4.5.2, volatility has less than 3% of its forecast error variance explained by a shock in the speculative ratio. This finding then contests the notion that the impact of speculation on volatility in white maize futures is considerable enough to destabilise spot maize prices and impair price discovery in this market. Hence, while the role of speculation has been analysed as a trigger for futures price volatility (Penone, Giampietri & Trestini, 2022), significant evidence to corroborate speculation as a strong determinant of volatility has not been found.

The results from the variance decomposition show that most of the forecast error variance for volatility in maize futures stems from its own lagged values. Forthcoming research therefore will benefit from decomposing this volatility and analysing its determinants. One such contribution that can be extended is Sayed and Auret (2019). In their examination of the South African white maize futures market, Sayed and Auret (2019) employed the Dynamic

Conditional Correlation (DCC) GARCH Model of Engle (2002) to investigate volatility spillover effects between grain futures, currency futures and equity futures listed on SAFEX. White maize futures was found to have a persistently strong interdependence with yellow maize, wheat, sunflower seeds and the Rand/US Dollar exchange rate.

Given the nature of agriculture and farming, agricultural commodities have their own volatility inducing factors. Drivers of grain price volatility have been classified as endogenous or exogenous (Tadesse, Algieri, Kalkuhl & Braun, 2016; Santeramo, Lamonaco, Conto, Nardone & Stasi, 2018). Endogenous causes include shifts in consumption and production levels, acreage allocation, crop yield responses and stock levels. Exogenous causes alternatively include climatic and weather shocks, natural and technological disasters, and shifts in the energy markets. Agents in the agricultural value chain continuously assess and examine both endogenous and exogenous causes to effectively evaluate their exposures so that they can hedge their risks in the futures market accordingly. More recently, Mitsas, Golitsis and Khudoykulov (2022) investigated the impact of real-time global geopolitical risks, geopolitical acts, and geopolitical threats on commodity futures. They found geopolitical threats to have a weak but positive effect on the volatility of corn futures listed on the Chicago Mercantile Exchange (CME).

4.7 Conclusion

The objective of this chapter was to estimate proxies for speculative and hedging activity in the South African white maize futures market in the absence of COT reports, using ratios estimated from daily trading activity data. The first ratio, of volume to open interest, was used to capture speculative market activity; and the second, the change in open interest to volume,

was used to reflect the activity of hedgers. The relative dominance of speculative activity over hedging activity was then examined against price volatility under a VAR framework testing Granger-causality, variance decomposition and impulse response functions. The results confirm a substantial presence of speculative activity relative to hedging activity in the South African white maize futures market for the period April 2000 to May 2022.

The results of the VAR model verify that a positive and significant relationship exists between excess-speculation and volatility. The results also reveal however, that the short-run dynamics displayed between speculative activity and price volatility are negligible in size. It is doubtful therefore that speculative activity substantially influences price volatility to the extent that strict position and price limits should remain in place. These findings add to the debate surrounding the use of price and position limits on the South African white maize futures market. The implications of the results are that price volatility is not being driven predominantly by excess-speculation, but still through changes in fundamentals, and that by imposing limits on futures exchanges, bona-fide hedging demand is being interrupted and impaired. Restrictive regulation of this nature runs the risk of affecting the liquidity and efficiency on futures exchanges that stakeholders such as farmers and food producers require in order to manage their risk.

The risk of regulatory tools impeding the efficient functioning of futures market is a debate that is common across global exchanges. On 30th January 2020, the Commodity Futures Trading Commission (CFTC) approved a "bona fide hedge" exemption to the rule on speculative position limits in futures and derivatives markets (Fatka, 2020). Going forward, position limits would be capped for traders with real hedging needs in futures markets for commodities such as wheat, corn, soybeans, cotton and cattle, but not for speculators. This ruling recognises that the main beneficiaries of efficiently functioning futures markets are the

hedgers and that their use of futures markets prevents the cost of risk-taking from filtering down to the price consumers pay for food.

The most apparent limitation of this chapter is that speculation ratio, as defined by Garcia et al.,, (1986), is dependent on the assumption that hedgers and speculators have different holding period lengths and can be distinguished on this basis. However, studies by Wiley and Daigler (1998) and Ederington and Lee (2002) have found that hedgers tend to hold their futures market positions longer than speculators. These studies however are based on evidence found in the financial and energy futures markets, and not in agricultural futures. This limitation further reiterates the need for futures exchanges, like SAFEX, to make accessible commitment of traders reports similar to the CFTC so that the open interest split between commercial (hedgers) and non-commercial (speculators) can be more accurately observed and examined.

The USDA WASDE (2022) forecasts world corn production to decline following the reductions observed in Ukraine, the United States and China. They argue however that these reductions will be partially offset by increases in Brazil, Argentina and South Africa. South Africa as a net exporter of maize therefore will continue to play an integral part in the global grains market, especially as price volatility is expected to increase. The informational efficiency of South African maize futures contracts therefore remains of critical importance and future studies will benefit from continuing to examine volatility, and its determinants, in this market.

CHAPTER FIVE: VOLATILITY SPILLOVER AND DYNAMIC CONNECTEDNESS IN MAIZE FUTURES OF MAJOR EXPORTERS

Abstract of Chapter Five

The U.S., Argentina, Brazil, Ukraine, Russia and South Africa are among the largest exporters of maize. This chapter examines dynamic connectedness and volatility spillover in maize futures listed on SAFEX, CBOT, MATBA (Argentina) and BMF (Brazil). A multivariate GARCH approach is used to examine both own-volatility and cross-volatility spillovers using daily data over the period 17 November 2008 to 17 June 2022. The Engle and Kroner (1995) Diagonal BEKK model is used to examine own-volatility spillovers and persistence within and across maize futures markets. The Engle and Kroner (1995) full BEKK model examines volatility spillovers within and across maize futures markets. The Bollerslev (1990) Constant Conditional Correlation (CCC) model tests for both the presence and size of interdependence between maize futures markets. The Engle (2002) Dynamic Conditional Correlation (DCC) model tests if the size of interdependence between maize futures markets has varied over time. In addition, dynamic connectedness among the five maize futures contracts is examined using the Diebold and Yilmaz Spillover Index, that has been improved by Gabauer (2020). The results confirm the existence of significant spillover effects of volatility between the futures markets of the leading exporters of maize. The results also highlight that the level and magnitude of interdependence between these markets has changed over time. The findings have important implications for risk management and regulation in agricultural futures markets.

5.1 Introduction

Increasing populations and consumption has placed unprecedented demands on agricultural markets. The challenge to achieve global food security increases the importance of examining grain price volatility in developing countries, where the cost of food absorbs most household income. Amid increasing competition for land and water which threatens the supply of food, population and consumption growth continue to rise, increasing the demand for grains like maize (Godfray, Beddington, Crute, Haddad, Lawrence, Muir, Pretty, Robinson, Thomas & Toulmin, 2010). In developed countries, maize is predominantly used in livestock feed for poultry, pork and cattle; while in developing countries, like South Africa, it is consumed directly, serving as a staple food for the population (du Plessis, 2003).

Examining price volatility in maize markets however not only has important implications for food security, but for renewable energy as well. The last decade has seen the use of maize in fuel production increase significantly, accounting for approximately 40% of the United States' corn production (Wallander, Claassen & Nickerson, 2011). According to Ranum *et al.,* (2014) as the ethanol industry continues to expand it will absorb a larger share of maize crops, intensifying demand competition and increasing maize prices for animal and human consumption.

Futures markets perform an essential function by creating a platform for price discovery as well as risk management. Assessing volatility in grain futures markets like the South Africa is of vital importance as rising volatility increases not only the risk of paying higher prices for a specific commodity, but also makes the use of derivative instruments that hedge against price risk more expensive (Geyser & Cutts, 2007). Volatility spillover and connectedness in grain futures markets therefore also has important implications for investors, who are concerned with

portfolio allocations, as well as commercial traders who are concerned with effective hedging strategies.

Given the price discovery function of futures markets, volatility is more appropriately examined using futures prices than spot prices. According to Yang, Bessler and Leatham (2001) futures markets play a better informational role in aggregating market information than cash markets. Futures markets also dominate their physical counterparts in sheer size. The CME Group (2022) reports corn futures contracts to be the most liquid and active market in grains, with 350 000 contracts traded per day. Each corn futures contract traded on CBOT represents 5000 bushels of corn. In contrast, in the physical market, corn production in the U.S. for 2020/2021 was reported at over 14,1 billion bushels, with projections for 2022/2023 at 13,944 billion bushels (USDA Wasde, September 2022).

Maize futures offer a central, transparent point of price discovery in a market that shifts frequently based on weather conditions, export and tariff changes, crop conditions and logistical issues. Previous research concerning grain price volatility have either examined maize futures or spots markets separately or the link between them. The interdependence across international futures markets however continues to rise, which makes isolated examination of single futures markets incomplete. This chapter therefore investigates volatility spillover effects and dynamic connectedness across four global futures exchanges. According to Ceballos, Hernandez, Minot and Robles (2017) understanding of the sources of food price volatility in developing countries and the extent to which it is transmitted from international markets is critical for designing global and regional policies that will mitigate food price volatility. Hernandez *et al.,* (2014) relate the increasing interdependence between agricultural futures markets to the structural changes and developments in futures markets that have taken

place in recent decades. As a reference, they highlight that the average daily volume of corn futures traded on the Chicago Board of Trade (CBOT) has increased by more than 250% over the last 25 years. Furthermore, many futures markets have shifted from the trading floor to electronic platforms and this has attracted automated and algorithmic traders who have induced changes both in the speed of price discovery as well as in price volatility, especially at the intraday level (Haynes & Roberts, 2017).

This chapter examines the level of interdependence and volatility spillover among maize futures contracts listed on the South African Futures Exchange (SAFEX), Chicago Board of Trade (CBOT), Mercado a Termino de Beunes Aires (MATBA) and the Brazilian Mercantile and Futures Exchange (BMF). These markets are selected based on their role as major exporters of maize together with the constraints of data availability. The United States Department of Agriculture (USADA) releases a monthly report which contains country-specific demand and supply estimates and projections for a wide range of agricultural commodities, including corn (McKenzie & Ye, 2022). According to the USDA Wasde September 2022 Report, the major exporters of corn (maize) globally are the United States, Argentina, Brazil, Ukraine, Russia, and South Africa (USDA Wasde, 2022). The United States is reported to have exported 69.78 million metric tons of corn for the 2020/2021 period. They were followed by Argentina with corn exports of 40.94 million metric tons, the Ukraine with 23.86 million metric tons, Brazil with 21.02 million metric tons, Russia with 3.99 million metric tons and South Africa with 3.73 million metric tons of corn exported. As there is no corn (maize) futures price data available for Russia and Ukraine, this chapter only includes the United States, Argentina, Brazil and South Africa in the analysis.

Beginning with the U.S., their Department of Agriculture reports that agriculture, food and related industries currently contribute 5% to U.S. GDP (USDA ERS, February, 2022). Furthermore, in March 2022, the Feeding the Economy annual report was released. According to Bode (2022), the report showed that in 2021, nearly 18% of the U.S.'s economy and 29% of all American jobs were linked to agriculture. The report also showed that the agricultural sector in the U.S. contributed to more than 43 million jobs, $2 trillion in wages and $718 billion in taxes. According to the CME Group (2022), global corn producers currently produce more than 525 million metric tons each year, with the U.S. positioned as the world's leading maize exporter. This chapter therefore includes CBOT-listed corn as most studies investigating volatility transmission in agricultural futures markets, have not only found the CBOT to be the leading exchange from which spillover effects emanate, but corn futures specifically have been found to be major transmitter of volatility. In his examination of U.S. agricultural futures markets, Grieb (2015) found CBOT-listed corn to be the commodity that most broadly transmitted volatility spillovers. A similar finding was made more recently by Umar, Sayed, Gubareva and Vo (2022) in their examination of dynamic connectedness and volatility spillovers between eleven agricultural commodities listed on CBOT. Specifically, Umar *et al.,* (2022) found corn to be a major spillover transmitter alongside feeder cattle and live cattle.

Brazil is discussed next using the latest report form the U.S. Department of Agriculture's Economic Research Service, published 27th September 2022 (USDA ERS, September 2022). Since the mid-2000s Brazil has transformed from exporters of predominantly tropical agricultural products such as cacao, coffee and citrus, to a major global exporter of commodities like soybeans and maize. A study by the University of Sao Paulo's Center for Advanced Studies on Applied Economics estimated that for 2021, crop and livestock production accounted for 8% of Brazil's GDP. The value of Brazil's agricultural exports are

also reported to have grown, with an increase an average of 9% per year from 2000 to 2021 and accounting for 37% of the country's total exports. Brazil is now the world's third largest exporter of agricultural products, only trailing behind the European Union (EU) and the U.S., and notably remains to date the largest country in terms of arable land. Studies by Cruz, Silveira, Capitani, Urso and Martines (2016) and Meade, Puricelli, McBride, Valdes, Hoffman, Foreman & Dohlman (2016) also highlight the significance of the Brazilian maize market. Cruz *et al.,* (2016) examined if changes in Brazilian corn production had caused significant changes in price and volatility transmission between Brazilian and U.S. markets. Their results showed that the level of market integration between the two markets had increased significantly over the period 2007 to 2014. Their findings also showed a substantial increase in Brazilian corn production over the last decade which nearly quadrupled since 1990, reaching 3.3 billion bushels in 2015. According to Mattos and Silveira (2015) this increase in production was attributed to the growth in Brazilian winter crop which they plant directly after the soybean harvest, as a result of early-maturing soybeans. This growth of the winter crop produces two corn crops per year in Brazil and amounts to 60% of total production. Brazil's ability to harvest two to three crops a year in the same plot of land makes it unique to other grain producing countries and makes it among the few countries in the world with the potential to increase agricultural productivity (USDA ERS, September 2022). Meade *et al.,* (2016) examined farm production costs and export competitiveness for the 2010/2011 period, for Argentina, Brazil and the U.S., who, at the time, accounted for an average of 73 percent of world corn exports. They found that average production costs per bushel of corn was the lowest in the U.S., followed by Argentina and then Brazil, with costs of 3 and 25 cents above U.S. costs respectively. Meade *et al.,,* (2016) also pointed out that although the U.S. economy is significantly larger than its South American counterparts, agriculture during the 2010/2011 period played a more prominent role in the Brazilian and Argentinian economies. They

reported that the U.S. agriculture contributed on average only 1 percent to America's GDP, compared with 5% for Brazil and 7% for Argentina. Furthermore, agriculture only accounted for 9 percent of U.S. exports, but 40 percent and 57 percent of Brazil and Argentina's exports respectively.

Argentina by comparison is smaller in land area than the U.S. and Brazil but uses the largest share of its land for agricultural purposes. Argentina is known as a giant of global agriculture with nearly half of the country's total area occupied by livestock farming and most of their grains exported. Argentina's influence on global maize markets has increased significantly in recent years brought on mainly due to changes in Argentina's maize export policies. In 2015, President Macri announced the elimination of the 20 percent export tax on maize expediting the role and influence of Argentina in maize markets. According to a 2020 report by the OECD, Argentina's agricultural sector contributed 4,7% to GDP in 2000 and 6,1% to GDP in 2018 (OECD, 2022).

As discussed in Chapter One, in South Africa, agriculture is a crucial sector and an important engine of growth for the economy. According to a 2020 report by NAMC on the Agricultural sector contribution to South Africa's GDP, following the first quarter of 2020, South Africa's agricultural sector continued to contribute positively to the country's GDP growth with an increase of 28,6%, becoming the strongest performer (15,1%) in the second quarter of 2020, despite the Covid-19 pandemic. South Africa, although a small producer compared to the top three, is the main maize producer on the African continent, as well the main emerging market for price discovery of maize in Africa. Maize futures contracts are also the largest and most liquid contract traded on SAFEX with the volume of white maize futures contracts traded over the last 20 years reported at over 16 million (Sayed & Auret, 2020).

Although most of the maize produced in South Africa is consumed locally, the recent expansion of global corn production and exports, coupled with improvements in agricultural technology, requires research that examines price volatility across international maize markets. The objective of this chapter is therefore to examine volatility spillovers and dynamic connectedness in maize futures markets using daily price data for the period 17 November 2008 to 17 June 2022.

Similar to other volatility transmission studies, this chapter uses multivariate generalised autoregressive heteroskedastic (GARCH) models to examine interdependence and volatility spillovers across corn (maize) futures market. The Engle and Kroner (1995) Diagonal BEKK model is used to identify own-volatility spillovers and persistence within markets. The Engle and Kroner (1995) Full BEKK model examines direct volatility transmissions and accounts for both own- and cross-volatility spillovers and persistence across markets. The Bollerslev (1990) Constant Conditional Correlation (CCC) model indicates whether there is interdependence between the markets as well as the magnitude of this interdependence. Finally, the Engle (2002) Dynamic Conditional Correlation (DCC) model examines if the degree of interdependence between markets has changed over time. To examine dynamic connectedness among the futures markets the methodology of Gabauer (2020) is employed which identifies which markets are net receivers of volatile and which are net transmitters of volatility.

The results confirm the presence of statistically significant volatility spillover effects and time-varying interdependence across maize futures markets listed in the U.S., Brazil, Argentina and South Africa. Volatility transmission is observed between each pair of exchanges evaluated, although the magnitude and degree of transmission differs. Further, a strong and positive

connectedness is found among the maize futures markets, with SAFEX white maize found to be the leading net transmitter of volatility within the system and SAFEX yellow maize found to be the leading net receiver of volatility. The results highlight that not only is white maize futures contracts important for farmers and food processors in South Africa who use these contracts for risk management; but given the level of contagion and connectedness, is also important for risk management in all of the other major net exporting regions as well.

5.2 Literature Review

Kyle (1985) and Andersen and Bollerslev (1997) were among the first to attribute price variability to reaction to information flows, highlighting the importance of information shocks and their resultant spillovers. Most studies on return and volatility transmission focus on testing for interdependence between different assets in single market or between several markets across countries. The initial studies empirically investigating volatility spillovers were confined to examining stock markets and foreign exchange markets (Engle, Ito & Lin, 1990; Hamao, Masulis & Ng, 1990; Conrad, Gultekin & Kaul, 1991; and Liu & Pan; 1997). The paper by Engle *et al.,* (1990), for instance, investigated Japanese and U.S. foreign exchange markets using a GARCH model and found evidence of yen/dollar volatility spillovers from one trading centre to another as global trading progressed. In their paper, Engle *et al.,* (1990) proposed two hypotheses on how volatility might manifest itself across trading centres (exchanges) which they coined the "heat wave" hypothesis and the "meteor shower" hypothesis. According to the "heat wave" hypothesis, volatility has only country-specific autocorrelation such that a volatile day in one market is likely to be followed by another volatile day in the same market, but not typically a volatile day in other markets. The "meteor shower" hypothesis asserts that foreign market news or information shocks follow a process likened to

a meteor shower hitting the earth as it revolves, with the impact of this process manifested in the form of volatility spillovers from one market to another.

As commodities were inadequately represented in the literature, several studies then began investigating information transfer effects across commodities. The first few studies to test for interdependence between agricultural markets related to global wheat prices. Spriggs, Kaylen & Bessler (1982), Gilmour and Fawcett (1987) and Goodwin and Shroeder (1991) all investigated price interactions for the principal exporters of wheat. Spriggs *et al.,* (1982) examined wheat prices for Canada and the U.S. using daily data over the period 1963 to 1979 and found no significant price leadership role between the two countries. Gilmour and Fawcett (1987) examined interactions and price linkages between the U.S., Canada, the European Union (EU), Argentina and Australia and found that major exporting countries responded asymmetrically to U.S. wheat price changes. Goodwin and Schroeder (1991) evaluated the relationships among international wheat prices using a vector autoregressive model and found significant dynamic relationships among prices in global wheat markets.

Recent studies that have examined volatility transmission for agricultural commodities by employing some form of multivariate GARCH model include Le Pen and Sevi (2010), Zhao and Goodwin (2011), Hernandez *et al.*, (2014), Beckmann and Czudaj (2014), Grieb (2015) and Gardebroek, Hernandez and Robles (2016). Le Pen and Sevi (2010) define volatility transmission as excess comovement in volatilities. They use a factor model - which is superior in capturing volatility clustering across several variables - to examine the interrelationship between eight agricultural and non-agricultural commodities and find moderate co-movement in prices and volatility. Zhao and Goodwin (2011) found volatility transmission between corn and soybean futures prices based on a BEKK model. Hernandez *et al.*, (2014) examined the

dynamics of volatility across global exchanges for corn, wheat and soybeans in the US, Europe and Asia by applying a multivariate GARCH approach. Their results indicate that agricultural markets are highly interrelated and both own- and cross-volatility transmission exists on most exchanges. Beckmann and Czudaj (2014) investigate short-run volatility transmission between futures prices of corn, wheat, and cotton, using a bivariate GARCH-in-mean model. Their results provide evidence in favour of short-run volatility spillover effects in agricultural futures markets. Grieb (2015) employed a two-stage multivariate GARCH model similar to Hamao *et al*., (1990) to study spillover effect between futures contracts traded on CME Group exchanges for corn, rice, soybeans, wheat, feeder cattle, lean hogs, live cattle, crude oil and natural gas. Grieb (2015) also examined volatility transmissions from the Eurodollar, S&P500 and currency futures contracts to each of the commodities. His results revealed a strong pattern of price spillovers indicating that price innovations for one commodity often have information that is transferred to other commodities. He also documented the presence of volatility spillover effects reflecting the transmission of risk-pricing between commodities. Most noteworthy was his result that corn was the commodity that most broadly received and transmitted both price and volatility spillovers. Finally, Gardebroek *et al*., (2016) investigated price and volatility spillover effects in corn, wheat and soybean spot markets using several multivariate GARCH model. used several multivariate GARCH models. They found little evidence of price transmission in levels, but significant transmission in price volatility at weekly and monthly frequencies.

The first significant study to examine linkages among global corn futures was Booth and Ciner (1997). The objective of their paper was to further their understanding of the interaction between Japan and the United States by examining the information transmission behaviour of maize futures contracts traded on the Tokyo Grain Exchange (TGE) and the CBOT. To achieve

this they used vector autoregression (VAR) models to examine intermarket spillovers present in unexpected returns and volatilities over the period 1993 to 1995. The results showed that intraday CBOT returns significantly affected overnight returns of the TGE maize futures. Therefore, the TGE was found to dependent on the CBOT for information generation, which was reflected in the opening price of the TGE maize futures. In contrast, no significant information spillover was found from CBOT trading returns to TGE trading returns and *vice versa*. According to Booth and Ciner (1997) these findings indicated that the new information created during CBOT's trading time was significant to the TGE and that this new information was incorporate overnight so that it reflected in TGE's opening price. All these initial studies discussed above however, examined price volatility following a univariate approach.

In contrast, Yang, Zang & Leatham (2003) examined volatility transmission in wheat markets between the U.S., Canada and Europe using a multivariate GARCH approach (specifically, a BEKK model) over the period 1996 to 2002. The authors found the EU to be self-dependent - neither affected by the U.S. nor the Canadian market- but transmitted volatility to the U.S. and Canada. Similarly, von Ledebur and Schmitz (2009) investigated for volatility transmission in corn between the U.S., Europe and Brazil using multivariate GARCH models. According to Hernandez *et al.,* (2014) examining futures markets interactions under a multivariate approach provides superior insight into the dynamic price relationship of international markets by incorporating volatility spillovers. Hernandez *et al.,, (*2014) examined the level of interdependence and volatility transmission across exchanges in the U.S., Europe and Asia for futures contracts in soybean, corn and wheat from 2004 to 2009. The authors used a multivariate GARCH approach to estimate BEKK and DCC models and found that the CBOT plays a major role in terms of spillover effects over other markets, especially for corn and wheat. This chapter is more in line with Hernandez *et al.,* (2014) as interactions in maize futures

markets will be explored in terms of the conditional second moment of return and under a multivariate GARCH approach.

Previous literature concerning price volatility in the South African maize futures market has been documented by Geyser and Cutts (2007), Auret and Schmitt (2008) and Monk *et al.,,* (2010) among others. Geyser and Cutts (2007) investigated how CBOT corn prices, the Rand/Dollar exchange rate and domestic supply and demand influenced the price and volatility of SAFEX listed maize over the period January 2002 to June 2006. The authors found SAFEX price levels are determined by the fundamentals, namely, the CBOT, the Rand/Dollar exchange rate, weather patterns and domestic stock levels and that daily SAFEX maize prices are more volatile than daily CBOT corn prices. The influence of CBOT however was not examined from the perspective of volatility transmission or volatility spillover effects. In their development of an explanatory model for South African white maize futures prices, Auret and Schmitt (2008) analysed the relationship between white maize futures prices and 12 variables over the period March 1996 to December 2005. The authors used a stepwise multiple OLS regression technique and found that weather, import parity prices and the JSE Top 40 were among the variables to significantly explain white maize futures prices. Despite the U.S. being the largest producer, consumer and exporter of maize and CBOT-corn serving as the world supply-demand price discovery mechanism, the authors did not find CBOT-corn prices to be a significant explanatory variable. Monk *et al.,* (2010) employed a univariate ARCH/GARCH approach to measure volatility in the price of July white maize futures contracts traded on SAFEX over the period 26 February 1996 to 31 January 2007. The found that increasing levels of volatility in July white maize futures prices can be attributed to the release of new information on local and international growing conditions. Most studies measuring grain

futures price volatility on SAFEX have done so using a univariate approach and have not examined the influence of international futures markets other than the CBOT.

The empirical analysis in this chapter contributes to the body of literature in volatility spillover analysis for maize futures as it is the first study to examine volatility spillovers in corn and maize futures between the U.S., Brazil, Argentina and South Africa. Volatility transmission research in emerging agricultural markets like South Africa is at best limited. The empirical analysis in this chapter therefore contributes to existing literature by providing an in depth-analysis of volatility transmission and time-varying connectedness across important markets of maize futures. Furthermore, this chapter makes a novel contribution in terms of its methodology as it employs multivariate GARCH models and time-varying connectedness – approaches yet to be used in the investigation of price volatility on SAFEX.

5.3 Data

The objective of this chapter is to examine volatility transmission and time-varying connectedness in maize futures traded on the Chicago Board of Trade (CBOT), Mercado a Termino de Beunes Aires (MATBA), the Brazilian Mercantile and Futures Exchange (BMF) and the South African Futures Exchange (SAFEX). All data is sourced from Bloomberg and daily prices for the nearby (active) contract is used to estimate returns. These returns are then used as inputs for the multivariate GARCH models, which are used to examine volatility transmission; as well as the dynamic connectedness model, which is used to identify which maize futures markets are the net transmitters and net receivers of volatility respectively. According to Booth and Ciner (1997) it is widely accepted that these contracts are the most active, liquid and informative. Further support for the use of futures prices instead of spot prices

for examining volatility spillovers is provided by Protopapadakis and Stoll (1983) who assert that interactions between commodity markets are investigated in its purest form by futures prices instead of spot prices. Yang *et al.*, (2001) also argue that futures prices play a better informational role than cash (spot) prices in aggregating market information, especially for commodities traded across international exchanges. Futures prices are also more appropriate for empirical analysis than spot prices, as they provide a single price for an underlying asset as opposed to the spot market which provides a range of prices depending on the locations of delivery and quality of the deliverable (Sayed & Auret, 2020). The returns at time t are calculated as $y_t = \ln(P_t/P_{t-1})$, where P_t is the daily closing price for each contract at time t.

Table 5.1 outlines the contract specifications of each of the five maize futures contracts examined in this chapter. The final sample period chosen for the empirical analysis of this chapter was subject to the exchange with the shortest data period available, which was Brazil with data available only from November 17, 2008. The final date in the sample was June 17, 2022. Due to different holidays across exchanges observations were only included for those days when price data was available for each of the four exchanges considered.

Volatility is not directly observable but can be represented by various measures related to the second moment of returns, with daily squared returns being the most common. Figures 5.1 and 5.2 show the closing prices and daily returns respectively for each of the maize futures contracts examined in this chapter. The plots show clear evidence of time-varying volatility in returns. It is clear that the data exhibits features of volatility clustering which further motivates for the use of multivariate GARCH models to capture the dependencies in the first and second moments of returns.

Table 5.1 Maize Futures Contract Specifications			
Exchange	Product	Price quotations	Contract unit
South African Futures Exchange (SAFEX)	White maize, WM1	Rand/ton	100 metric tons
South African Futures Exchange (SAFEX)	Yellow maize, YM1	Rand/ton	100 metric tons
Chicago Board of Trade (CBOT)	Corn no. 2 yellow, C	$cents/bushel	5 000 bushels
Brazilian Mercantile and Futures Exchange (BMF)	Yellow corn	BRL/kg	27 60 kg/bags
Mercado a Termino de Beunos Aires (MATBA)	Corn no. 2 yellow, C	USD/ton	100 metric tons

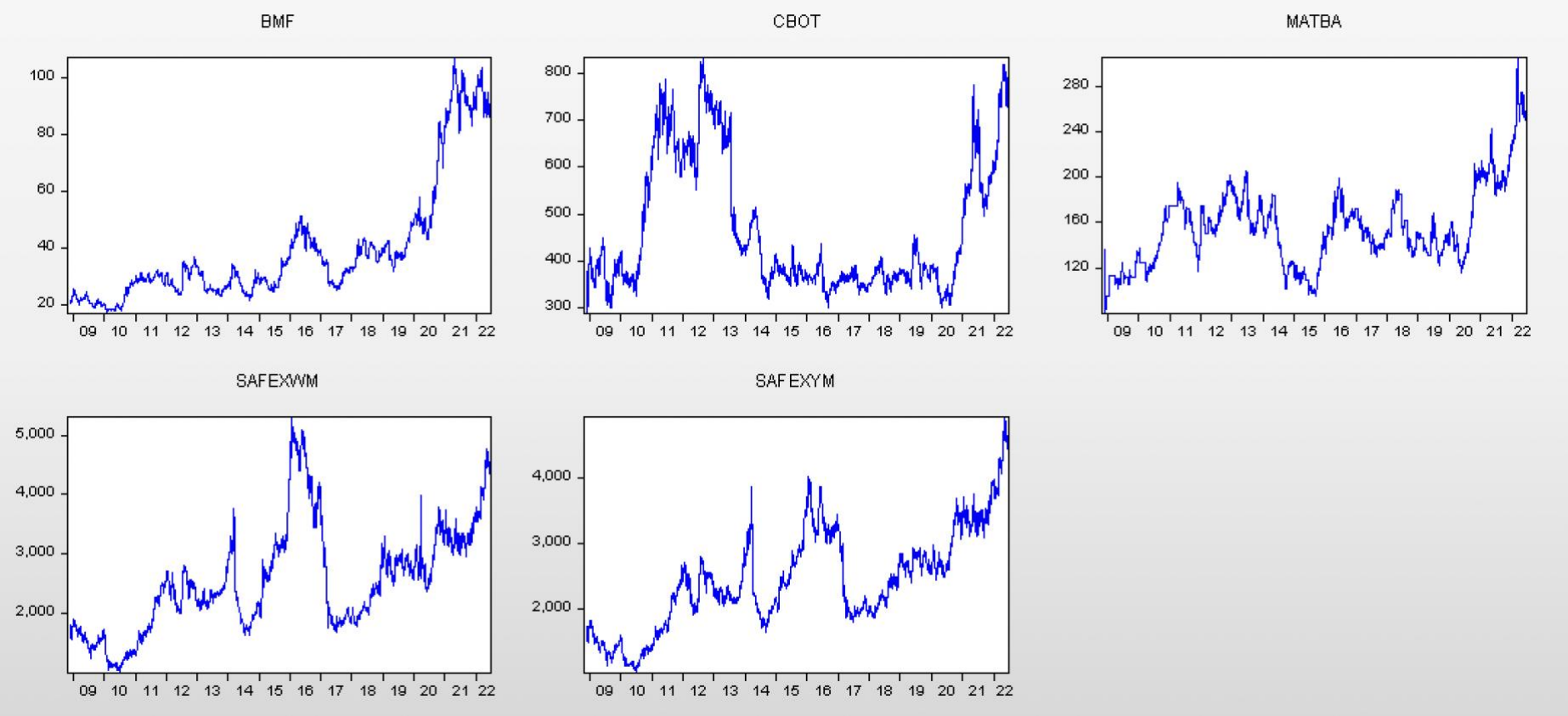


Figure 5.1 : Time-Series of Maize Futures Closing Price of Major Exporters

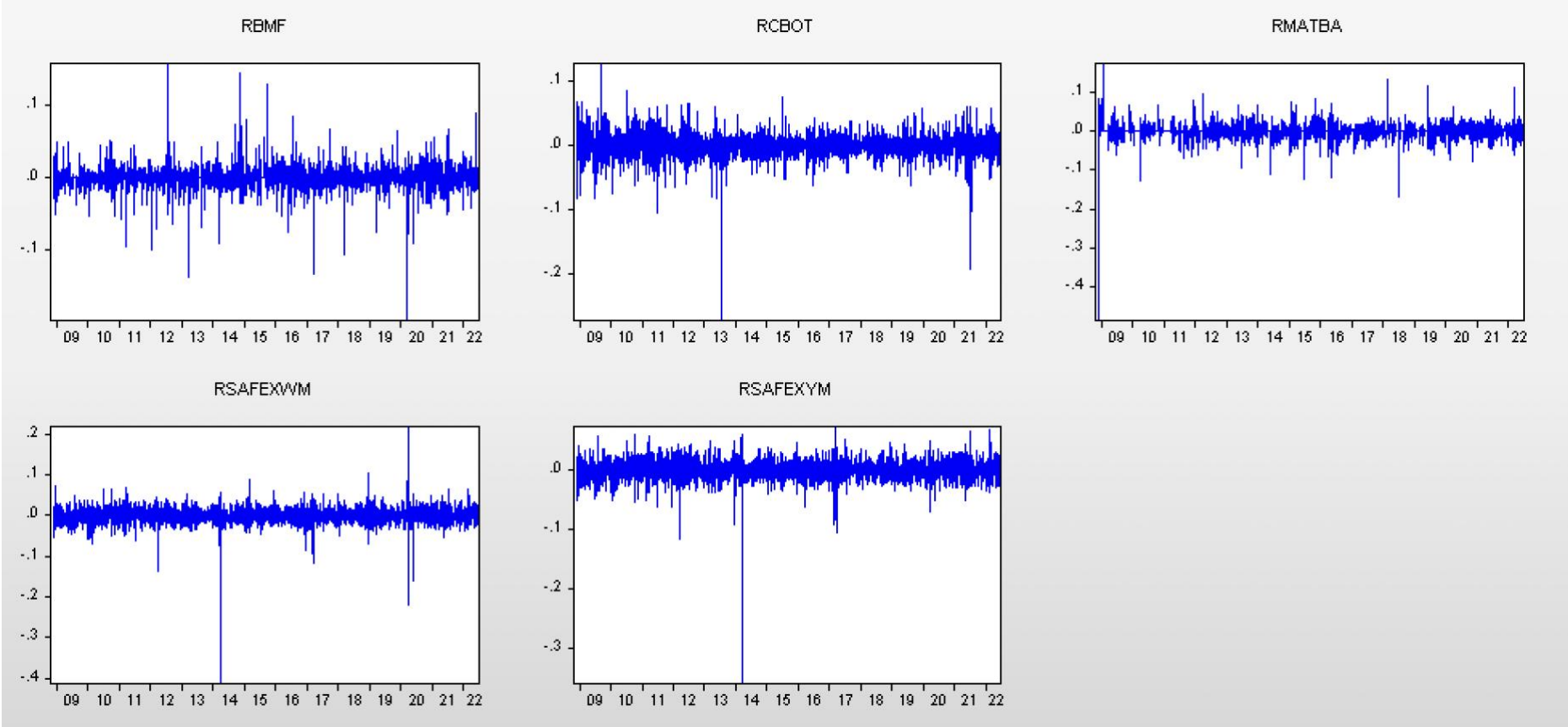


Figure 5.2 Time-Series of Returns of Maize Futures Closing Price of Major Exporters

Descriptive statistics and the results from unit root tests are shown in Table 5.2 with daily mean returns ranging from 0.041for BMF to 0,017 BP for MATBA. SAFEX white maize displays the highest variance, while BMF is the lowest. Skewness measures the symmetry of distribution from an assumed value of zero, negative skewness can be seen for each of the futures markets with MATBA at the highest and BMF at the lowest. The kurtosis results show a clear presence of leptokurtosis as all the values are considerably above 3, indicating fat tails and a larger possibility of extreme movements. The Jarque-Bera statistics reject the null hypothesis that the return series are normally distributed at the 1% level. The Elliot, Stock and Rothenberg (1996) unit root test is displayed in the table under ERS and confirms stationarity for each of our variable's return series. The ERS test is a modified version of the ADF unit-root test proposed by Elliot *et al.*, (1996) and has recently been typically preferred over the ADF test in studies examining dynamic connectedness (Gabauer, 2020; Sayed & Charteris, 2022). It has been argued to employ a more robust estimation procedure that corrects for potential issues related to serial correlation and heteroskedasticity (Otero & Baum, 2017).

Table 5.3 shows the results from the Correlation Matrix. Aside from SAFEX white maize and SAFEX yellow maize which have a high correlation of 0.86, the other pairs of maize futures contracts all show low but positive correlations. Each of the correlations are statistically significant at the 1% level.

Table 5.2 Descriptive Statistics and Unit Root Tests

	SAFEXWM	**SAFEXYM**	**CBOT**	**BMF**	**MATBA**
Mean	0.026	0.027	0.020	0.041	0.018
Variance	4.000	2.823	3.289	2;279	3.298
Skewness	-2.952***	-2.903***	-1.216***	-0.474***	-5.297***

Kurtosis	61.929***	57.921***	19.436***	22.613***	149.330***
Jarque-Bera	571482.675***	500384.363***	56655.777***	75641.190***	3309469.679***
ERS	-19.648***	-23.588***	-24.563***	-20.851***	-27.681***
*** denotes significance at the 1% level.					

Table 5.3: Correlation Matrix

	SAFEXWM	SAFEXYM	CBOT	MATBA	BMF
SAFEXWM	1				
SAFEXYM	0.86***	1			
CBOT	0.09***	0.08***	1		
MATBA	0.06***	0.07***	0.32***	1	
BMF	0.12***	0.13***	0.27***	0.16***	1
*** Denotes significance at the 1% level					

5.4 Methodology

Volatility in financial markets has been a key issue for academics and practitioners following the landmark contributions of Engle (1982) and Bollerslev (1986). These authors introduced the ARCH and GARCH models respectively which allowed volatility clustering and conditional variance to be accurately captured. Multivariate GARCH models were then developed to extend on univariate GARCH models in order to predict and measure the dependence in the co-movement of asset returns.

In order to examine volatility transmission and spillover effects across maize futures markets, this chapter makes use of four multivariate GARCH models, namely, the full BEKK and the

Diagonal BEKK proposed by Engle and Kroner (1995), the CCC proposed by Bollerslev (1990) and the DCC proposed by Engle (2002).

According to Hernandez *et al.,* (2014) the crucial feature when modelling multivariate GARCH models is to provide a realistic but parsimonious specification of the conditional variance matrix, H_t, ensuring that it is positive definite. Baba, Engle, Kraft, and Kroner (BEKK) (1990) defined a parameterization of the conditional variance matrix, H_t, which achieves positive definiteness by formulating the model in a manner that this feature is implied by the model structure. The BEKK model proposed by Engle and Kroner (1995) measures the direction, magnitude and persistence of volatility transmission across exchanges and its form is defined as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \quad (1)$$

where c_{ij} represent elements of an NxN upper triangular matrix of constants C, a_{ij} of the NxN matrix A measures the degree if innovation from exchange i to exchange j, and b_{ij} of the NxN matrix B measures the persistence in conditional volatility between exchange i and exchange j. The model in equation (1) represents the Full BEKK model while the Diagonal BEKK model further assumes that A and B are diagonal matrices.

The CCC model of Bollerslev (1990) measures the degree of interdependence between markets and proposed a multivariate specification which models the conditional covariance matrix indirectly by estimating the conditional correlation matrix. In this model the conditional correlations are assumed to remain constant while the conditional variances change. In this model, the conditional variance matrix, H_t, is defined as:

$$H_t = D_t R_t D_t, = (\rho_{i_j}\sqrt{h_{i_{i_t}} h_{j_{j_t}}}) \quad (2)$$

where

$$D_t = \text{diag}\left(h^{\frac{1}{2}}11_t \ldots h^{\frac{1}{2}}NN,_t\right), \tag{3}$$

$$h_{ii_t} = \omega_i + \alpha_i \varepsilon_i^2,_{t-1} + \beta_i h_{ii_{t-1}}, \tag{4}$$

where $h_{ii,t}$ is defined as a GARCH(1,1) specification, i = 1.. N, and

$$R = \rho_{i_j} \tag{5}$$

is a symmetric positive definite matrix that contains the constant conditional correlations and illustrates how markets are interrelated in the long run. This assumption of constant conditional correlations is however unrealistic and necessitated the development of the DCC model proposed by Engle (2002) which examines if the degree of interdependence between markets has changed over time. The DCC model modified the CCC by introducing a time-dependent conditional correlation matrix and is defined as:

$$H_t = D_t R_t D_t, \tag{6}$$

with D_t defined as in (3) and h_{iit} defined as in (4), and

$$R_t = \text{diag}(q_{ii,t}{}^{-\frac{1}{2}}) Qt \text{diag}(q_{ii,t}{}^{-\frac{1}{2}}), \tag{7}$$

with the N x N symmetric positive-definite matrix $Q_t = (q_{ii,t})$ given by

$$Qt = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \mu_{t-1} \acute{\mu}_{t-1} + \theta_2 Q_{t-1}, \tag{8}$$

where θ_1 and θ_2 are nonnegative scalar parameters satisfying $\theta_1 + \theta_2 < 1$.

and R_t has the form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{ij,t}}} \tag{9}$$

The most common method to estimate the conditional covariance matrix in the multivariate GARCH models is by quasi maximum likelihood. This process was performed by the econometric package RATS 10.0 (Regression Analysis Time Series). The maximum likelihood estimation method estimated in RATS was BFGS proposed by Broyden (1970), Fletcher (1970), Goldfarb (1970) and Shanno (1970) which uses iteration routines to obtain coefficient estimations.

The second part of this chapter examines the time-varying connectedness among the maize futures markets of SAFEX, CBOT, MATBA and BMF by employing the DCC-GARCH Connectedness approach of Gabauer (2020), similar to Sayed and Charteris (2022). This methodology is an extension and improvement of the popular Spillover Index developed by Diebold and Yilmaz (2009, 2012, 2014). In economics, a propagation mechanism has been defined as the means through which a disturbance (for instance, a volatility shock) spreads through an economy (Mankiw, 1989). The topic of volatility spillovers across financial markets has garnered much popularity and interest in recent years with studies examining propagation mechanisms on the rise. This interest has been matched with an increase in the development of methodologies that seek to capture the transmission process. In order to decompose the variances of variables in a system, several studies follow the Diebold and Yilmaz (2012, 2014) approach. In their seminal paper on financial market interdependence, King, Sentana and Wadhwani (1994) assessed sixteen national stock markets in order to explain the time-variation in the covariances between stock markets. The objective of their study was to explain the excess volatility of stock markets - and changes in correlations between markets - by identifying the factors responsible for changes over time in stock market volatility. They used data on sixteen

national stock markets to estimate a multivariate factor model in which the time-varying volatility of returns was induced by varying the underlying factor's volatility. This allowed them to obtain a parsimonious representation of the conditional variance-covariance matrix of excess returns as a function of the variances of a handful of factors. Excess returns were assumed to depend on innovations in observable and unobservable economic variables. They then altered the conditional variances of the underlying factors to change over time and parametrised this in terms of Bollerslev's (1986) GARCH processes. Next they modelled the risk premium on assets as a linear combination of the volatility associated with the factors.

Diebold and Yilmaz (2009) followed the same objectives of King *et al.,* (1994) and Forbes and Rigobon (2002) in order to formulate a measure of interdependence of asset returns and volatilities known as the *Spillover Index*. They base their measurement of return and volatility spillovers on vector autoregressive (VAR) models in the context of Engle *et al.,* (1990). Contrary to King *et al.,* (1994), Diebold and Yilmaz (2009) focus instead on variance decompositions which allow them to aggregate spillover effects across markets.

The spillover index of 2009 by Diebold and Yilmaz therefore followed a variance decomposition of an *N*-variable VAR, where, for each asset *i* they simply added shares of its forecast error variance originating from shocks to asset *j*, for all $j \neq i$, and then summed all $i = 1, \dots, N$.

Improving on their initial framework, the spillover index of Diebold and Yilmaz (2012, 2014) measures the directional spillovers in a VAR framework that excludes the likely dependence of the results on ordering. This framework allows the total, net, directional and pairwise connectedness among variables to be estimated.

The Diebold and Yilmaz (2012, 2014) approach is a two-step procedure based on the notion of generalised forecast error variance decomposition (GFEVD) that tests whether the propagation mechanism is time-varying or not. The first step involves the use of multivariate GARCH models to capture time-varying volatilities. These are then used as inputs for a rolling-window VAR estimation in the second step. Gabauer (2020) however notes several shortcomings here. He argues that the second step is always at risk due to possibly inaccurate results from the first step. He also notes that the window size is in most cases chosen arbitrarily and therefore the rolling-window analysis leads to a loss of observations.

The DCC-GARCH-based connectedness approach of Gabauer (2020) therefore improves the Diebold and Yilmaz (2012, 2014) connectedness approach as it requires no arbitrarily chosen window size to be selected to retrieve dynamic connectedness measures. The DCC-GARCH model of Engle (2002) examines if the degree of interdependence between variables changes over time and estimates the time-varying conditional variances and covariances in a system. In the DCC model, the time-varying (dynamic) conditional correlation matrix is defined as:

$$H_t = D_t R_t D_t, \tag{1}$$

The DCC model is however a modification of the Bollerslev (1990) Constant Conditional Correlation (CCC) model in which R_t changes overtime. In the CCC model, H_t, is instead defined as:

$$H_t = D_t R D_t, = \rho_{i_j} \sqrt{h_{i_{i_t}} h_{j_{j_t}}} \tag{2}$$

where

$$D_t = \text{diag}\left(h^{\frac{1}{2}} 11_t \dots h^{\frac{1}{2}} NN_t\right) \tag{3}$$

$$R_t = \text{diag}(q_{iit}{}^{-\frac{1}{2}}, \dots, q_{mmt}{}^{-\frac{1}{2}}) Qt \text{diag}(q_{iit}{}^{-\frac{1}{2}}, \dots, q_{mmt}{}^{-\frac{1}{2}}), \tag{4}$$

with the *N* x *N* symmetric positive-definite matrix $Q_t = (q_{ijt})$ given by

$$Q_t = (1 - a - b_2)\bar{Q} + a\mu_{t-1}\mu'_{t-1} + bQ_{t-1} \tag{5}$$

where $\bar{Q}$ is the unconditional correlation matrix of μ, and a and b are non-negative scalar parameters satisfying $a+ b < 1$.

The connectedness approach introduced by Diebold and Yilmaz (2012, 2014) is based on the generalised impulse response functions (GIRFs) of Pesaran and Shin (1998). GIRFs have the advantage of being independent of the variable ordering and are interpreted as the *J*-step ahead impact of a shock in variable *i* on variable *j*. Gabauer (2020) maintains this same premise and sets volatility impulse response functions (VIRFs) as the impact of a shock in variable *i* on variable *j'*s conditional volatilities, defined as:

$$\begin{aligned}\Psi^{g}_{j,t}(J) = \text{VIRF}\left(J, \delta_{j,t}, \boldsymbol{F}_{t-1}\right) = E\left(\boldsymbol{H}_{t+J} \mid \boldsymbol{\epsilon}_{j,t} = \delta_{j,t}, \boldsymbol{F}_{t-1}\right) \\ -E\left(\boldsymbol{H}_{t+J} \mid \boldsymbol{F}_{t-1}\right)\end{aligned} \tag{6}$$

Gabauer (2020) therefore pioneers the use of VIRFs for DCC-GARCH models in order to estimate dynamic connectedness measures. Following on from the VIRF, the GFEVD is calculated. It is defined as the portion of variance one variable explains on others. These variance shares are defined as:

$$\tilde{\phi}^{\mathrm{g}}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2,\mathrm{g}}_{ij,t}}{\sum_{j=1}^{NJ-1} \sum_{t=1}^{J-1} \Psi^{2,\mathrm{g}}_{ij,t}} \tag{7}$$

where $\sum_{j=1}^{N} \tilde{\phi}^{g}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}^{g}_{ij,t}(J) = N$. The aggregated effect of the *i*th shock is defined in the numerator and the denominator is the sum of all the effects.

Following on from the GFEVD, the total connectedness index (TCI) is defined as:

$$C^{g}_{t}(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(J)}{N} \tag{8}$$

The net total directional connectedness which measures the influence that variable *i* has on the entire system is defined as:

$$C_{i,t}^{g} = C_{i\rightarrow j,t}^{g}(J) - C_{i\leftarrow j,t}^{g}(J) \quad (9)$$

where, $C_{i\rightarrow j,t}^{\mathrm{g}}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ji,t}^{\mathrm{g}}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^{\mathrm{g}}(J)}$ measures the spillovers that variable *i* transmits to other variables in the system; and $C_{i\leftarrow j,t}^{\mathrm{g}}(J) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(J)}{\sum_{i=1}^{N} \tilde{\phi}_{ij,t}^{g}(J)}$ measures the spillovers that variable *i* receives from other variables in the system.

A positive value for $C_{i,t}^{g}$ or the net directional connectedness indicates that variable *i* is a net transmitter of shocks or that variable *i* is driving the system; while a negative value means that variable *i* is a net receiver of shocks and that variable *i* is influenced by the system.

Lastly, when the net pairwise directional connectedness (NPDC) is positive, it indicates that variable *i* influences variable *j* and *vice versa*. The NPDC is defined as:

$$\mathrm{NPDC}_{ij}(J) = \tilde{\phi}_{ji,t}^{\mathrm{g}}(J) - \tilde{\phi}_{ij,t}^{\mathrm{g}}(J) \quad (10)$$

5.5 Results

Standard multivariate GARCH models could not be employed as a leptokurtic distribution was observed for each of the return series and the assumption of normality was rejected at the 1% level. Therefore, the T-BEKK, T-CCC and T-DCC models, which use the student's t-distribution, were estimated.

5.5.1 Diagonal T-BEKK

The Engle and Kroner (1995) Diagonal BEKK model is used to identify own-volatility spillovers and own-volatility persistence within exchanges. The results for the Diagonal T-BEKK Model estimation is reported in Table 5.4 The tables report the estimated coefficients of the conditional variance matrix, H_t in equation (1).

The a_{ii} coefficients, where i=1…5, quantify own-volatility spillovers (i.e. the effect of lagged own innovations on the current conditional return volatility in exchange i). The results indicate that own-volatility spillovers are statistically significant at the 1% level for each of the maize futures markets examined. White maize futures traded on SAFEX appear to have the highest own innovation shock, with a statistically significant coefficient of 0.3357. This is followed by SAFEX yellow maize, BMF and CBOT with statistically significant coefficients of 0.3231, 0.1960 and 0.1933, respectively. MATBA has the lowest own innovation shock, although it is still positive and statistically significant at the 1% level, with a coefficient of 0.1653.

The b_{ii} coefficients in Table 5.4 measure own-volatility persistence (i.e. the dependence of the conditional volatility in exchange i on its own past volatility). Each of the maize futures markets examined exhibit high volatility persistence from within each of their own domestic markets and each of the coefficients are statistically significant at the 1% level. The highest own-volatility persistence is recorded for CBOT with a coefficient of 0.9737. This is followed by MATBA with a coefficient of 0.9457. The results also show that own-volatility persistence is almost identical for SAFEX yellow maize and SAFEX white maize with coefficients of 0.9362 and 0.9363, respectively. BMF has the lowest coefficient for own-volatility persistence at 0.9212.

5.5.2 Full T-BEKK

The full T-BEKK model examines direct volatility transmissions. Contrary to the diagonal T-BEKK, this model does not assume that A and B in equation (1) are diagonal matrices. This model caters for own- and cross-volatility spillovers as well as own- and cross-volatility dependence between exchanges. The off-diagonal elements provide evidence of increased interdependence between the exchanges, while the diagonal elements capture persistence.

Table 5.4 – Diagonal T-BEKK Model Estimation Results					
	SAFEX white maize $i = 1$	SAFEX yellow maize $i = 2$	CBOT $i = 3$	BMF $i = 4$	MATBA $i = 5$
c_{i1}	0.0042***	0.0038***	0.0002*	0.0006***	0.0002
c_{i2}		0.0014***	-0.0000	0.0000	0.0000
c_{i3}			0.0026***	0.0015***	0.0013***
c_{i4}				0.0044***	0.000
c_{i5}					0.0036***
a_{i1}	0.3357***				
a_{i2}		0.3231***			
a_{i3}			0.1933***		
a_{i4}				0.1960***	
a_{i5}					0.1653***
b_{i1}	0.9363***				
b_{i2}		0.9362***			
b_{i3}			0.9737***		
b_{i4}				0.9212***	
b_{i5}					0.9457***
** Denotes significance at the 5% level *** Denotes significance at the 1% level					

The Full T-BEKK Model estimation results are shown in Table 5.5. The off-diagonal coefficients of matrix A, a_{ij} captures the effects of lagged innovations originating in exchange *i* on the conditional return volatility in exchange *j*. For instance, the coefficients a_{i2} to a_{i5} in the first column of the table show the volatility spillovers onto SAFEX yellow maize, CBOT, BMF and MATBA, that originate from SAFEX white maize. None of these off-diagonal coefficients are statistically significant however. This confirms that there is no volatility transmission or spillovers from SAFEX white maize onto any of the other four maize futures markets examined. Examining volatility spillovers originating from SAFEX yellow maize onto SAFEX white maize shows a statistically significant cross-volatility spillover, at the 1% level, with an off-diagonal coefficient of -0.2089 observed. Statistically significant volatility spillover, at the 1% level is also evident from SAFEX yellow maize onto BMF with a coefficient of -0.0579. There are no cross-volatility spillovers observed from SAFEX yellow maize onto CBOT and MATBA. There is no statistically significant cross-volatility spillovers observed from CBOT onto SAFEX white maize, SAFEX yellow maize and BMF. However, a statistically significant off-diagonal coefficient can be seen from CBOT onto MATBA, but only at the 10% level. BMF has no statistically significant cross-volatility transmissions. MATBA has significant spillovers onto CBOT, at the 1% level with a coefficient of 0.0495; and onto BMF, at the 5% level with a coefficient of 0.0282. All the own-volatility spillovers shown on the diagonals are statistically significant at the 1% level. In summary therefore, SAFEX white maize does not transmit volatility onto any of the other four maize futures contracts examined, and only receives volatility spillovers from SAFEX yellow maize. SAFEX yellow maize transmits volatility to SAFEX white maize and BMF, but does not receive volatility spillovers from any of the maize futures contracts. CBOT only transmits volatility onto MATBA, albeit at the10% level of significance and only receives volatility spillovers from MATBA. BMF does not transmit volatility to any of the other maize futures contracts, and receives volatility spillovers

from SAFEX yellow maize and MATBA only. Finally, MATBA transmits volatility spillovers to CBOT and MATBA only, and receives volatility spillovers from CBOT.

The off-diagonal coefficients of matrix *B*, b_{ij} quantifies the dependence of the conditional volatility in exchange *j* on that of exchange *i*. There is no significant cross-volatility dependence observed between SAFEX white maize and any of the other maize futures contracts. Significant cross-volatility dependence is observed in the conditional volatility of BMF from SAFEX yellow maize, at the 1% level with a coefficient of 0.0215. There is also significant dependence in the conditional volatility of SAFEX yellow maize, BMF and MATBA from CBOT; and on the conditional volatilities of CBOT and MATBA from BMF. Lastly, significant cross-volatility persistence can be seen from MATBA onto CBOT. The own-volatility persistence effects shown in the diagonal coefficients of matrix *B* are large and and statistically significant, confirming the presence of strong GARCH effects.

The results from the Full T-BEKK Model reveal SAFEX white maize to be largely independent of the other exchanges, with no volatility spillovers either transmitted or received, save from SAFEX yellow maize. According to CIMMYT (1997), white maize is biologically and genetically identical to yellow maize, as both varieties share the same production conditions and cultivation methods; although a difference in appearance can be seen, brought on by the absence of carotin oil pigments in the kernel. This could would explain why the only volatility spillover observed for SAFEX white maize was from the lagged innovations originating in SAFEX yellow maize. Furthermore, Prakash (2011) asserts that consumer preferences also play a role in incomplete price (and volatility) transmissions, even under free and competitive market conditions. He argues further that domestically produced grain often exhibits characteristics that differ from internationally traded grains and that despite some of their

similarities, white maize is not necessarily substitutable with yellow maize. According to Prakash (2011), if consumers prefer domestically produced grain, this limits the scope for substitution between domestic and imported grains. He substantiates this claim with an example from Eastern and Southern Africa and Mexico, where consumers generally prefer white maize over internationally traded yellow maize. As consumers are hesitant to substitute one maize for another, domestic prices (and volatility in prices) for white maize would depend largely on regional supply and demand shocks, instead of on global market conditions, and on volatility in other internationally traded yellow maize markets. The volatility spillover effects and transmission in SAFEX white maize futures is therefore weak as the price changes and volatility in this variety of maize is largely independent of the internationally traded yellow maize market. Instead, volatility in SAFEX white maize futures is largely inherent to both its own domestic fundamentals, and to price and position limits imposed on white maize futures, and not on shocks experienced in the other exchanges, which all trade yellow maize instead.

Moving away from SAFEX white maize and analysing the cross-volatility spillovers of the maize futures contracts trading yellow maize, or yellow corn, several significant transmission are observed. Unidirectional volatility spillover is observed from SAFEX yellow maize onto BMF and from MATBA onto BMF. In addition, bidirectional volatility is observed between CBOT and MATBA. The results therefore allude to a clear interdependence and connectedness between the exchanges which is analysed in more detail next.

Table 5.5 Full T-BEKK Model Estimation Results					
	SAFEX white maize $i = 1$	SAFEX yellow maize $i = 2$	CBOT $i = 3$	BMF $i = 4$	MATBA $i = 5$
c_{i1}	0.0060***	0.0052***	-0.0002	0.0000	0.0000
c_{i2}		0.0013***	0.0003	-0.0010	0.0008**
c_{i3}			0.0019***	-0.0026**	0.0012***
c_{i4}				0.0047***	-0.0007
c_{i5}					0.0027***
a_{i1}	0.4624***	-0.2089***	0.0143	0.0038	-0.0002
a_{i2}	0.0074	0.2380***	0.0277	-0.0104	-0.0026
a_{i3}	0.0099	0.0177	0.1784***	0.0063	0.0495***
a_{i4}	0.0309	-0.0579**	-0.0061	0.2257***	0.0282**
a_{i5}	-0.0215	0.0279	0.0211*	0.0018	0.1627***
b_{i1}	0.8942***	0.0203	-0.0088	0.0172	0.0060
b_{i2}	-0.0084	0.9324***	-0.0141**	0.0271	-0.0003
b_{i3}	-0.0002	0.0136	0.9752***	0.0301*	-0.0194***
b_{i4}	-0.0103	0.0215*	0.0187**	0.8832***	-0.0016
b_{i5}	0.0076	-0.0151	-0.0084*	0.0552***	0.9514***

*** Denotes significance at the 1% level

** Denotes significance at the 5% level

* Denotes significance at the 10% level

5.5.3 T-CCC

The T-CCC model measures the level of interdependence across exchanges captured by the correlation coefficients p_{ij}. All the correlations in Table 5.6 are positive and statistically significant at the 1% level, confirming that all five of the maize futures markets examined are interrelated. In terms of the magnitude of interdependence, the highest correlation is observed between SAFEX white maize and SAFEX yellow maize with a coefficient of 0.8984. SAFEX white maize also exhibits low, but statistically significant correlations with BMF (0.1385), CBOT (0.1004) and MATBA (0.0398). Similarly, SAFEX yellow maize also has low correlations with BMF (0.1398), CBOT (0.0877) and MATBA (0.0474). In addition, CBOT has slightly positive correlations with BMF at 0.2742 and with MATBA at 0.2813. Lastly, BMF and MATBA also exhibited a low positive correlation with a coefficient of 0.1203.

5.5.4 T-DCC

Table 5.7 shows the estimation results for the T-DCC model which examines if the degree of interdependence has changed over time. Coefficients for the DCC-GARCH parameters, α_i and β_i are presented. These coefficients show the effect of innovations on the conditional correlations over time and their persistence. The coefficient α_i, interpreted as a news or reaction parameter, is the extent to which a volatility shock today spills over onto tomorrow's volatility. The α_i coefficients for all maize futures markets all statistically significant at the 1% level, with coefficients in descending order of 0.3881 (MATBA), 0.3400 (BMF), SAFEX white maize (0.3329), SAFEX yellow maize (0.3216) and CBOT (0.2321).

The coefficient β_i, known as the decay or persistence parameter, measures adjustments to past volatility. The persistence parameters are all high, positive and statistically significant at the 1% level, implying that the effects of past volatility takes long to dissipate over time. The

Table 5.6 T-CCC Model Estimation Results					
	SAFEX white maize	SAFEX yellow maize	CBOT	BMF	MATBA
	i = 1	*i = 2*	*i = 3*	*i =4*	*i = 5*
ω_i	0.0000***	0.0000***	0.0000***	0.0000***	0.0000
α_i	0.3954***	0.4004***	0.2086***	0.3404***	0.8181***
βi	0.6351***	0.5866***	0.8519***	0.6361***	0.5796***
ρ_{i1}	1	0.8984***	0.1004***	0.1385***	0.0398***
ρ_{i2}		1	0.0877***	0.1398***	0.0474***
ρ_{i3}			1	0.2742***	0.2813***
ρ_{i4}				1	0.1203***
ρ_{i5}					1

*** Denotes significance at the 1% level

** Denotes significance at the 5% level

* Denotes significance at the 10% level

Table 5.7 T-DCC Model Estimation Results					
	SAFEX white maize	SAFEX yellow maize	CBOT	BMF	MATBA
	i = 1	*i = 2*	*i = 3*	*i =4*	*i = 5*
ω_i	0.0000***	0.0000***	0.0000***	0.0000***	0.0000
α_i	0.3329***	0.3216***	0.2321***	0.3400***	0.3881***
βi	0.6460***	0.5788***	0.8231***	0.5947***	0.7470***
θ1					0.0154***
θ2					0.9800***
*** Denotes significance at the 1% level ** Denotes significance at the 5% level * Denotes significance at the 10% level					

highest persistence parameter is observed for CBOT with a coefficient of 0.8231, followed by MATBA (0.7470), SAFEX white maize (0.6460), BMF (0.5947) and SAFEX yellow maize (0.5788).

The DCC-GARCH (1,1) correlation parameters are presented by θ1 and θ2. If these parameters are significant, then the correlations can be interpreted as dynamic (varying over time); and if the sum of these parameters is very close to 1, this implies that the conditional covariance is highly persistent.

It is clear from the results in Table 5.7 that the interdependence between the exchanges has been varying over time.

The dynamic relationship between the exchanges is further reiterated by the DCC graphs in Figures 5.3 to 5.12 , as high variability is evident in all the graphs. The DCC graphs largely reinforce the results observed in the tables for the Multivariate GARCH models. Figures 5.3 to 5.6 confirm a high dynamic conditional correlation between SAFEX white maize and SAFEX yellow maize, with correlations reaching almost a perfect 1 and low correlations at 0.4 and lower coinciding with the severe drought experienced in South Africa in 2016, and the advent of Covid-19 in the first quarter of 2020. In contrast, the DCC graphs for SAFEX white maize and CBOT, BMF and MATBA all show similarly low correlations, that are often almost indistinguishable from zero. Specifically, the correlations between SAFEX white maize and CBOT range between 0.09 and 0.13, the correlations between SAFEX white maize and BMF range between 0.08 and 0.12, with a noticeable exception observed in last quarter of 2019 where correlations fall to zero. Lastly, the correlations between SAFEX white maize range between 0.04 and 0.12 with a high degree of variability, but with most correlations concentrated between 0.06 and 0.08.

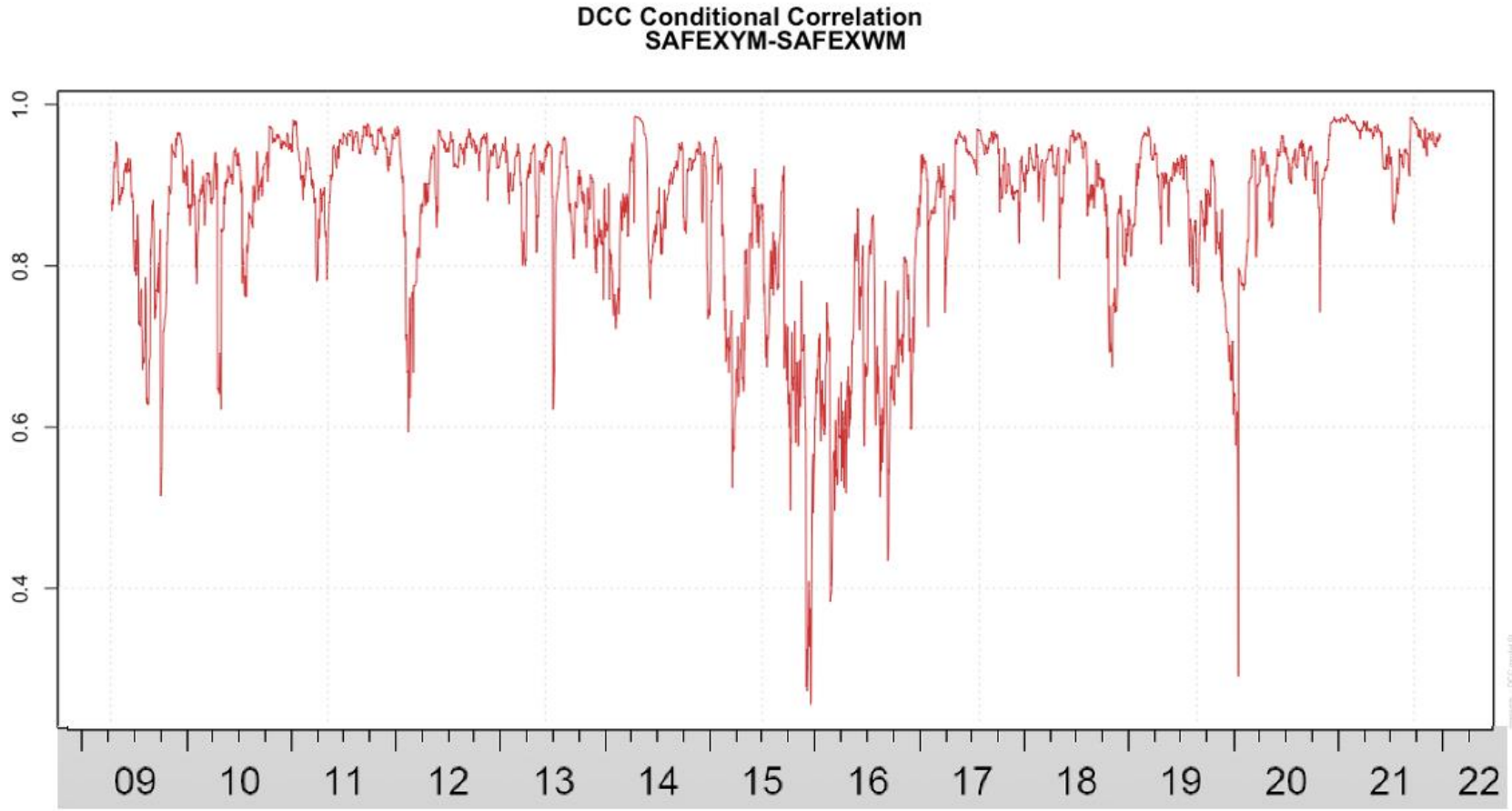


Figure 5.3 : DCC Graph for SAFEX yellow maize and SAFEX white maize

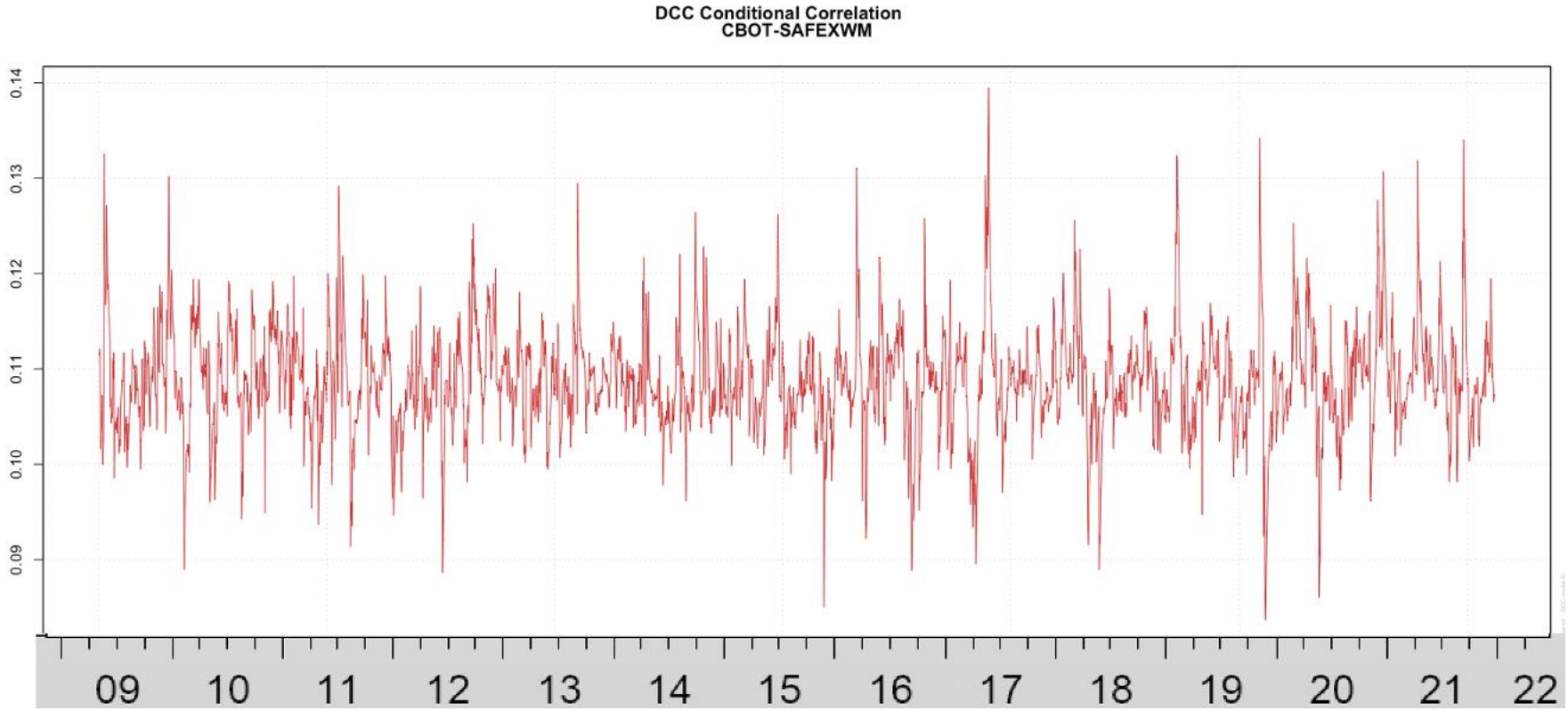


Figure 5.4 : DCC Graph for CBOT and SAFEX white maize

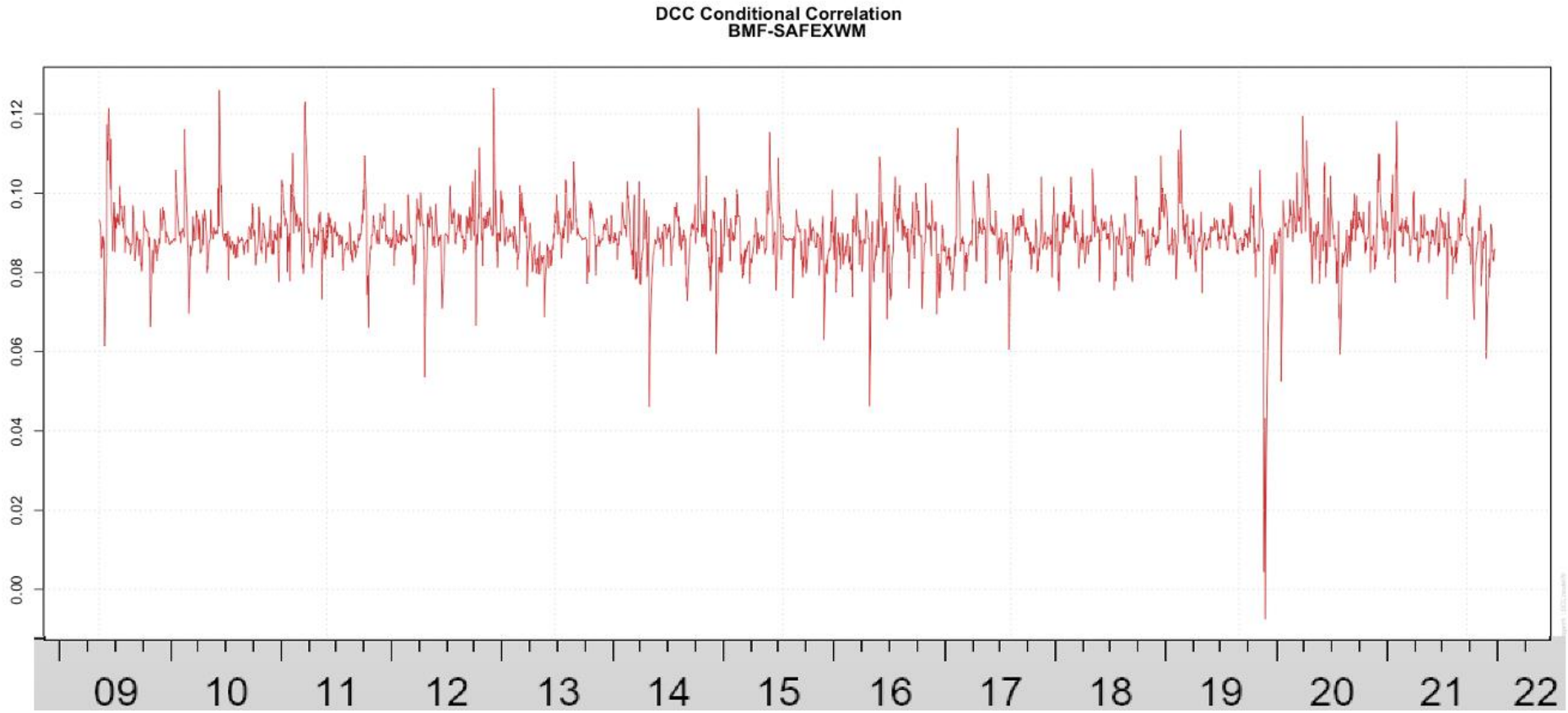


Figure 5.5 : DCC Graph for BMF and SAFEX white maize

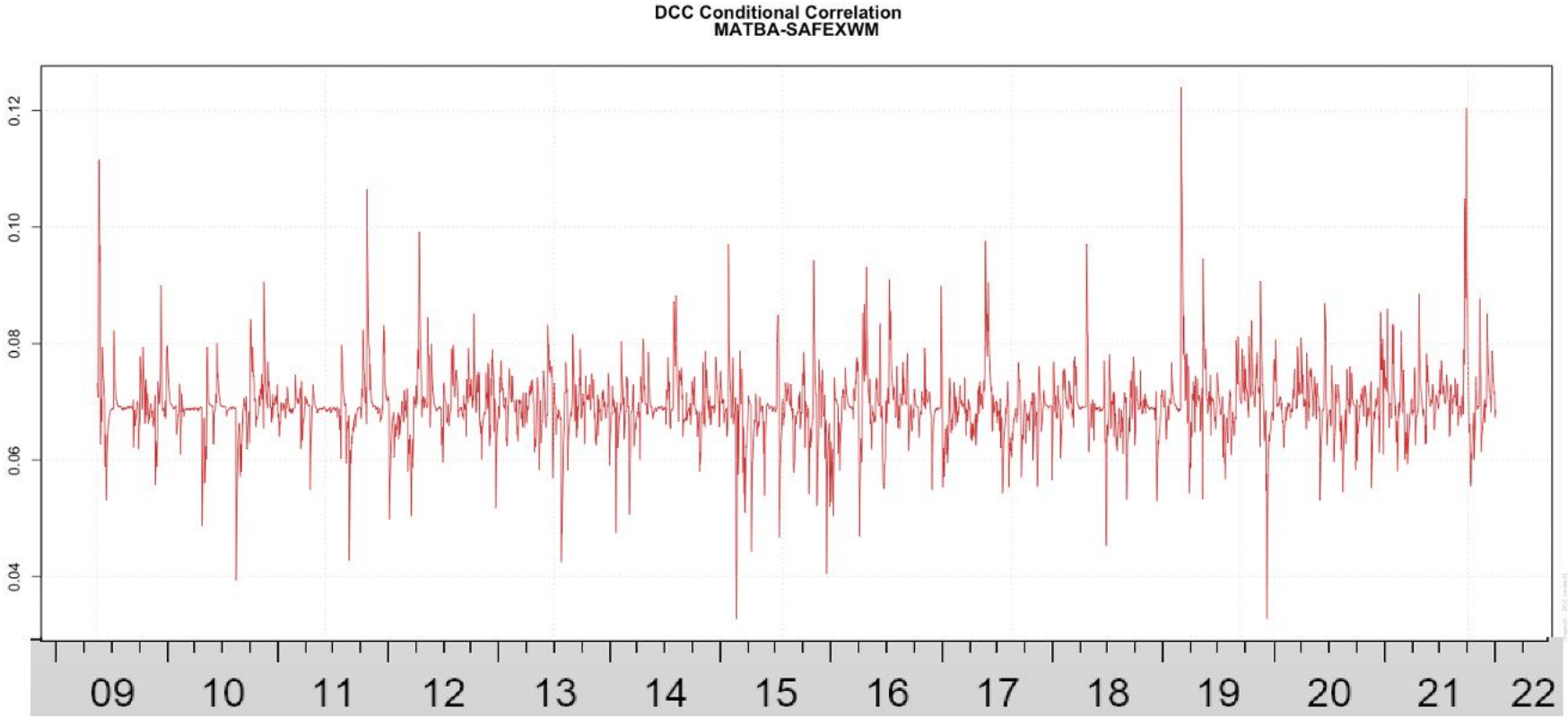


Figure 5.6 : DCC Graph for MATBA and SAFEX white maize

The next set of DCC graphs in Figures 5.7 to 5.9 show the time-varying correlations between SAFEX yellow maize with CBOT, BMF and MATBA. The dynamic conditional correlations between SAFEX yellow maize and CBOT range between 0.06 and 0.18, with the highest spike of 0.18 observed in the first quarter of 2013. Figure 5.8 plots the DCC-graph between SAFEX yellow maize and BMF. From this figure it can be seen that there is a low and consistent correlation between these two exchanges with a coefficient of 0.1031 that is maintained throughout the 14 year sample period. Lastly, figure 5.9 plots the time-varying correlations between SAFEX yellow maize and MATBA. Similar to Figure 5.8, the correlation remains constant throughout the sample period with a coefficient of 0.07839. It is clear therefore that there is strong interdependence between SAFEX white maize and SAFEX yellow maize, followed by a slight interdependence between SAFEX yellow maize and CBOT. However, SAFEX yellow maize remains largely independent of BMF and MATBA.

The next pair of DCC graphs looks at the interdependence between CBOT with BMF and MATBA and these are plotted in Figures 5.10 and 5.11, respectively. CBOT and MATBA experience a high degree of variability with their dynamic conditional correlations with coefficients ranging between 0 and 0.5. The DCC graph for CBOT and MATBA exhibits the most variability as the correlation coefficients range between -0.2 and 0.6, with a steady increase in the coefficients observed from the second quarter of 2020 until the end of the sample period in June 2022 as correlations for that period range between 0.2 and 0.6 only.

Figure 5.12 plots the last DCC-graph between BMF and MATBA. The dynamic conditional correlations range between 0 and 0.25. Similar to Figure 5. 11, it its evident that the correlations are increasing with time, i.e. that the interdependence between the maize futures markets listed

on BMF and MATBA has been rising over time. The highest correlation coefficients are observed since 2020 and range between 0.20 and 0.25. It can be argued therefore that the crises periods of Covid-19 and the Russia-Ukraine conflict has increased the interdependence of MATBA with BMF and CBOT.

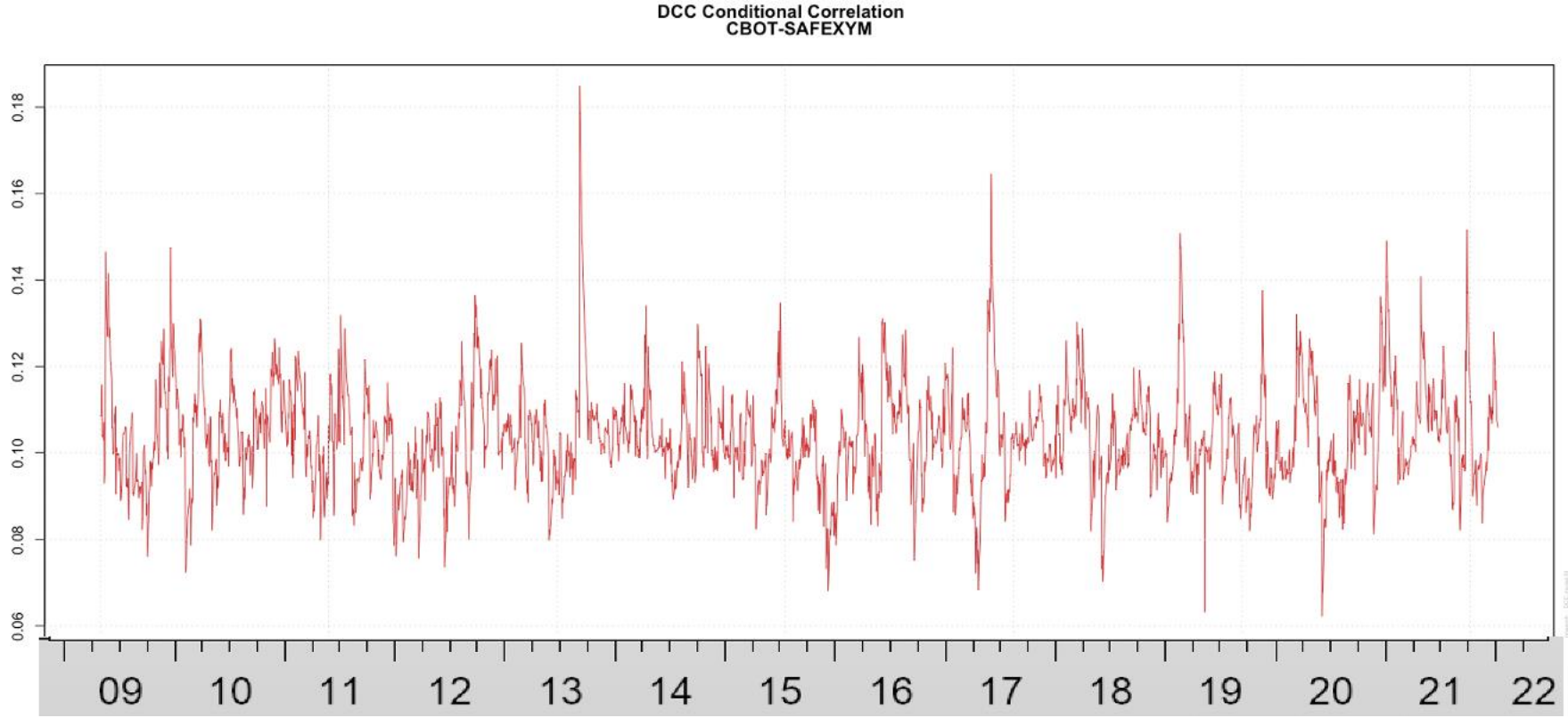


Figure 5.7 : DCC Graph for CBOT and SAFEX yellow maize

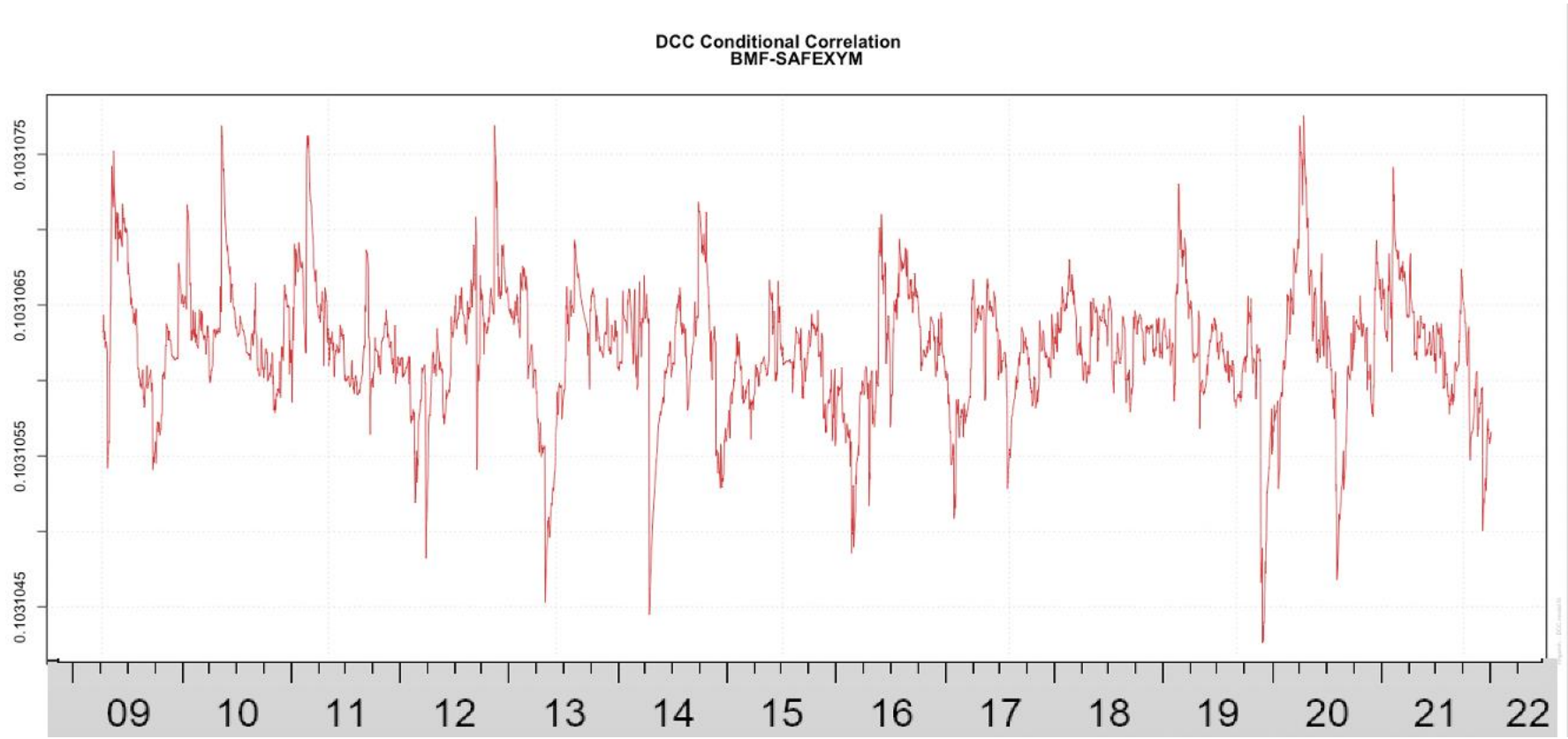


Figure 5.8 : DCC Graph for BMF and SAFEX yellow maize

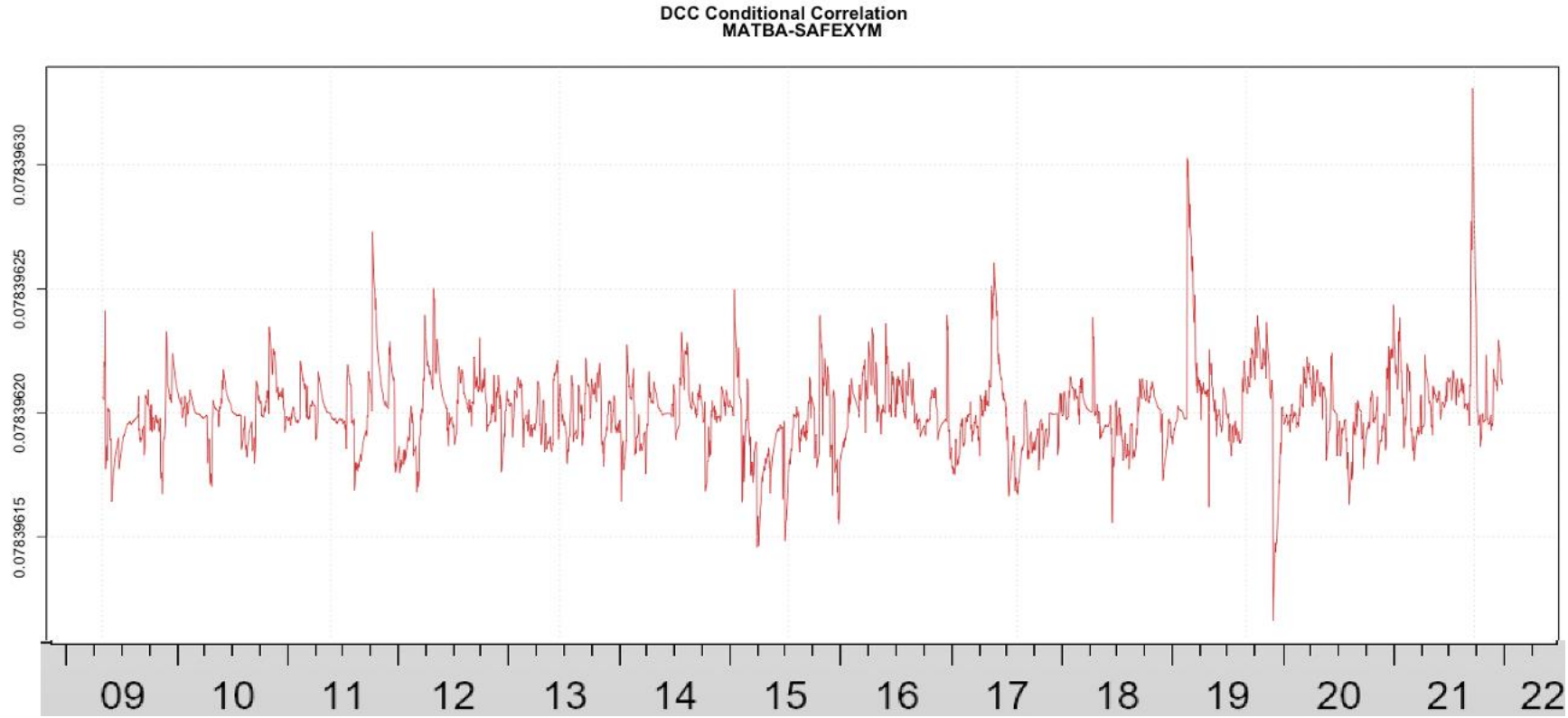


Figure 5.9 : DCC Graph for MATBA and SAFEX yellow maize

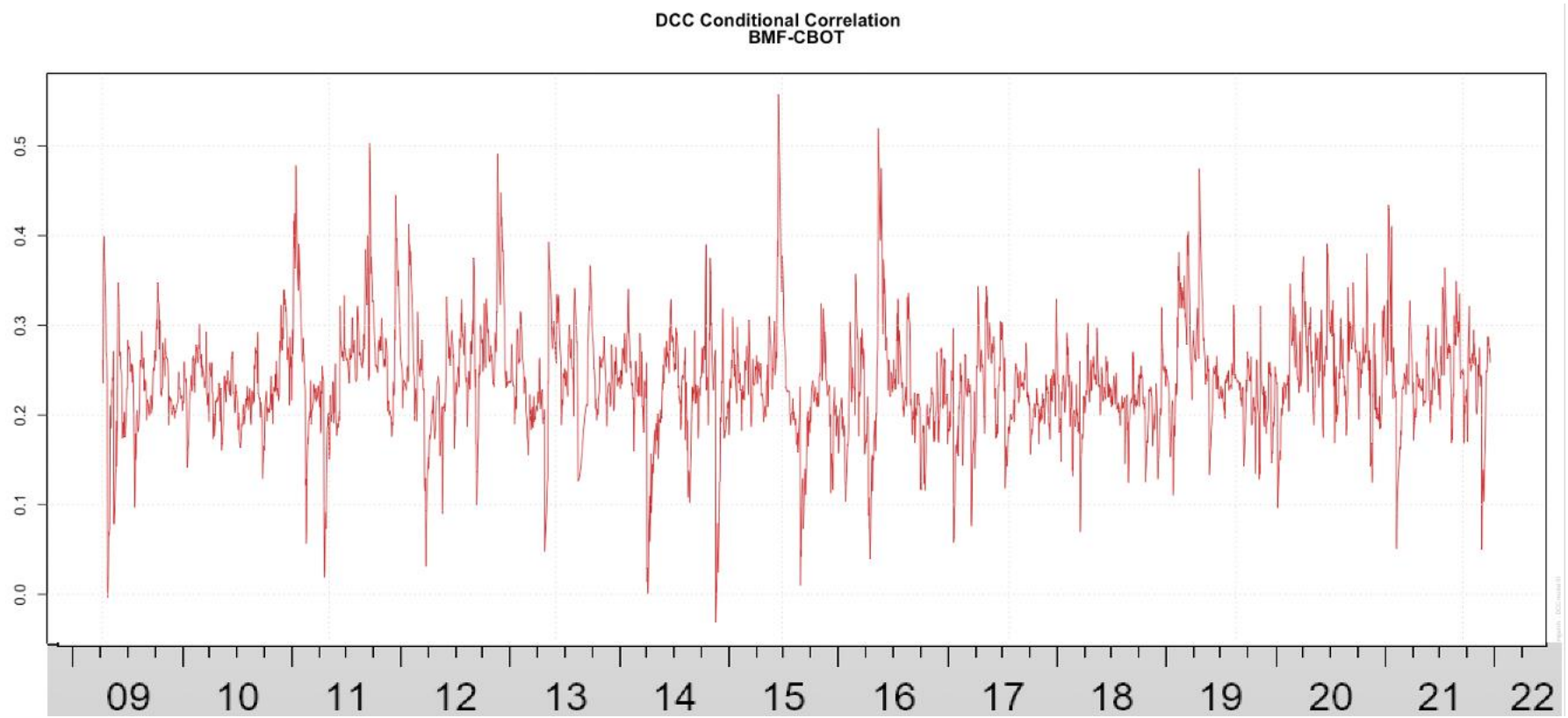


Figure 5.10 : DCC Graph for BMF and CBOT

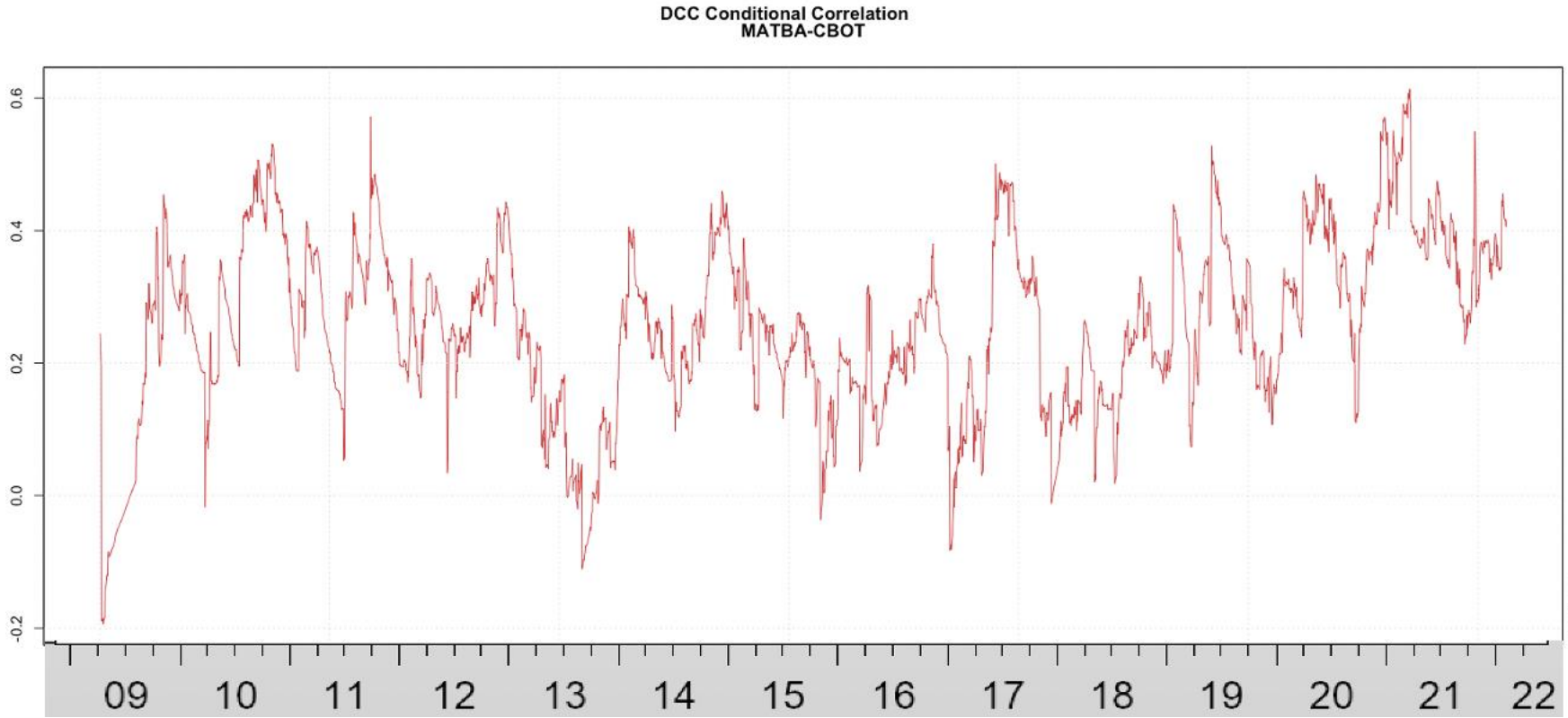


Figure 5.11 : DCC Graph for MATBA and CBOT

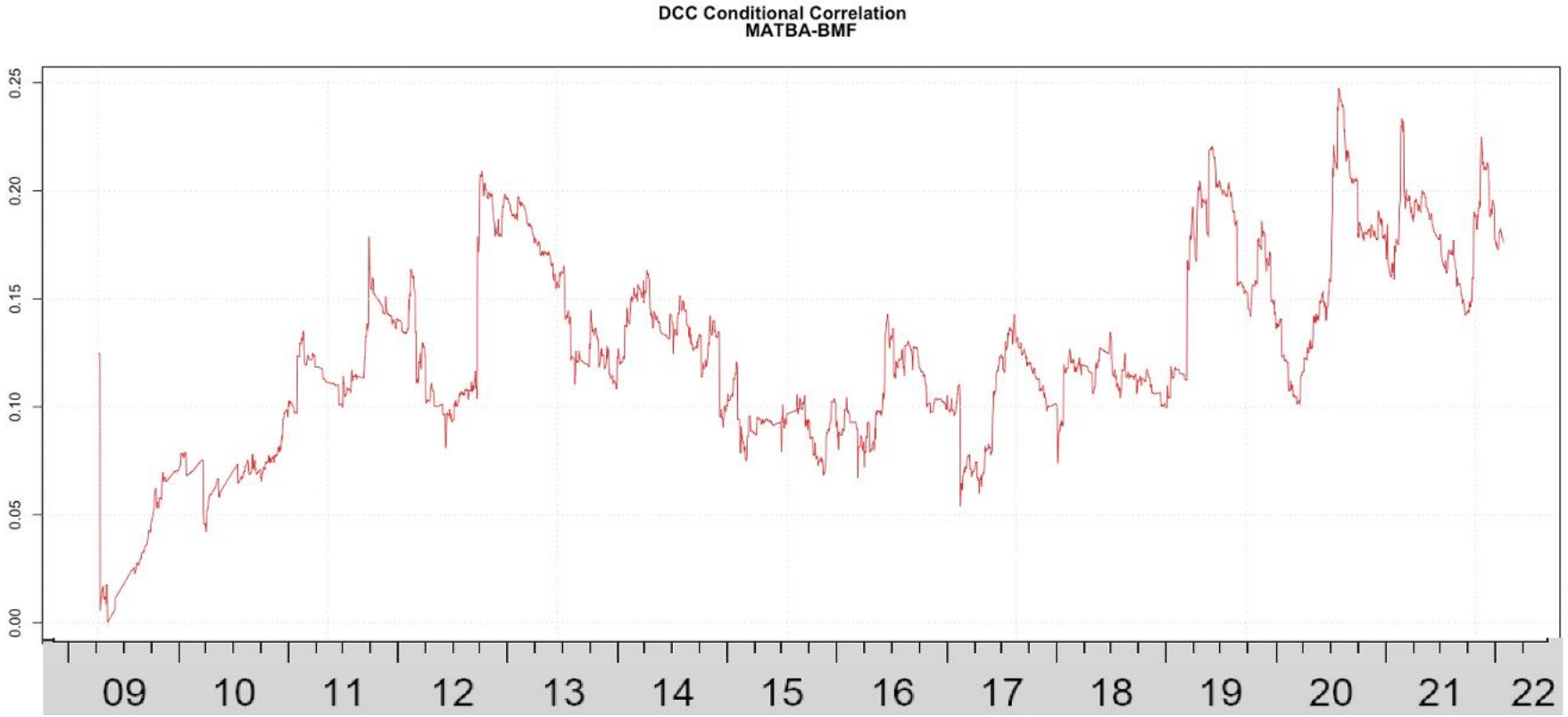


Figure 5.12 : DCC Graph for MATBA and BMF

5.5.5 DCC-GARCH Connectedness

Table 5.8 Shows the results for the dynamic connectedness approach. The static TCI (total connectedness index) is 25%, indicating an strong and positive connectedness among the futures markets examined. This can be interpreted as the average influence of a shock in the system being 25%. This static TCI figure however does not account for the connectedness among them changing over time. Figure 5.13 Shows the dynamic total connectedness of maize futures in major exporters which ranges between 20% and 60%. High levels of connectedness are observed around 2013 to 2014, with the lowest connectedness observed between 2015 and 2016. TCI also seems to fall during 2020, coinciding with the onset of the Covid-19 pandemic.

A review of the graph depicting net total directional connectedness of maize futures of major exporters in Figure 5.14 shows additional insights. The graph for BMF shows this market as a net receiver of volatility predominantly from the end of 2008 until 2014, the graph then moves closer above the zero line up until 2019 when it reverts below the zero line again as a net receiver of volatility. The graph for CBOT shows that this market is a strong net transmitter of volatility throughout the full sample period, with significant spikes observed in 2011, 2014 and 2021. There is one negative trough observed at the beginning of 2014. The graph for MATBA shows that this market is predominantly a net receiver of volatility throughout the entire sample period. Extreme periods of negative net total direction connectedness are observed in 2011, 2014 and 2021, the exact opposite as that observed for CBOT. The graph for SAFEX white maize confirms this market as largely a net transmitter of volatility, with exceptions observed in 2012, 2014 and 2016 when it changed to a net receiver of volatility. The largest positive spikes are observed for SAFEX white maize is during 2020. In contrast, the graph for SAFEX yellow maize shows this market to be a net receiver of volatility almost throughout the entire

sample period with exceptions seen in 2012, 2014 and 2016 when it became a net transmitter of volatility. The strongest negative spike observed for SAFEX yellow maize is during 2020.

Table 5.8 Also shows the values for the net dynamic connectedness for each maize futures market. These results highlights SAFEX white maize as the leading net transmitter of volatility within the system, with CBOT following close behind in second place. The results also show that while SAFEX white maize is the leading net transmitter in the entire network, it is not entirely unaffected by volatility in the other maize futures markets. In particular, the forecast error variance decomposition for SAFEX white maize is largely a component of itself, with 59,06% of its volatility explained by its own-volatility and the other 40.94% explained from volatility spillovers from the other futures markets. This 40.94% is made up of 37.49% from SAFEX yellow maize, 1.60% from CBOT, 1.04% from BMF and 0.81% from MATBA. This result aligns with the results found in the full T-BEKK Model which showed SAFEX white maize to be largely independent of the other exchanges, with no significant volatility spillovers transmitted or received, save from SAFEX yellow maize. Figure 5.15 shows the Net Pairwise Directional Connectedness for SAFEX white maize. The plots reiterate the strong dependence between SAFEX white maize and SAFEX yellow maize with a clear dominant influence of SAFEX white maize transmitting volatility onto SAFEX yellow maize, especially during the onset of Covid-19 where the highest spike is seen. The plots also illustrate the time-varying relationships that SAFEX white maize has with the other exchanges and how it is largely a net transmitter of volatility for BMF and MATBA where large positive spikes are apparent. When examining the time-varying connectedness between SAFEX white maize and CBOT, the period of 2013, when global food crises and food price inflation was at its height, shows that CBOT was transmitting volatility to SAFEX white maize, which was then followed by a large

positive spike in 2014 where SAFEX white maize becomes the net transmitter of volatility to CBOT.

In contrast to SAFEX white maize, SAFEX yellow maize is found to be the strongest net receiver of volatility with a net directional connectedness of -8.18. If one decomposes the variance of SAFEX yellow maize, 51.65% of its volatility is from itself, followed by 44.32% from SAFEX white maize, 1.78% from CBOT, 1.33% from BMF and 0.93% from MATBA. Figure 5.16 shows the Net Pairwise Directional Connectedness for SAFEX yellow maize. The strong interdependence and influence of SAFEX white maize can be seen, as well as the time-varying relationship between SAFEX yellow maize and BMF which still shows SAFEX yellow maize as the net receiver of volatility. The spillovers between SAFEX yellow maize and CBOT and SAFEX yellow maize and MATBA are quite stable with exceptions noted in 2013 and 2014.

The results for CBOT show that almost 86% of its variance is explained itself with the balance explained mostly by MATBA (6.55%), BMF (5.58%), SAFEX white maize (1.29%) and SAFEX yellow maize (1.05). Figure 5.17 shows the Net Pairwise Directional Connectedness for CBOT. The influence of CBOT as a net transmitter to BMF can be seen, with the strength of this relationship declining from 2012, although CBOT still largely remains a net transmitter of volatility to BMF. CBOT also has a strong influence on MATBA in terms of transmitting volatility, with the strength of this relationship weakening over the 2012 to 2018 and then strengthening again with the onset of Covid-19.

Finally, BMF and MATBA have NDC values of -0.24 and -0.82 respectively, indicating that these two maize futures markets neither predominantly transmit nor receive volatility within

the system, but instead have an almost neutral contribution to connectedness and volatility within the entire system. If one splits their forecast error decomposition for each of the futures markets into their components it is clear that most of the variation is from own-volatility (almost 90% for BMF and almost 89% for MATBA. Further, both BMF and MATBA have most of their cross-volatility from CBOT with almost negligible influence from SAFEX white maize and SAFEX yellow maize. Figures 5.18 and 5.19 show the Net Pairwise Directional Connectedness for BMF and MATBA respectively. Both these exchanges exhibit noticeable variability in their relationships with the other exchanges and with each other.

Table 5.8 Dynamic Connectedness in Maize Futures of Major Exporters						
	SAFEXWM	**SAFEXYM**	**CBOT**	**BMF**	**MATBA**	**FROM**
SAFEXWM	59.06	37.49	1.60	1.04	0.81	40.94
SAFEXYM	44.32	51.65	1.78	1.33	0.93	48.35
CBOT	1.29	1.05	85.54	5.58	6.55	14.46
BMF	0.94	0.91	6.45	89.74	1.96	10.26
MATBA	0.71	0.73	7.55	2.08	88.94	11.06
Contribution TO others	47.25	40.17	17.38	10.03	10.24	125.07
NET directional connectedness	6.31	-8.18	2.92	-0.24	-0.82	TCI
NPDC transmitter	3.00	4.00	0.00	1.00	2.00	25.01

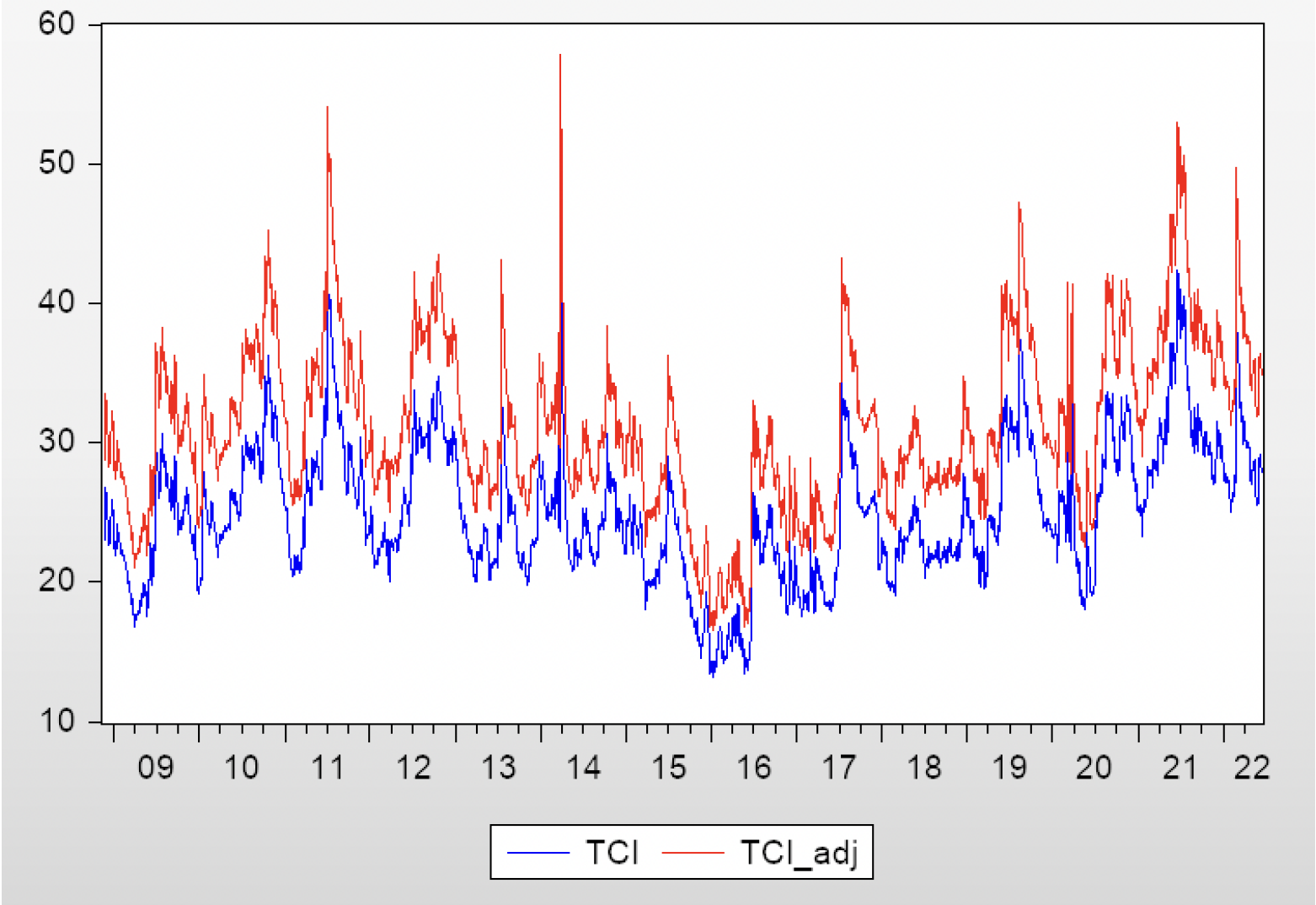


Figure 5.13 : Dynamic Total Connectedness in Maize Futures of Major Exporters

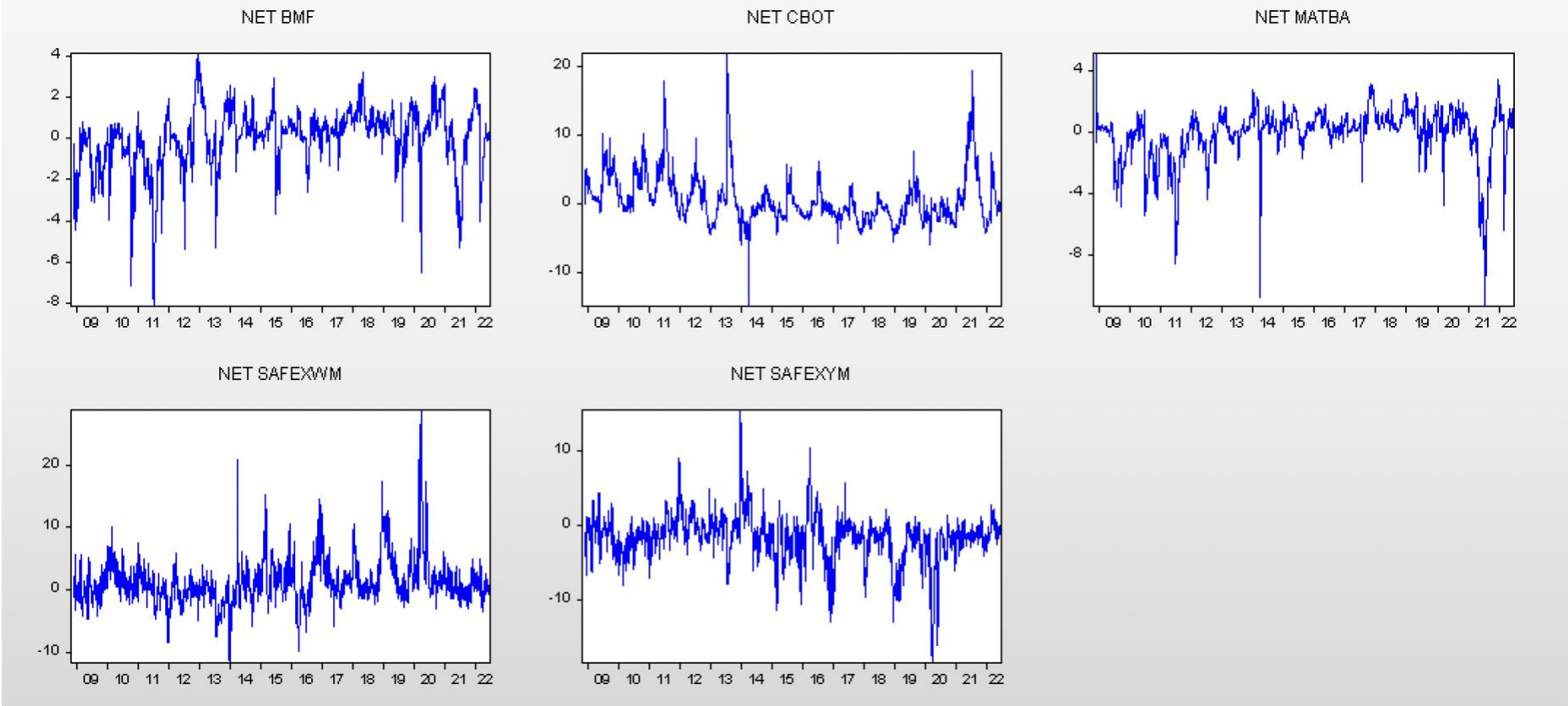


Figure 5.14 : Net Total Directional Connectedness of the Maize Futures of Major Exporters

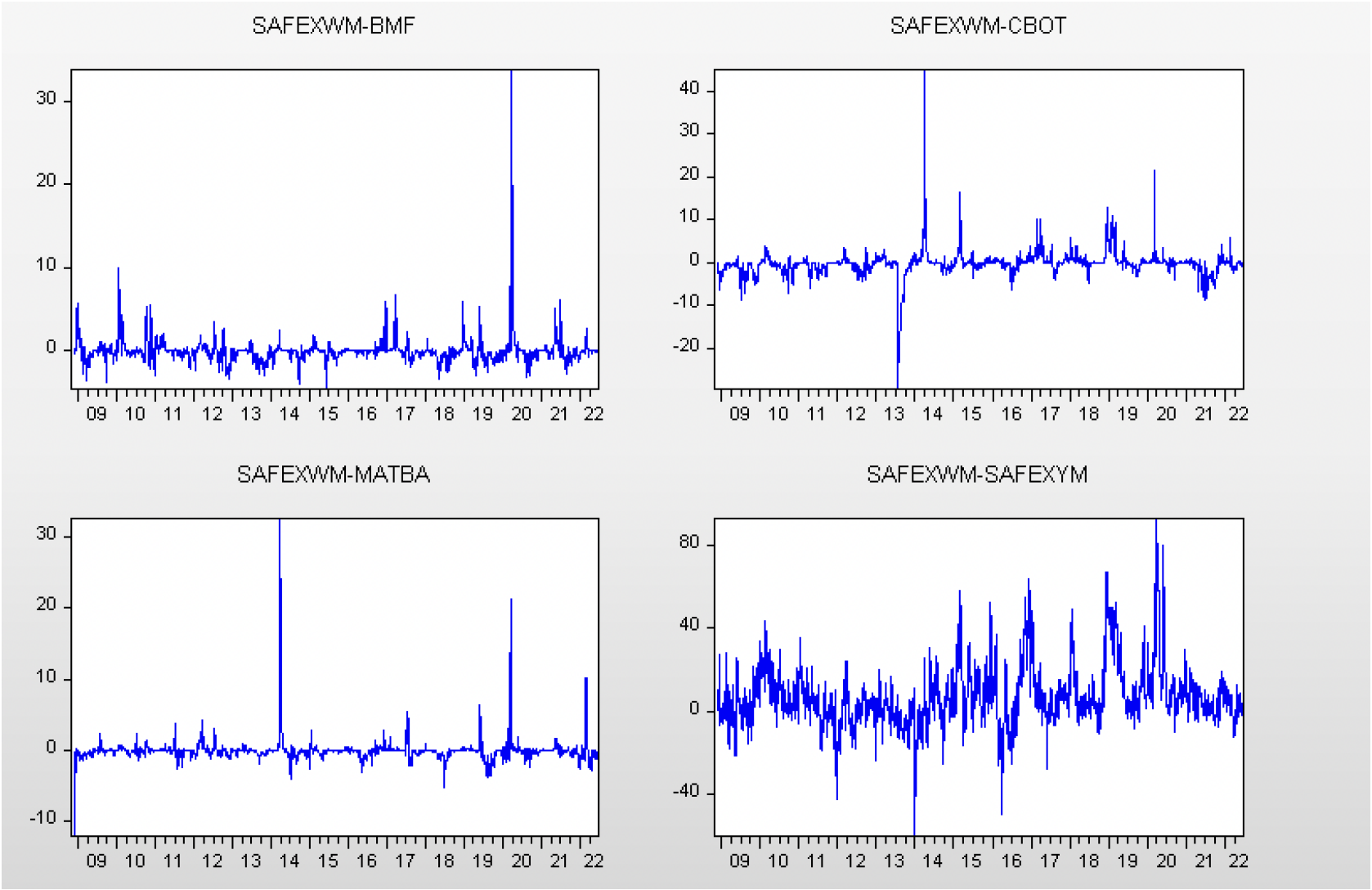


Figure 5.15 : Net Pairwise Directional Connectedness: SAFEX white maize

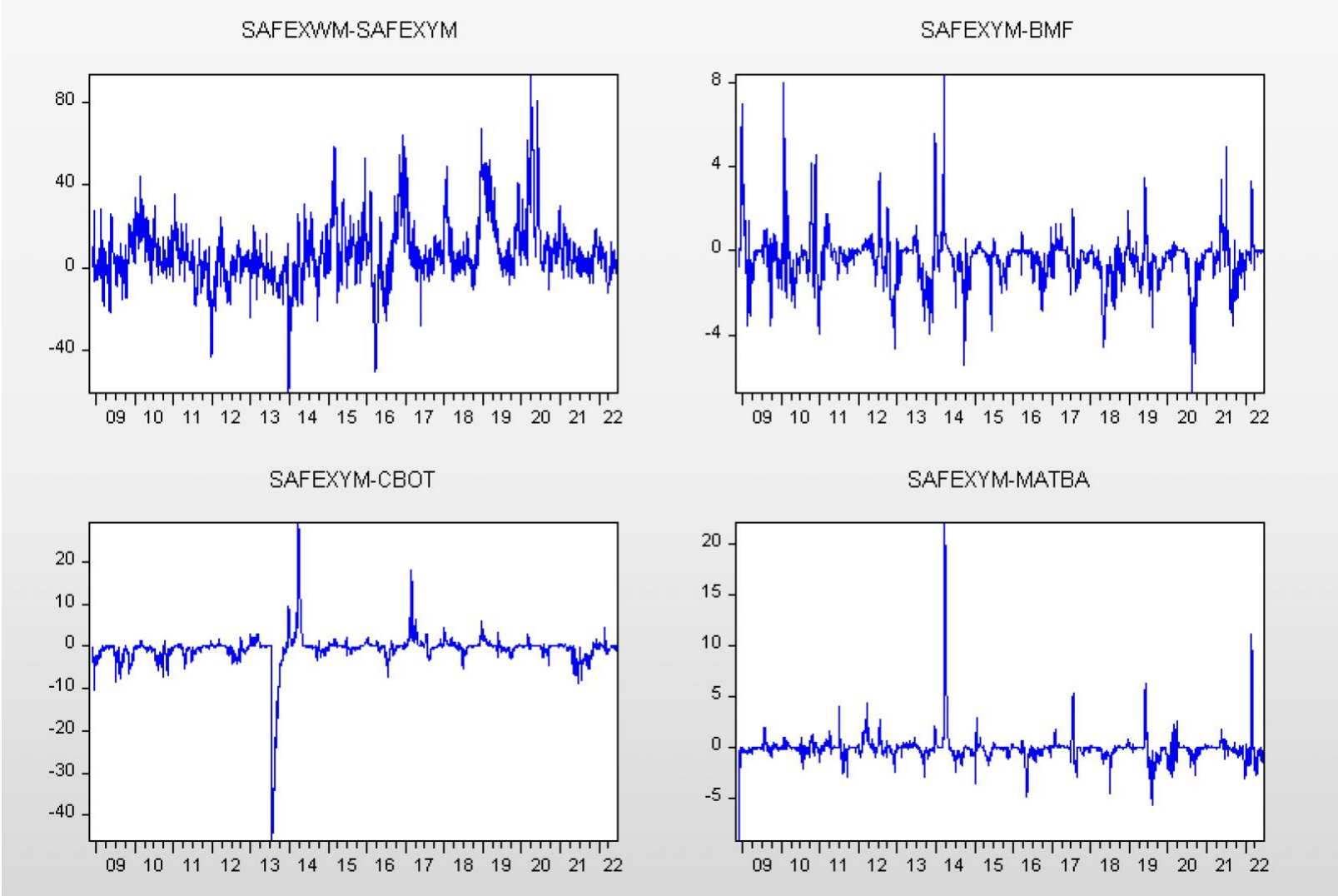


Figure 5.16 : Net Pairwise Directional Connectedness: SAFEX yellow maize

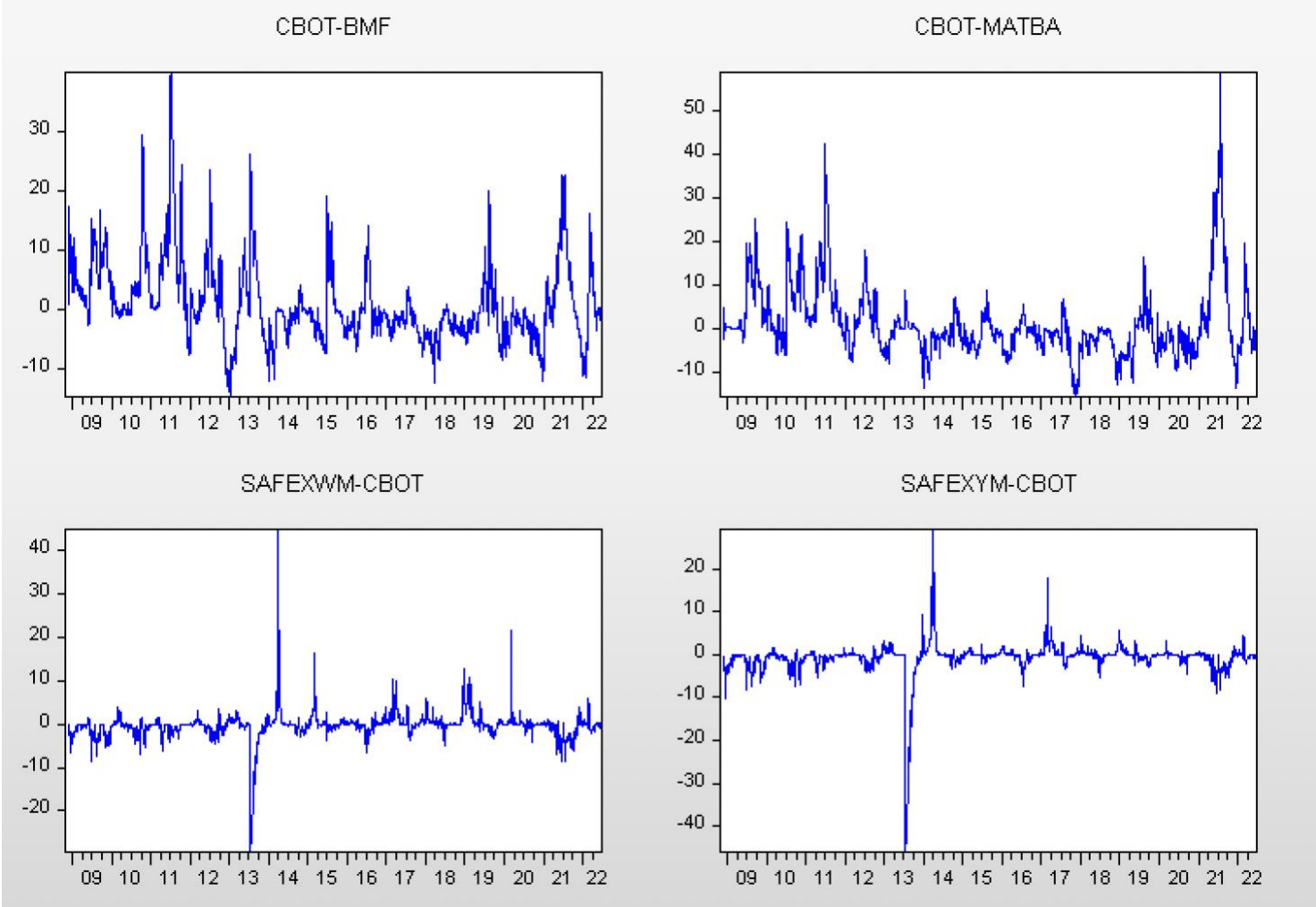


Figure 5.17 : Net Pairwise Directional Connectedness: CBOT corn

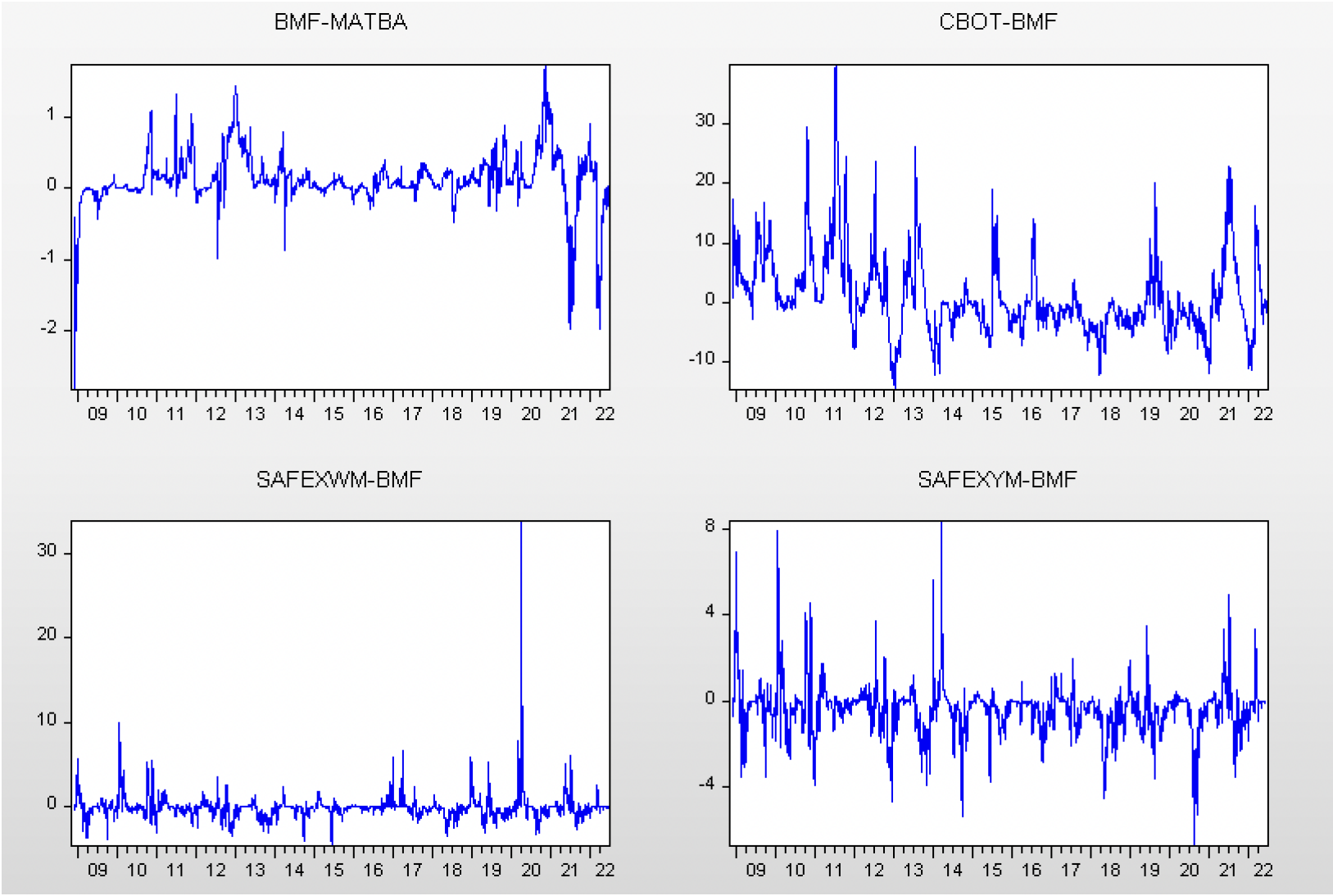


Figure 5.18 : Net Pairwise Directional Connectedness: BMF yellow maize

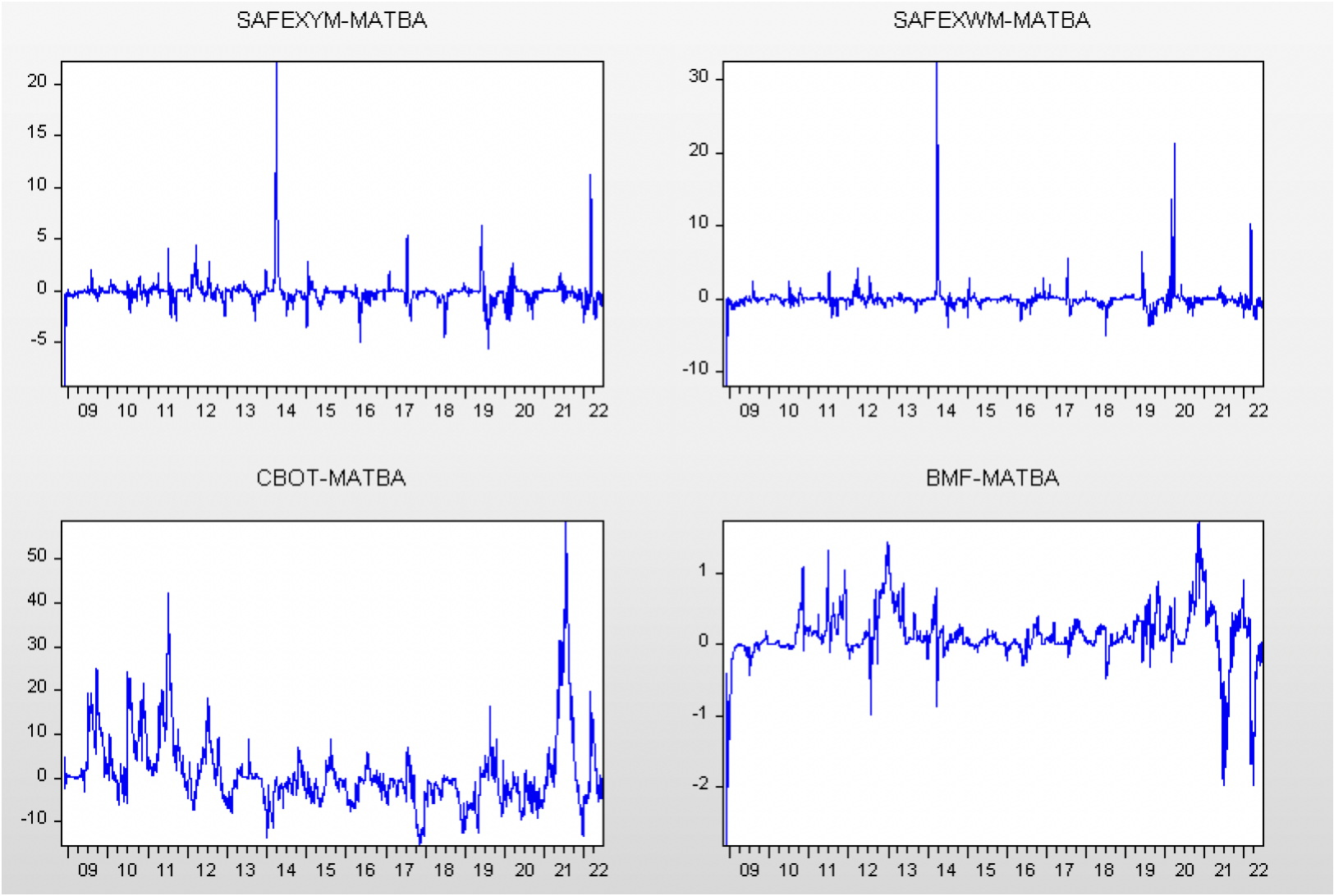


Figure 5.19 : Net Pairwise Directional Connectedness: MATBA

In summary, both the multivariate GARCH results and the results from the dynamic connectedness show that while each of the futures markets are interconnected and interdependent, the degree of this connectedness varies over time. The results also show that volatility for SAFEX white maize is largely independent from volatility spillovers and transmissions from other international futures markets, but that the domestic SAFEX yellow maize does have an influence and is influenced by SAFEX white maize.

5.6 Conclusion

The objective of this chapter was to examine the dynamics and cross-dynamics of volatility spillover and transmission in maize futures listed on SAFEX, CBOT, MATBA and BMF. Daily interactions in the futures markets of the leading exporters of maize were analysed in terms of the conditional second moment of returns. A multivariate GARCH approach was employed to test for the presence of spillover effects over the period 17 November 2008 to 17 June 2022. The results show that the maize futures markets of the U.S., Argentina, Brazil and South Africa are highly interrelated and that the level of interdependence between these markets changes over time. While most South African maize futures studies do include the influence of CBOT in their analysis of volatility, the results of this chapter highlight the importance and influence of Argentinian and Brazilian markets for maize as well. The multivariate GARCH results also showed that no significant volatility spillover occur from the South African white maize futures market onto CBOT, MATBA or BMF. However, statistically significant bidirectional volatility spillover effects are observed between SAFEX yellow maize, CBOT, MATBA and BMF. The results also highlight that the magnitude of interdependence between maize futures markets is higher for SAFEX yellow maize than white maize, although higher variability in the dynamic conditional correlations are observed for

white maize than yellow maize. The results from the time-varying connectedness analysis showed that while most of SAFEX white maize volatility originates from itself, the other futures markets do contribute to the balance of its forecast error variance decomposition, albeit by much less.

These results have important policy implications in the regulation of futures markets and provides a possible explanation for the ineffectiveness of regulatory tools like price limits. In chapter two, the effectiveness of price limits in the South African white maize futures market was evaluated for the period March 2010 to December 2017. It was found that price limits on average had been ineffective in constraining excess volatility and in some cases even exacerbate it. According to Hernandez *et al.,* (2014) any regulatory initiative in a market influenced by exogenous volatility spillovers will have limited effects. The authors instead suggest a coordinated, inclusive regulatory scheme that can be imposed across global agricultural futures markets in order to control excess-volatility.

While this chapter only investigated volatility transmission across the four leading exporters of maize according to the USDA Crop Production Report; future studies may benefit from expanding this database to include other maize markets like the Ukraine and Russia and could even examine the influence of other grains on maize, such as soybeans and wheat.

CHAPTER SIX: CONCLUSION AND FUTURE RECOMMENDATIONS

Despite the growing integration of global agricultural markets, price volatility in domestic grain markets like white maize in South Africa remains an integral topic of concern to be investigated. This thesis investigated price volatility in maize futures by examining four related, but standalone problems: the effectiveness of price limits in stabilising futures markets to avoid excessive price volatility; the impact of sentiment on both daily trading behaviour in futures markets and price volatility; measuring for both the presence of speculation in the absence of detailed open interest data as well as its influence on price volatility; and the investigation of volatility transmission and time-varying connectedness among global maize futures markets, based on their joint role as major exporters of maize.

A particular focus on the South African white maize futures market was maintained throughout this thesis. This was ascribed to the liquidity of this contract on SAFEX, as white maize futures contracts remain to date the most widely traded contract (Sayed & Auret, 2018, 2019, 2020). In addition, SAFEX-listed white maize is also unique as no other futures exchange anywhere else in the world, other than SAFEX, trades this futures contract. This is despite white maize being commonly consumed across Africa, Central America and the southern United States (Ranum *et al*., 2014). Every other exchange that trades maize futures, or corn futures as it is commonly referred to in the United States, trades contracts of the yellow maize variety instead. Furthermore, white maize is South Africa's largest locally produced field crop and also the main staple food for majority of a population. Recent stats published by Statista (2022) report the consumption of processed maize in South Africa between 2001 and 2020. According to their findings, the consumption of processed maize in South Africa was approximately 5.2 million metric tons for the 2019/2020 period, an increase of 1.6% when compared with the

2018/2019 period. They also reported observing a gradual and steady increase in maize consumption.

This thesis was inspired by the debate surrounding the role of speculators in futures markets, whose renewal was sparked by the unprecedented growth observed in commodity derivatives in early 2000. Basu and Gavin (2011) discuss in detail the massive increase in trading among commodity derivatives observed between 2000 and 2010 which they argue far outstripped both growth in commodity production as well as the need for derivatives to hedge risk by commercial producers and users of commodities. This financialisation of commodities and the debate surrounding the ills of speculation remained a sustained interest among academics and practitioners as institutional investors were further blamed for driving up food and energy prices, and causing a food crisis between 2007 and 2008, which was argued by Golay (2010) as being the worst food crisis experienced since 1974. According to several studies conducted in 2008 by the World Bank, the Food and Agriculture Organisation and the International Food Policy Research Institute, global food prices rose by 40% between March 2007 and March 2008, by 56% between January 2007 and June 2008, and by 83% between February 2005 and February 2008 (Golay, 2010). Masters and White (2008) investigated the trading behaviour of institutional investors in commodity futures markets. Their results showed a titanic wave of speculative money flowing into commodity futures markets, which they believed drove up food and energy prices dramatically. They found the total open interest of the 25 largest and most important commodities in 2004 to be $183 billion. In particular, they reported that index speculators poured $173 billion into these 25 commodities between 2004 and 2008. Masters and White (2008) therefore recommended stronger speculative position limits for all speculators in commodity futures markets as well as the elimination of, or at least severe restriction on, index speculation. In South Africa, position and price limits were instituted in

2003 and 2007 respectively. Unlike the abundance of research that was conducted on the financialisation of commodities in the United States, published research on futures speculation on SAFEX and its ability to destabilise commodity prices in South Africa was almost entirely absent with most studies being conducted on a practitioner or white paper[4] level. It is this gap in literature for the risk management function of futures markets, including futures speculation, and the use of position and price limits that this thesis aimed to fill.

The first chapter, titled, *The effectiveness of price limits in the South African white maize futures market*, investigated the relationship between price limits, price volatility and trading volume for SAFEX-listed white maize futures contracts. In so doing, this chapter evaluated four distinct hypotheses. Evidence for the volatility spillover hypothesis was found as the implementation of price limits resulted in heightened volatility on subsequent trading days. This chapter also tested the delayed price discovery hypothesis which showed that price limits prevented rational and informed trading which in turn kept futures prices from efficiently reaching their equilibrium. The liquidity interference hypothesis was also examined which observed sharp reductions in trading volume, followed by intense reversals once limits were lifted. Finally, support for the gravitation or magnetic hypothesis was also found. This showed that the anticipation of an impending price limit caused prices to accelerate towards their limit prematurely, proving price limits to be self-fulfilling and disruptive to trading activity. Overall, price limits were found to be ineffective for white maize futures in curbing excess-volatility, and instead amplified volatility and impaired liquidity.

The second chapter titled, *The effects of uncertainty on investor expectations and price volatility in the South African white maize futures market* had two objectives The first objective

[4] A white paper is an informational document usually issued by a company on not-for-profit to promote or highlight the features of a solution that it plans to offer.

examined the effects of uncertainty as proxied by three forward-looking indices - the SAVI Top 40, SAVI Dollar and SAVI White Maize - on investor expectations as proxied by three momentum indicators – the Moving Average Convergence Divergence (MACD), the Relative Strength Index (RSI) and the Rate of Change (ROC) – each constructed from the closing prices of South African white maize futures. The second objective of this chapter examined the effects of uncertainty as proxied by the volatility indices on the price volatility of the South African white maize futures, as proxied by the fitted time series of the standard deviation of a GARCH (1,1) model. The results reflected that traders shift their expectations during periods of uncertainty at the daily level. The results in the chapter suggest that price volatility in the South African white maize futures market are driven not only by market fundamentals, but that changes in the decision making of day traders, following shifts in sentiment, are also responsible for influencing price volatility.

Following the results, and the implications thereof of chapter two, the third chapter, titled, *Speculative ratios and price volatility in the South African white maize futures market*, empirically investigated the impact of speculative activity, as proxied by trading volume and open interest, on price volatility in the South African white maize futures market, as proxied by the fitted time-series of the standard deviation a GARCH (1,1) model. This chapter measured speculative and hedging ratios, given the absence of the split of open interest data similar to that found in the CFTC's Commitment of Traders Reports (COT), in order to examine if excess-speculation influences price volatility. The results revealed that a high level of speculative trading activity was present in the South African white maize futures markets. The results also identified a positive and significant relationship between excess-speculation and volatility, but the magnitude of this relationship was almost negligible in size. These results and the implications thereof once again questioned the validity of imposing strict position and

price limits on SAFEX-listed white maize futures contracts. These results also question if their imposition impairs liquidity and efficiency in the market, particular in the context of recent studies who view speculators as informed traders, whose investment decisions instead expedite price equilibrium.

The fourth chapter, titled, *Volatility spillover and dynamic connectedness in maize futures of major exporters*, investigates volatility spillover and time-varying connectedness among maize futures listed on SAFEX, CBOT, MATBA and BMF in order to ascertain if a significant component of the price volatility in SAFEX-listed white maize futures is as a result of spillover from volatility in other maize futures markets. This chapter also examines the interdependence between maize futures markets, while evaluating how the degree of interdependence between them has changed over time. When quantifying own-volatility spillovers, SAFEX white maize exhibits the highest own innovation shock and also shows strong and statistically significant own-volatility persistence. SAFEX white maize is also found to not transmit any volatility to any of the other maize futures contracts examined, but receives volatility spillovers from SAFEX-listed yellow maize. Despite the independence in volatility exhibited by SAFEX white maize, the connectedness results shows SAFEX white maize to be the largest net transmitter of volatility within the system, followed only by CBOT. SAFEX yellow maize, BMF and MATBA are all found to be net receivers of volatility within the system. This final result reiterates the importance of examining price volatility for a unique, regional futures contract like SAFEX-listed white maize, as volatility observed in this market not only spills over domestically onto SAFEX-listed yellow maize contracts, but also affects the volatility of maize futures contracts listed in Brazil and Argentina as well.

Among the most significant contributions of this thesis, the examination and exposition of speculation is by far the most noteworthy. Distinguishing between investing and speculation

has been both interesting and contentious for several hundred years. In the book, *Confusion of Confusions* written by Joseph de la Vega in 1688, de la Vega categorized men into three classes. The wealthy investors were termed 'financial lords', the merchants were the 'occasional speculators' and the last class was known as the 'persistent speculators' or the 'gamblers' (de la Vega, 1957). When embarking on this thesis journey in early 2017, very little research had been done on speculation in South African markets, and in particular, on agricultural grains listed on SAFEX when compared against the volume of equities research available in South Africa. The majority of published papers at the time concentrated on the price discovery function of futures markets. It should be acknowledged that the lack of substantial research available for the risk management function was possibly due to the lack of available data. Hypotheses are formed in order to pursue the truth and adequately understand and investigate a problem. However, one can often only test what one can observe. The lack of a direct and acceptable measurement of speculation therefore contributed to the paucity of research in this subject. As a prelude to the rest of the research problems investigated in the thesis, and accepting the lack of data available to examine speculation in white maize futures directly, the first area of research that this thesis contributed to was the examination of price limits.

Despite price limits being imposed on SAFEX, and in particular on white maize futures, since 2007, no published work examining their effectiveness had been done. This thesis therefore contributed to the body of knowledge on price limits by empirically investigating its effectiveness through the investigation of price volatility and liquidity, as proxied by trading volume. Chapter two's findings showed price limits to be ineffective in moderating volatility, and was found instead to affect liquidity, disrupt price discovery and even exacerbate volatility levels. The thesis recommends that the JSE consider the possibility of a dynamic price limit that is based on a percentage price change, instead of the current static price limit. It should be

noted as well that during the inception of price limits, the JSE initially agreed in principal that limits should represent 2,5% of the value of the underlying commodity (NAMC, 2009). Given the increased levels of prices in white maize, both at the spot and futures levels, it is unclear if this has been maintained. The benefits of widening price limits has also been documented more recently by Jin, Yuan, Ma and Lian (2022). In their analysis of the Chinese stock market, Jin *et al*., (2022) explored the net effect of price limits on price discovery efficiency based on a quasi-natural experiment of widening price limits for Chinese equities. They used intraday data to calculate speed and accuracy which they argue provides a more comprehensive and accurate measure of price discovery efficiency. Their results showed that widening price limits were beneficial for improving price discovery efficiency as it allowed more private and public information to be incorporated into the stock prices through trades and quotes.

This thesis also significantly contributed to the body of knowledge surrounding the impact of speculative trading in the South African white maize futures market. Given the lack of data required to directly measure speculation, this thesis made use of speculative and hedging ratios similar to Lucia et al.,, (2015) and Bohl et al.,, (2018). The results from this chapter highlighted that while a high level of speculative activity is present in the South African white maize futures market, it is unlikely that the magnitude of its influence is sufficient to justify for the position and price limits currently imposed on SAFEX. Following the result in both chapters two and four, this thesis recommends the adoption of weekly trading reports by the JSE, similar to the Commitment of Trader reports published by the CFTC that splits open interest data into commercial and non-commercial, and further, between long and short positions. This will allow academics and practitioners to calculate the proportion of net long positions held by speculators which will reflect the true level of excessive speculation in a futures market. This can then be used as an input into financial and statistical models to more accurately assess the impact of

speculative trading on price volatility and to test if futures speculation destabilises commodity prices. We note the complexity involved however for regulators and policymakers to implement these recommendations. This is further supported by Masters and White (2008) who recognise the importance of direct intervention by policymakers, especially in the case of destabilising speculation. Masters and White (2008) however also assert that the ability of any regulator to intervene effectively relies upon its ability to not only understand the market, but to also collect the required data, and they too recommended extending the product coverage of the CFTC's COT reports. They assert that the availability of such data would provide regulators and policymakers with early warning signals that would allow them to recognise impending commodity price bubbles.

Another contribution that this thesis makes is in chapter three where sentiment in the South African white maize futures market is examined. Again, despite the SAVI White Maize index being launched in 2009, no study at the time of the beginning of this thesis had investigated the relationship between SAVI White Maize, or any of the other SAVI indices, with South African white maize futures. The contributions of this chapter are noteworthy and highlight the successful use of technical analysis in a commodity market over and above its widespread use in equities. This chapter also contributes to the growing body of knowledge in behavioural finance for an emerging commodity market as sentiment was found to affect the decision of traders as well as the price volatility.

Finally, chapter four contributes to studies that examine volatility spillover and connectedness in agricultural futures. Prior to this thesis, the influence of other maize (or corn) futures markets on SAFEX white maize had not been directly investigated. Instead, CBOT-traded corn was always included in maize futures analyses as it has generally been accepted that the CBOT-

corn near futures price serves as the world supply-demand price discovery mechanism (Auret & Schmitt, 2008). Chapter four also makes a notable contribution in terms of the methodology used. Chapter four made use of four multivariate GARCH models to examine volatility spillover, while also employing the DCC-GARCH Connectedness approach of Gabauer (2020) which extends and improves upon the Diebold and Yilmaz (2012, 2014) spillover index. This research is unique as there were no South African studies prior to this that had made use of these four multivariate GARCH models to assess price volatility in futures markets. Most South African studies had instead examined price volatility in grain futures under a univariate GARCH approach. According to Hurditt (2004) and Felipe and Diranzo (2006) the univariate GARCH approach suffers from two shortcomings. Firstly, it does not account for the possibility of having causality between volatilities in both directions. Secondly, it neglects the information contained in the covariance matrix of the residuals.

For maize farmers in South Africa, stability in prices remains a top priority given their reliance on rain-fed agricultural output and the uncertainty that seasonality brings. The use of maize futures contracts listed on SAFEX both for price discovery as well as risk management will therefore continue to play an important role for commercial market participants in the maize industry. These contracts help limit losses stemming from increased rainfall volatility and expected reduced output. As climate change continues to deepen, increased intensity and frequency of extreme weather will only exacerbate the price volatility observed in grains like maize. Ray, West, Clark, Gerber, Prishchepov and Chatterjee (2019) contend that climate change has already likely affected global food production. In their analysis of weather and reported crop data, the authors found that within North and Central America, recent climate change impact was found to be significant over 89% of maize-harvested areas. Future research concerning maize in South Africa will therefore benefit from collaborations between topics in

climate change and the economic analyses of commodity prices and volatility. In particular, investigations concerning precipitation levels in South Africa and how these have changed over time given the impact of climate concerns and the increase in the severity of extreme weather events like droughts and floods.

Forthcoming research should also take the Russia-Ukraine conflict into consideration to examine the impact that grain shortages in Europe might have in the rest of the world, particularly in emerging markets like South Africa and Brazil. Ukraine is one of the world's largest producers and exporters of maize in the world (USDA WASDE, 2022). According to a report released in July 2022 by the Food and Agriculture Organisation on Ukraine, between 20% to 30% of the crops sewn in the Ukraine will remain unharvested and as harvesting season has already begun, the Ukraine will soon exhaust all its available grain storage capacity. In addition, there has been a fall in yields which will further reduce cereal production by up to 40% when compared with production levels of the preceding year. Apart from maize, Ukraine is a net exporter of several other agricultural products and a leading supplier of foodstuff and fertilizers to the global market. Many of the production shortfalls that will exist because of the war will only partially be compensated by alternative sources during the 2022/2023 marketing season. This will place additional capacity constraints on many exporting countries trying to boost outputs and shipments as they will be limited by higher production and input costs. The report further highlights that if the war continues, a considerable supply gap would remain in global grain markets, which will in turn elevate grain prices well above their baseline levels, ultimately increasing global food insecurity.

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