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**OPTIMAL CROSS HEDGING RELATIONSHIPS OF
INTERNATIONALLY PRICED COMMODITIES IN THE
SOUTH AFRICAN CONTEXT**

By

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SUMMARY

Commodities, which are a type of alternative investment, do not follow the normal characteristics of traditional investments. Because commodities do not act the same as traditional investments, the use of commodities for diversification purposes arises. Commodities can be used in normal investment decisions, which allows financial participants to improve the selection of assets included in an investment portfolio and ensure that returns are protected to some extent.

Commodities have shown continuously changing co-movement over the last twenty-five years. This development has made investment decisions related to commodities more difficult and therefore resulted in more risk being present within the alternative investment class. Commodities have also shown a shift in fundamental behaviour over time, which results in findings that are not necessarily applicable to current market conditions.

A second development that has occurred over the last ten to fifteen years is the financialisation of commodities as financial participants demand more investment opportunities. Without an understanding of the interaction of commodities with other financial variables or between other commodities, commodities as investment assets are limited and underutilised.

The financialisation of commodities has emphasised the market efficiency related to commodities. The market efficiency has increased over the last decade as the speed of market reactions as well as the quantity of information to the market increased. These two concepts have made investing within traditional investments more difficult. With fewer traditional investment opportunities, investors have started searching for opportunities in other parts of the financial market, which has allowed alternative investments to develop as quickly as they have. Commodities have allowed for another avenue for diversification as well as hedging opportunities.

With the uncertainty currently facing the investment environment, the possibility of loss situations is managed and efforts are put in place to avoid or at least reduce the loss situation. Diversification and hedging practices are used to reduce the risk that is carried within an investment portfolio. The information about the long run and short run relationships as well as optimal cross hedging relationship results obtained in the study can be used to utilise commodities as part of diversification and hedging practices within an investment portfolio. The use of these relationships ensures that investment practices utilised in investment portfolios keep up with the evolving nature of the investment environment.

Commodity prices also show a tendency to move together, even if they have no reason to be related (Abdullah, Saiti & Masih, 2016; Baffes, 2007; Pindyck & Rotemberg, 1993; Pindyck & Rotemberg, 1990). It is for this inexplicable reason that the study was undertaken. The unexplained relationships that will be identified in the study can be used to reduce the risk that is present in an investment portfolio. By understanding the relationships, alternative investments, with the focus on commodities, can be included in the investment decisions to reduce risk. The possible reasons that commodities show a tendency to move together is the financialisation of commodities as well as the fundamental shift that occurs over time in the co-movement of commodities.

Commodities have become more financialised; therefore, the opportunity exists to diversify risk by means of commodities that are an alternative asset. The relationships and interactions commodities have with other variables in the financial markets are still not fully understood, which creates a problem when including commodities in an investment portfolio or risk management strategy. By not fully understanding the relationships present between commodities, as well as between commodities and other financial variables, the use of commodities is limited and inefficient.

Commodities have emerged as an investable asset class that is sought by institutional investors holding larger quantities as there are diversification benefits outside traditional assets. The financialisation of commodities has created access to the commodities to be used as investment tools both for investment outside of traditional investment opportunities as well as for risk management strategies that have not previously been exploited (Büyükkahin & Robe, 2014; Singleton, 2014; Basak & Pavlova, 2013).

The purpose of the study was to determine which cross hedging relationships exist between commodities in the South African financial market. The investigation aimed to determine the long run relationships and the short run dynamics between the variables with a final purpose of obtaining optimal hedge ratios and cross hedging relationships. In order to determine the overall research question, the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index, between each commodity price and the South African Rand (ZAR), and between the FTSE/JSE Top 40 Index and the ZAR had to be determined so that the interrelationships between the variables could be understood. The optimal cross hedging relationships obtained are important for investment decisions and portfolios as well as the risk management strategies related to the investments as they allow for new additional uses of commodities.

The study included a subset of the selection of commodities grouped according to categories of commodities, namely metal commodities, which included precious metals; soft commodities, which was focused on agricultural commodities; and energy commodities. The relationships were used as a starting point in order to obtain cross-hedging relationships using commodities in the South African financial market. The analysis that was performed in Chapters 4 to 6 included stationarity tests, visual representations, descriptive statistics, correlation, vector autoregression (VAR), Johansen cointegration, Granger causality and Toda Yamamoto test, vector error correction model (VECM), block exogeneity, impulse responses, variance decompositions. Chapter 7 applied correlation, Granger causality, ordinary least squares (OLS), error correction model (ECM), VECM in relation to hedge ratios, ECM-GARCH (Generalised Autoregressive Conditional Heteroscedasticity) model, asymmetric dynamic conditional correlation (ADCC) GARCH model, hedging effectiveness using variance, Value at Risk and Expected Shortfall; mean-variance analysis, and maximum drawdown.

A number of long run and short run relationships were identified when investigating the groups of commodities. The relationships identified gave an indication of the interrelationship among variables and how variables reacted after a shock was applied. By establishing that long and short run dynamics existed among the variables, further analysis was required to determine what investment opportunities existed

between the variables for investment portfolios as well as risk management strategies. This created the need to determine the hedging opportunities available (1) between commodities in the same category of commodities, (2) between different categories of commodities, and (3) between a commodity and the ZAR or FTSE/JSE Top 40 Index.

Significant relationships were identified between each category of commodity, namely metal, soft and energy, and the FTSE/JSE Top 40 Index and the ZAR. The results indicated that both long run and short run relationships were present in the data. Positive and negative correlations were identified, followed by only a small number of causal relationships related to the ZAR and the FTSE/JSE Top 40 Index.

The vector error correction model (VECM) results identified statistically significant variables in the cointegrating equation, when the FTSE/ JSE Top 40 Index was the normalised variable as well as when the ZAR was the normalised variable. The VECM also identified a number of short run relationships when testing the ZAR and FTSE/JSE Top 40 Index.

The relationships identified throughout the study were used as exploratory investigation for the final analysis to determine the optimal hedge ratios and the cross hedging relationships. Positive and negative correlations were found between different groups of commodities. The strong correlation relationships identified create the opportunity for diversification within the investment and risk management practices and therefore the optimal hedge ratios were investigated to determine the best cross hedging relationships available among the included variables.

The cross hedging results indicated that the time-varying model provided the top results with regard to hedging effectiveness, followed by OLS and ECM-GARCH. When analysing the cross hedging relationships between the variables, the same spot and future combination was seldom identified as the best option, except when using the 95% and 99% Value at Risk and Expected Shortfall measures. The FTSE/JSE Top 40 Index, the ZAR, commodities from different commodity classes as well as different commodities in the same asset class provided more optimal cross hedging opportunities.

The contribution of this study is important for fellow academics who conduct research in similar fields as well as for market participants who are interested in having a better

understanding of the relationships present between the variables. The findings will add to the current body of literature available on this topic by expanding on the sample size with regard to the variables included, the time period selected, as well as an extended methodology. This kind of research has not been done before and therefore this is an original contribution in the field of commodities, linked to alternative investments and risk management. Available literature that includes the financial econometric methodology is limited to a few commodities. Existing studies have focused either on the relationships between commodities, or otherwise the relationships between commodities and monetary policy variables. Hedging literature has focused on selected hedging methods with limited hedging effectiveness measures. No literature was found that applied the full methodology used in this study, including the cross hedging relationship analysis. This is significant, as it is an adapted application of traditional financial econometric and risk management methods.

Commodity price movement changes continuously, with market implications of commodity price movements affecting many aspects of the financial markets, such as the equity market, the foreign exchange market as well as alternative investments. The second contribution was the identification of relevant relationships between commodities, the FTSE/JSE Top 40 Index and the ZAR. This creates an understanding of how the variables move when compared together and asymmetries were identified in the optimal hedge ratios that are creating a new diversification opportunity with alternative investments. The asymmetries identified showed that the hedge ratios differed between independent variables compared to dependent variables. The asymmetry finding is consistent with the findings of Kurihara and Fukushima (2014) and Groenewold and Paterson (2013).

The research available on alternative assets is limited in scope and time; alternative assets are a continuously developing field, which adds to the significance of this study. The third contribution was the adaptation and application of a known financial econometric methodology of calculating the optimal hedge ratios to the context of commodities in the South African market. The cross hedging relationships and optimal hedge ratios were focused on relationships between different commodity classes. This resulted in a contribution to academic literature as the full methodology process in this study as well as the combination of variables studied has not been applied before.

The results of this study relate to all the relationships identified as well as the optimal cross hedging relationships. This creates new opportunities that are needed in the evolving fields of investment management and risk management. This study indicates that there is an opportunity to use commodities as hedging instruments within investment portfolios that consist of equities, exchange rates and other commodities. It is possible to use commodities as a risk management tool as well by using them more efficiently and effectively through minimising the cost of hedging, which creates larger profit opportunities.

Key words

Commodities, comovement, cross hedging, FTSE/JSE Top 40 Index, relationships, South African Rand.



DECLARATION OF ORIGINAL WORK

I, Corlise Liesl le Roux declare that *Optimal cross hedging relationships of internationally priced commodities in the South African context* is my own unaided work, that it has not been submitted before for any degree or examination at this or any other University, and that all the sources I have used or quoted have been indicated and acknowledged as complete references.

Signature

Date



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LIST OF ABBREVIATIONS AND ACRONYMS

The followings terms, abbreviations and acronyms have been used in this thesis:

| | |
|--------|---|
| ADCC | Asymmetric Dynamic Conditional Correlation |
| ADF | Augmented Dickey-Fuller |
| AIC | Akaike's information criterion |
| BDS | Brock, Dechert and Scheinkman |
| BRICS | Brazil, Russia, India, China and South Africa |
| B-SVAR | Bayesian Structural Vector Auto-Regression |
| CCC | Constant Conditional Correlation |
| CIA | Central Intelligence Agency |
| CVaR | Conditional Value at Risk |
| DCC | Dynamic Conditional Correlation |
| ECM | Error correction model |
| ES | Expected Shortfall |
| FPE | Final prediction error |
| GARCH | Generalised autoregressive conditional heteroscedasticity |
| GDP | Gross domestic product |
| GJR | Glosten, Jagannathan, and Runkle |
| GSCI | Goldman Sachs Commodity Index |
| HQ | Hannan-Quinn |
| IMF | International Monetary Fund |
| JSE | Johannesburg Stock Exchange |
| LME | London Metal Exchange |
| OLS | Ordinary Least Squares |
| PP | Phillips-Perron |
| PVAR | Panel VAR |
| RBOB | Reformulated Gasoline Blendstock for Oxygen Blending |
| S&P | Standard and Poor's |
| SC | Schwarz information criterion |

| | |
|---------|---|
| StatsSA | Statistics South Africa |
| US | United States |
| USD | United States Dollar |
| USDA | United States Department of Agriculture |
| USGS | United States Geological Survey |
| VAR | Vector autoregression |
| VARMA | Vector autoregression moving average |
| VaR | Value at Risk |
| VECM | Vector Error Correction Model |
| WTI | West Texas Intermediate |
| WTO | World Trade Organization |
| ZAR | South African Rand |



CHAPTER 1

INTRODUCTION AND BACKGROUND TO THE STUDY

1.1. INTRODUCTION

“Do not dwell in the past, do not dream of the future, concentrate the mind on the present moment” (Brainy Quote: Buddha, 2016).

The movement of commodity prices over the last decade has confused many investors as the pattern in which the commodities were and are moving has become more extreme and inconsistent with economic principles. The issue faced when investing with commodities is that one cannot focus on the past as the changes are inconsistent and no one knows where the prices are going because of the erratic nature of the past. What this study attempted to do was to understand the past and get to a point from which to advance, based on the development of relationships.

Commodities are referred to as alternative investments and do not follow the normal characteristics of traditional investments. Because commodities do not act the same as traditional investments, the possibility of the use of commodities for diversification purposes arises. Commodities can be used in normal investment decisions, which allows for financial participants to improve the selection of assets included in an investment portfolio while ensuring that returns are protected to a certain extent.

1.2. PROBLEM STATEMENT

Commodities have shown continuously changing comovement over the last twenty-five years. This development has made investment decisions related to commodities more difficult and therefore resulted in more risk being present within the alternative investment class. Commodities have also shown a shift in fundamental behaviour over time, which has resulted in findings that are not necessarily applicable to current market conditions.

A second development that has occurred over the last ten to fifteen years is the financialisation of commodities as financial participants demand more investment opportunities. Because of a lack of understanding of the interaction of commodities with

other financial variables or between other commodities, commodities as investment assets are limited and underutilised.

The amount of literature available on commodities is limited, while existing studies are focused only on narrow aspects related to commodities. When research about commodities is undertaken, the focus is normally on how a commodity reacts with other commodities, limited to a single commodity class or a few commodities only. In studies that compare commodities to other financial variables, the interaction is limited to the relationship, market and period that are being tested.

Commodities are interlinked; however, the extent of the linkage effects has not been determined, as studies undertaken to determine the linkages are focused on a limited number of commodities, in selected markets, for a selected period of time. These selections limit the information available to determine the interrelationships between commodities and the larger classes of commodity. Consider the interrelationships of agricultural commodities. If the ideal environmental conditions required for agricultural commodities to produce crops of substantial size and quality around the world result in the production of large high-quality crops, the income earned from the crop enables farmers to redeploy their income to labour, machinery, transport, and technology, which links to other commodity classes.

The market linkage effects of the increased size of the agricultural commodities reaches metal and energy commodities, leading to the increased use of these commodities. The linkage results in interrelationships between commodities, which leads to the idea that one class of commodities can cause another.

The interrelationship between commodity classes is not analysed by commodity analysts in financial and other institutions. Commodity analysts normally focus on selected classes of commodities and seldom base their decisions on the interlinking nature of commodities. Would it be possible to make improved investment decisions if the relationships between commodities were more clearly understood and analysed?

This lack of research creates the problem that commodities are not fully understood within the full context in which they should be understood. The lack of understanding creates a further problem, which was linked to the financial crisis of 2007. Financial instruments were developed that were not fully understood in extreme events. When the extreme event occurred, the extent of losses was much larger than what was calculated. An understanding of how commodities interact and react could lead to more insight into the risk management

opportunities and processes involving commodities. Therefore, when faced with an extreme event, more prudent actions can be taken if required.

This study aimed to address the gap in knowledge within the South African market regarding international commodities classes. An understanding of relationships will assist stakeholders in making more informed investment and risk management decisions related to the selection of the included commodities and commodity classes.

1.3. RESEARCH QUESTION AND OBJECTIVES

The main research question of this study was: What optimal cross hedging relationships are present within the South African financial market context in relation to a selection of commodities? In order to answer the research question regarding relationships, the following objectives needed to be explored in Chapters 4, 5, 6 and 7. The main objective in this study was to:

Investigate optimal cross hedging relationships between the variables.

The sub-objectives to reach the main objective in order to answer the research question were:

- Determine the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index.
- Determine the long run and short run relationships between each commodity price and the ZAR.
- Determine the long run and short run relationships between the FTSE/JSE Top 40 Index and the ZAR.
- Determine the cross hedging opportunities between the variables.
- Determine the comovement between the variables.

The research objectives of the study were to investigate the relationships present between the variables included. The relationships were used as a starting point in order to obtain optimal cross hedging relationships using commodities in the South African financial market as well as relationships between the commodities. These objectives were achieved by means of theoretical and empirical analyses that were conducted over eight chapters.

Chapters 4, 5, and 6 will include a subset of the selection of commodities grouped according to categories of commodities, and Chapter 7 will build on the results presented in Chapters 4, 5, and 6 in order to answer the research question stated above. Chapter 7 will investigate cross hedging relationships present between the sixteen variables included in the study.

The analyses were based on spot and future data as the overall objective of the study was to understand the long run and short run relationships and to obtain the cross hedging relationships between the variables. This knowledge could then be used to create diversification opportunities for individual and institutional financial market participants.

1.4. PURPOSE OF THE STUDY

The purpose of the study was to investigate the relationship between sixteen selected variables. The investigation would be to determine the long run relationships and the short run dynamics between the variables with a final purpose of obtaining optimal cross hedging relationships. The optimal cross hedging relationships obtained are important for investment decisions as well as the risk management strategies related to the investments. The aim of the research was to contribute to the field of commodities as an alternative asset.

Commodity prices show a tendency to move together, even if they have no reason to be related (Abdullah *et al.*, 2016; Baffes, 2007; Pindyck & Rotemberg, 1993; Pindyck & Rotemberg, 1990). It is for this inexplicable reason that the study was undertaken. The unexplained relationships which were identified in the study could be used to reduce the risk that is present in an investment portfolio. By understanding the relationships, alternative investments, with the focus on commodities, could be included in the investment decisions in order to reduce risk.

Commodities have become more financialised, therefore the opportunity exists to diversify risk by means of commodities, which are an alternative asset. Financialisation of commodities occurs when inflows into commodity investments increase at an abnormal rate. In 2003, commodity investments were \$15 billion as compared to 2009, when commodity investments reached \$250 billion. The increase in inflows was mainly due to institutional investors who started to utilise commodity investments. The increase in the financialisation of commodities has led to an increase in co-movement or correlation between different commodities (Baldi, Peri & Vandone, 2016; Adams & Glück, 2015; Hamilton & Wu, 2015; Henderson, Pearson & Wang, 2015; Basak & Pavlova, 2013; Singleton, 2014; Tang &

Xiong, 2012; Irwin and Sanders, 2012; Irwin and Sanders, 2011; Büyükşahin & Robe, 2009; Korniotis, 2009; Domanski & Heath, 2007).

The relationships and interactions commodities have with other variables in the financial markets are still not fully understood, which creates a problem when including commodities in an investment decision or risk management strategy. Because of a lack of understanding of the relationships present between commodities, as well as between commodities and other financial variables, the use of commodities is limited and inefficient. Therefore, the purpose of the study was to identify the relationships between commodities that are included in the study, as well as between commodities included in the study and the FTSE/JSE Top 40 Index and the ZAR which are unexplained.

1.5. RESEARCH METHODOLOGY

The research methodology applied in the study was of a quantitative nature, using secondary data. The primary quantitative methodology was based on financial econometric tests. The tests used within the study related to Chapters 4 to 6 include unit root tests, correlation, the vector autoregressive model, Johansen cointegration test, Granger causality test, Toda Yamamoto test, vector error correction model and innovation accounting methods. Chapter 7 uses correlation, Granger causality test, OLS, ECM, VECM, ECM-GARCH, asymmetric DCC-GARCH with GJR specification, hedging effectiveness combined with more advanced hedging effectiveness methods as well as mean variance analysis, drawdown, Value at Risk and Expected Shortfall.

1.6. COLLECTING AND ANALYSING THE INFORMATION

All the spot and future data collected for use in the study was secondary data obtained from Thomson Reuters DataStream from 1 January 2000 to 31 December 2016. The data was split into two in order to analyse the before crisis period (1 January 2000 – 30 June 2007) and the after crisis period (1 October 2009 – 31 December 2016). The data was analysed by the use of EViews, R and Excel in order to obtain the necessary results for Chapters 4, 5, 6, 7 and 8.

1.7. LIMITATIONS OF THE STUDY

Limitations to the study were created by the variables used as well as the literature available on the specific research question and objectives. The first limitation relates to the variables that were used in the study. Not all commodity variables are included in the study and only

selected commodity benchmarks were selected to represent each commodity class included. The second limitation was based on the currency selected as well as the index selected. The final limitation is that taxation, transaction costs and investments in other securities were ignored.

South Africa is the country of focus and therefore the South African Rand was the selected currency. A number of indices are available in the South African financial market and only one index was selected to represent the market. The index was chosen as it was the most representative of the South African financial market.

The knowledge and understanding available on commodity markets is limited to the analysis that has been done based on the types of commodities as part of the study, the time frame included in the study as well as the method of analysis. This study was limited to a time frame, namely a period before and after the financial crisis of 2007, but the commodities included in the study were chosen with the aim of being broad, and hence by including metal, soft and energy commodities. The methodology applied to the data was formal analysis procedures based on the financial econometrics and risk management aimed to identify both long and short run relationships present between the variables. The relationships were further analysed to determine investable opportunities that market participants and academics could apply.

The analysis of the data was based on accepted econometric and risk management standards as well as on other peer-reviewed research conducted. A limitation on this concept was whether other methods of analysis would be applied to the same datasets. This difference could result in different research findings and conclusions.

1.8. CHAPTER OUTLINE

Table 1.1: Summary of chapters and content

| CHAPTER | CONTENT |
|-------------------|--|
| Chapter 1: | Orientation and motivation of the study In the first chapter the study is introduced. The background to the study which resulted in the research problem is explained. |
| Chapter 2: | Literature review In the second chapter a critical review of the current literature on the research problem is presented. |

| | |
|----------------------|--|
| Chapter 3: | Research methodology The research design and methodology used in the study are explained in the third chapter. The chapter commences with a discussion of the issues of research design, the methods for collecting and measuring the data. Techniques to ensure the validity and reliability of the data are also considered. |
| Chapters 4–7: | Results and findings The results of the study are presented in the fourth, fifth, sixth, seventh and eighth chapter. The data is presented and interpreted in various statistical formats such as graphs and tables, etc. |
| Chapter 8: | Conclusion Conclusions are drawn based on the results of the study. Limitations and recommendations for further study are also addressed. |

Source: Own deductions.



CHAPTER 2

LITERATURE REVIEW

2.1. INTRODUCTION

Volatility of price movement is a characteristic present in financial time series data which creates the opportunity to profit when making short and long-term investment decisions. The property that financial time series data is exposed to is the trend that prices follow, either in an upward movement or downward movement. The trend movement is the basis of bull and bear markets that financial markets are continuously experiencing (Wei, 2006).

The co-movement experienced between financial assets is associated with two fundamental economic theories that would hold when the markets are viewed as competitive. The economic theories of the law of one price and the law of supply and demand form the basis of economic theory. A further requirement would be that there would be no transaction costs as well as no barriers present when trading. When markets are competitive and the two further requirements are met, no arbitrage opportunities should be available (Lamont & Thaler, 2003).

The law of one price states that price of a specific asset will be the same in different locations, with the assumption that the exchange rate between the different locations is taken into account (Isard, 1977). The law of one price therefore means that a particular identical good is uniformly priced around the world. The law of one price is based on three assumptions. It assumes that there are: (1) no restrictions on the movement of assets around the world, (2) no tariffs imposed by the countries and no transaction costs associated to the transfer of the asset; and (3) no transportation costs related to the movement of the asset (Miljkovic, 1999).

The law of supply and demand is linked to the notion that the market will be in a general economic equilibrium, which will determine the price of an asset. If the demand and supply of an asset are not in equilibrium, it means that the price of an asset will not be different to what it should be based on economic equilibrium. If demand is higher than supply, the price of an asset will increase, which will result in an asset that is overvalued as more will be paid

than what it is worth at an equilibrium price. If the demand is lower than supply, the price of the asset will be undervalued, which means that it will be lower than the economic equilibrium. The difference in price creates profit opportunity, especially when volatility and trend in price movement are present, which defies the notion of no arbitrage opportunities present within the market (Gale, 1955).

The relationships between the three financial variable classes included in the study, namely commodity prices, the exchange rate as well the price of an index representing the financial market are linked together by the law of supply and demand and, in certain cases, the law of one price. The literature review will discuss the three financial variables and the related change in detail as well as the relationships present between the variables in order to form a basis required for the remainder of the study.

In order to discuss the financial variables, commodities will be discussed in the next section, as one of the financial variable classes included in the study is the prices of selected commodities. The link between commodities and the related currency of countries that produce and export a large number of commodities will be discussed in order to link to the South African currency, which is the next section. The last financial variable included in the study is the FTSE/JSE Top 40 Index, which will be discussed in the South African equity index section. As the financial crisis of 2007 had a large impact on the financial variables, a brief introduction to the financial crisis will be presented as it is an important breaking point in the data period.

The final sections of the literature review will cover the literature available that discusses the review of hedging relationships, both cross hedging as well as optimal hedging relationships, which are linked to the final research objective of the research undertaken in this study. The literature review will be concluded with the review of relationships between the three financial variables as well as other applicable literature that includes the methodology utilised within this study.

2.2. COMMODITIES

Commodities are viewed as alternative investments since they do not fit the standard definition of traditional investments, based on asset classes and investment strategy. Equities and bonds are two of the asset classes that are classified as traditional investments, and have different characteristics as compared to alternative investments. The definition of alternative investments is not standardised in the literature, but revolves around the type of

asset class, which is either different to traditional investments or a subset or a traditional investment asset class, and the investment strategy that is different to the traditional investment strategy (Anson, Fabozzi & Jones, 2011).

Examples of alternative asset classes are hedge funds, real estate, and private equity. Commodities are also an example of an alternative asset class. Alternative investments can be invested in through traditional methods or through alternative investment strategies (Anson *et al.*, 2011).

A commodity is defined as a resource that is both tangible and marketable globally. A commodity can be used in different forms as per the requirements of the user. It is an asset that is seen as a scarce resource as there is a limited number available around the world (Fabozzi, Füss & Kaiser, 2008; Geman, 2005).

The first major classification of commodity classes is between two categories. The categories are hard and soft commodities. Soft commodities are physical assets that are perishable. These types of commodities are grown, which results in a type of commodity that is renewable. The opposite of soft commodities is hard commodities, which are mined or extracted from the earth, and not perishable. An alternative classification of commodities is commodities that are consumable versus commodities that are transformable (Chatnani, 2010; Fabozzi *et al.*, 2008; Anson, 2006). Examples of hard and soft commodities are shown in Table 2.1.

Table 2.1: Examples of hard and soft commodities

| Hard Commodities | Soft Commodities |
|--|---|
| Energy <ul style="list-style-type: none"> • Coal • Crude/heating oil • Natural gas Metals <ul style="list-style-type: none"> • Aluminium • Copper • Lead • Zinc • Precious metals <ul style="list-style-type: none"> ○ Gold ○ Platinum ○ Palladium ○ Silver | Agriculture <ul style="list-style-type: none"> • Coffee • Corn • Cotton • Soyabeans • Sugar • Wheat Livestock <ul style="list-style-type: none"> • Cattle • Milk • Pigs • Poultry |

Source: Chatnani, 2010; Fabozzi *et al.*, 2008.

Soft commodities are further divided into the categories of livestock and agriculture. Agricultural commodities are comprised of a class of commodities named softs as well as grains and seeds. The soft commodities included in this study and discussed in Chapter 5 are corn, cotton, soyabean, sugar and wheat. Other examples of soft commodities are cocoa, coffee, hogs, and rubber (Chatnani, 2010; Fabozzi *et al.*, 2008).

Hard commodities are separated into energy and metal commodities with precious metals part of metal commodities. The hard commodities included in this study will be divided into two different chapters, Chapter 4 and Chapter 6. Chapter 4 will include the metal commodities aluminium, copper, gold, palladium and platinum. Chapter 6 will include the energy commodities crude oil-brent, jet kerosene, naphtha and natural gas. Other examples of hard commodities are ethanol, gasoline, nickel and silver (Chatnani, 2010; Fabozzi *et al.*, 2008).

Anson (2006) states that exposure to commodities is obtained in diverse ways and is therefore available by different means, either through traditional methods or through alternative investment strategies. The strategies available to obtain exposure to commodities are: (1) purchasing the underlying commodity; (2) purchasing shares in a natural resource company; (3) purchasing commodity futures contracts; (4) purchasing commodity swaps and forward contracts; (5) purchasing commodity-linked notes; and (6) purchasing commodity exchange-traded funds.

The most direct way to gain access to commodities is by purchasing the underlying commodity, which results in the investor having full ownership of the underlying commodity. An alternative to purchasing the underlying commodity is to purchase shares in the company that is exposed to commodities, which is less direct than purchasing the underlying commodity. Other indirect ways of gaining exposure to commodities is by using financial instruments such as futures, forwards, options and exchange-traded funds (Fabozzi *et al.*, 2008; Anson, 2006; Geman, 2005).

2.2.1. Global commodity prices

The recent history of global commodity prices as represented by the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI) main commodity index and sub-indices has been volatile, as illustrated in Figure 2.1. After a drastic fall in prices in 2008 due to the global financial crisis, a low point was reached in early 2009. Global commodity prices rallied from 2009 to 2011 due to optimistic forecasts related to the traditional business cycle

expectations. Since 2011, prices have been on a steady decrease, with sudden brief spikes from 2011 to 2016. The steady decline in commodity prices is consistent with the deteriorating global economic outlook as well as risk appetite that was lower compared to prior years as a result of the European sovereign debt crisis as well as concerns linked to the Chinese economy.

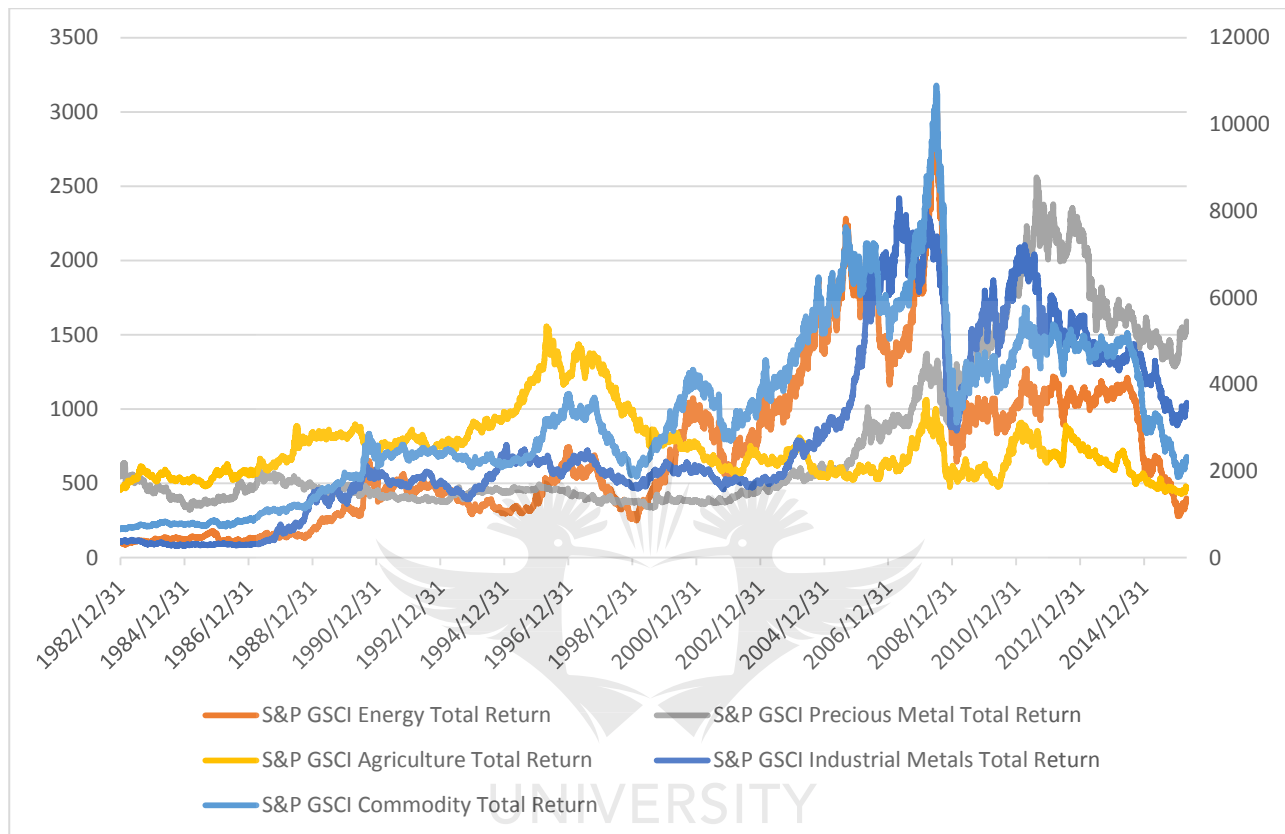


Figure 2.1: S&P GSCI Commodity Indices from 1982 to 2016

Source: Thomson Reuters DataStream and Excel.

Focusing on the last ten years, commodity prices from 2006 to 2010 can be seen in Figure 2.2 showing the sudden decrease in prices in 2008 as a result of the global financial crisis and the movement of prices from 2009 to 2016. The commodity prices are currently at different levels compared to before the 2007 financial crises, but have come down significantly from 2008. The S&P GSCI shows that the real prices of commodities have decreased compared to 2006, which means that commodities have been affected by deflation as it is cheaper to buy a commodity in 2016 than what it cost in 2006.

The S&P GSCI is one of the most widely recognised benchmarks with regard to commodity prices. It is an investable commodity index that is production-weighted with the objective of being representative of the global commodity market beta. The index includes commodities

from various sectors, namely agriculture, livestock, energy, industrial metals and precious metals (S&P Dow Jones Indices, 2016).

The agricultural commodities included in the index are Chicago wheat, Kansas wheat, corn, soyabeans, coffee, sugar, cocoa and cotton. The energy commodities are WTI crude oil (West Texas Intermediate), brent crude oil, gas oil, heating oil, RBOB gasoline (Reformulated Gasoline Blendstock for Oxygen Blending), and natural gas. The industrial metals are aluminium, LME copper (London Metal Exchange), lead, nickel and zinc. The precious metals consist of gold and silver only (S&P Dow Jones Indices, 2016).

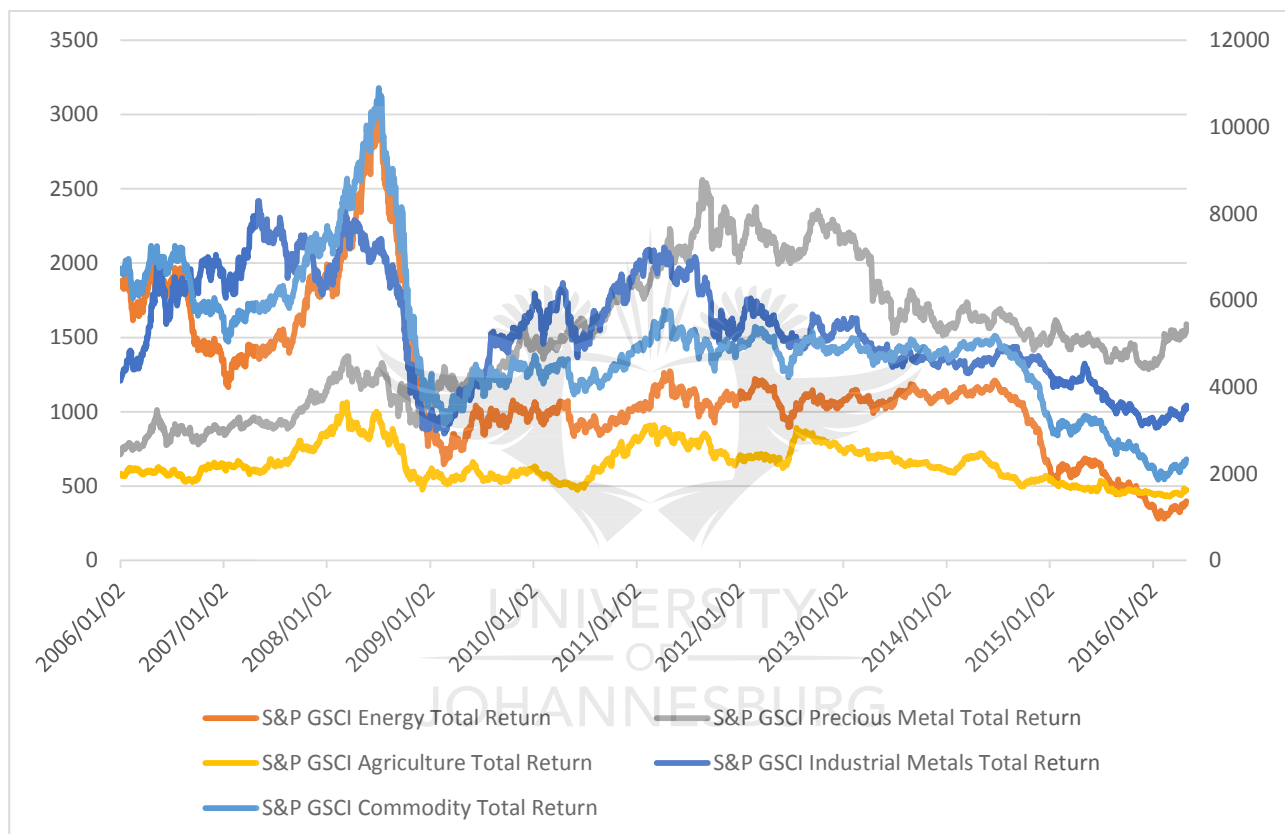


Figure 2.2: S&P GSCI Commodity Indices from 2006 to 2016

Source: Thomson Reuters DataStream and Excel.

2.2.2. Commodity characteristics

Commodity prices do not follow the same trend as traditional investments in that the movement of the price is often very volatile. The volatility of the price makes investing decisions more difficult, but provides additional benefit if judged correctly (Myers, 1994; Newbury & Stiglitz, 1981). The volatility of the price of the S&P GSCI Commodity Total Return Index is shown in Figure 2.3. The index shows signs of volatility clustering as well as extreme volatility periods followed by tranquil volatility periods.

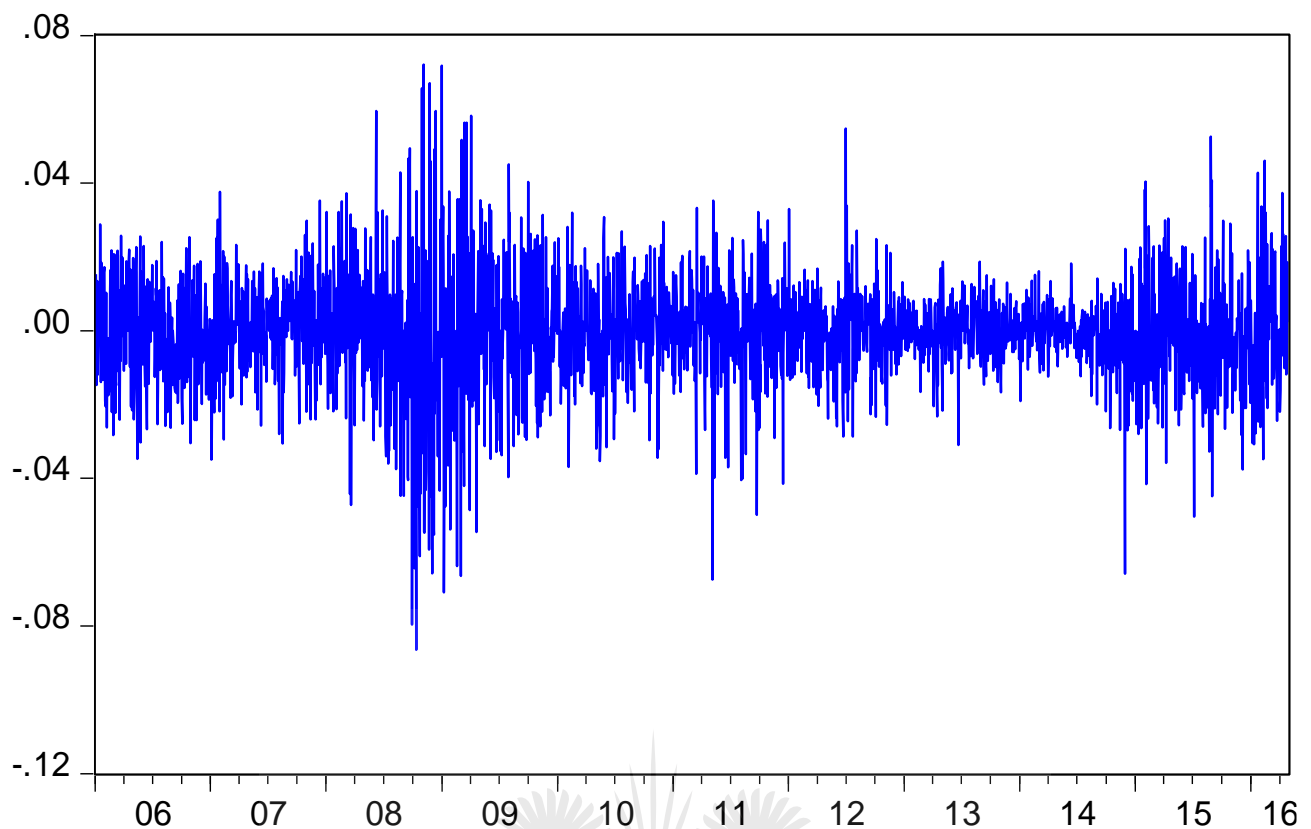


Figure 2.3: Volatility of S&P GSCI Commodity Indices from 2006 to 2016

Source: Thomson Reuters DataStream and EViews.

A second characteristic of commodity prices is that they seem to contain stochastic trends over high frequency time intervals (Myers, 1994; Goodwin, 1992; Baillie & Myers, 1991; Goodwin & Schroeder, 1991; Ardeni, 1989). A stochastic trend is similar to a random walk with drift. If a time series has a stochastic trend, the movement in the time series in any given period is an unpredictable random amount (Myers, 1994; Stock & Watson, 1988).

Commodity prices also show a tendency to move together, even if they have no reason to be related (Abdullah *et al.*, 2016; Baffes, 2007; Pindyck & Rotemberg, 1993; Pindyck & Rotemberg, 1990). Three possible reasons are available to explain the co-movement of commodity prices. The three reasons are: (1) Shocks to the demand and supply of one commodity affects other commodities, which results in a specific group of commodities to show co-movement. (2) Common macroeconomic shocks occurring in the economic system could affect all commodities or at least a large portion of commodities in a similar manner. (3) Market speculation actions and overreaction in the market could cause the spill-over effect in the market between commodities. However, the first reason is unlikely to cause changes in unrelated commodity prices and in terms of the second reason, evidence has

been found that macroeconomic shocks only explain a small component of co-movement in commodity prices (Myers, 1994; Pindyck & Rotemberg, 1990).

Time-varying volatility has also been found to be present in commodity prices. Time-varying volatility is where a time series shows periods of different volatility movements, from volatile periods to tranquil periods of volatility movement, which can be seen in Figure 2.3 (Myers, 1994; Yang & Brorsen, 1992; Baillie & Myers, 1991).

An additional characteristic of commodity prices is that the distribution of prices shows excess kurtosis, which means that the tails of the distribution are fatter than the normal distribution (Myers, 1994; Deaton & Laroque, 1992; Gordon, 1985).

2.2.3. Commodities included in the study

Fourteen commodities were included in the study, which were selected from the metal, soft and energy commodity categories. The spot commodities are included below. The closest futures of these commodities were included in the study as well.

The metal commodities selected for the study were:

- Aluminium: LAHCASH (London Metal Exchange (LME)-Aluminium 99.7% Cash United States Dollar Per Metric Tonne (London Metal Exchange)
- Copper: LCPCASH (London Metal Exchange (LME)-Copper Grade A Cash United States Dollar Per Metric Tonne (London Metal Exchange)
- Gold: GOLDBLN (Gold Bullion London Bullion Market US\$ / Troy Ounce (ICE Benchmark Administration Ltd)
- Palladium: PALLADM (Palladium US\$ / Troy Ounce (London Metal Exchange)
- Platinum: PLATFRE (London Platinum Free Market United States Dollar Per Troy Ounce (London Metal Exchange).

The soft commodities, focused only on agricultural commodities selected for the study, were:

- Corn: CORNUS2 (Corn Number 2 Yellow Cents / Bushel (US Department of Agriculture)
- Cotton: COTTONM (Cotton, 1 1/16STR Low - Middling, Memphis UC/Pound (US Department of Agriculture)

- Soyabean: SOYBEAN (Soyabeans, Number 1 Yellow C / Bushel (US Department of Agriculture))
- Sugar: WSUGDLY (Raw Sugar-International Sugar Agreement (ISA) Daily Price UC/Pound; International Sugar Organization(ISO))
- Wheat: WHEATSF (Wheat Number 2, Soft Red Cents / Bushel (US Department of Agriculture)).

The energy commodities selected for the study were:

- Crude Oil-Brent: OILBRNP (Crude Oil-Brent Dated Free on Board United States Dollar Per Barrel (ICIS Pricing))
- Jet Kerosene: JETCIFC (Jet Kerosene-Cargoes Cost, Insurance and Freight North West Europe United States Dollar Per Metric Tonne (ICIS Pricing))
- Naphtha: OILNAPH (Naphtha Europe Cost, Insurance and Freight United States Dollar Per Metric Tonne (ICIS Pricing))
- Natural Gas: NATGHEN (Natural Gas, Henry Hub U United States Dollar Per Million British Thermal Units (Thomson Reuters)).

The commodities listed above are produced in South Africa, with certain commodities forming a larger component of production than others. Related to the production is the actual export and import quantity of each of the commodities, as the direction of trade affects the currency and equity index differently. Table 2.2 shows the amount and ranking of each commodity's production within South Africa, as well as the export and import ranking globally.

Table 2.2: Commodity production, exports and imports

| Commodity | Production | Export | Import |
|------------------|---|------------------|------------------|
| Aluminium | 822 (1 000 MT) - 11 th | 11 th | 47 th |
| Copper | 77 000 (1 000 MT) - 24 th | 16 th | 24 th |
| Gold | 160 000 (KG) - 6 th | 7 th | 17 th |
| Palladium | See Platinum | 1 st | 13 th |
| Platinum | 75 118 (KG) - 2 nd | 1 st | 16 th |
| Corn | 8000 (1 000 MT) - 12 th | 77 th | 12 th |
| Cotton | 65 (1 000 480 lb. Bales) - 43 rd | 27 th | 29 th |

| Commodity | Production | Export | Import |
|-----------------|---|------------------|------------------|
| Soyabean | 725 (1 000 MT) - 23 rd | 54 th | 40 th |
| Sugar | 1 750 (1 000 MT) - 19 th | 10 th | 67 th |
| Wheat | 1 500 (1 000 MT) - 28 th | 37 th | 30 th |
| Crude Oil-Brent | 181 000 (bbl/day) - 40 th | 76 th | 17 rd |
| Jet kerosene | N/A | N/A | N/A |
| Naphtha | N/A | N/A | N/A |
| Natural gas | 1 280 000 000 (cubic meters) - 61 st | 53 rd | 41 th |

Source: CIA World Factbook, 2016; The Observatory of Economic Complexity, 2016; United States Department of Agriculture, 2015; United States Geological Survey, 2016.

2.2.4. Financialisation of commodities

Financialisation is defined as the “increasing dominance of the finance industry in the sum total of economic activity, of financial controllers in the management of corporations, of financial assets among total assets, of marketed securities and particularly equities among financial assets, of the stock market as a market for corporate control in determining corporate strategies, and of fluctuations in the stock market as a determinant of business cycles” (Falkowski, 2011; Dore, 2010). Financialisation is also defined as the “vastly expanded role of financial motives, financial markets, financial actors and financial institutions in the operation of domestic and international economies” (Falkowski, 2011; Casey, 2011).

In the early 2000s, the investment into commodities started increasing at a phenomenal rate. Figure 2.4 illustrates the increase in the commodity market through the year on year increase in allocation into the Standard & Poors Goldman Sachs Commodity Index (SP-GSCI) and the Dow Jones American International Group Commodity Index (DJ-AIG). The Standard & Poors GSCI Spot Price Index shows the drastic increase in price from 2002 to 2008. This rapid increase in investment has given rise to the term financialisation of commodities (Falkowski, 2011).

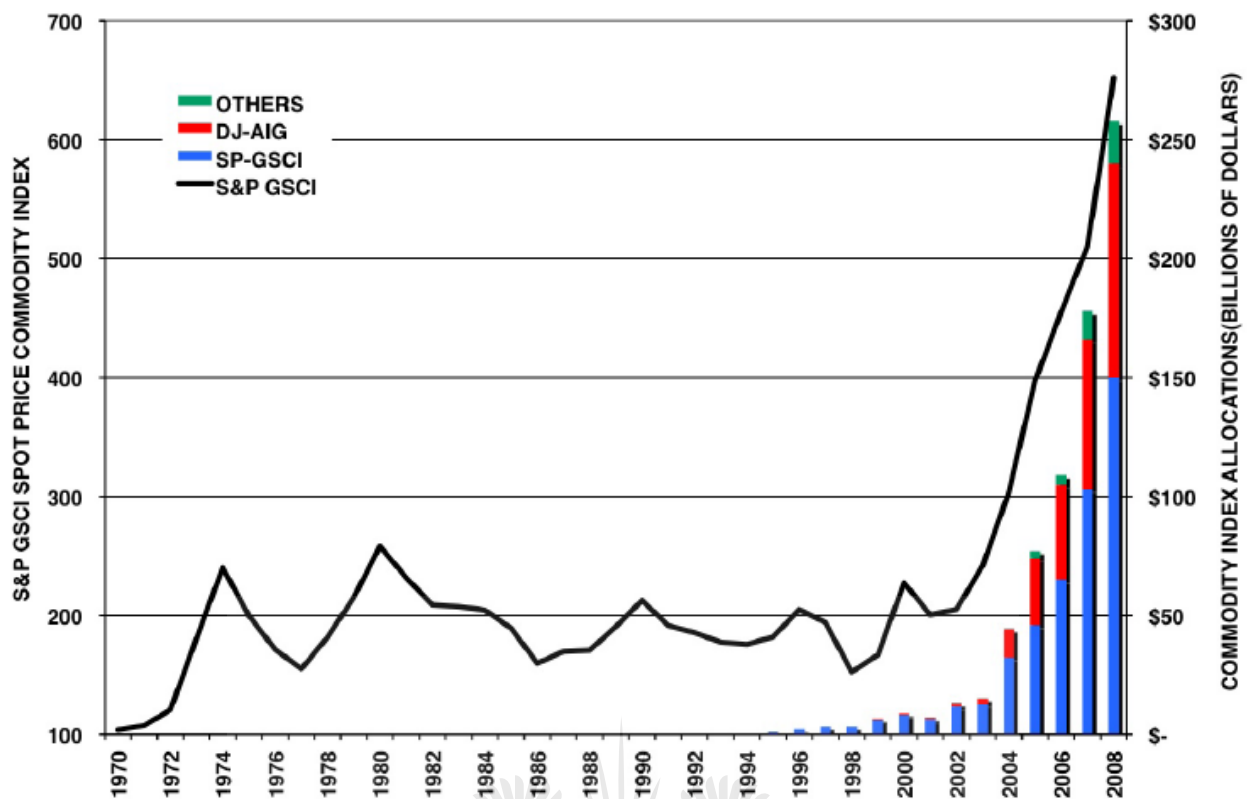


Figure 2.4: Commodity Index allocation

Source: Falkowski, 2011.

In 2003, commodity investments were \$15 billion, which then increased to \$250 billion in 2009. The increase was the result of institutional investors who started to increase their investment allocation into commodity instruments. The financialisation of commodities has resulted in an increase in the co-movement or correlation between different commodities (Baldi, Peri & Vandone, 2016; Adams & Glück, 2015; Hamilton & Wu, 2015; Henderson, Pearson & Wang, 2015; Basak & Pavlova, 2013; Singleton, 2014; Tang & Xiong, 2012; Irwin and Sanders, 2012; Irwin and Sanders, 2011; Büyükşahin & Robe, 2009; Korniotis, 2009; Domanski & Heath, 2007).

The use of commodity derivative instruments since the early 2000s has increased more than the increase in commodity production. The requirement of hedging instruments for use by commercial producers and users of commodities was substantially below the use of commodity derivatives instruments due to the increase in the investment allocation into commodity instruments (Knoepfel, 2011).

2.3. COMMODITY CURRENCIES AND CURRENCY COMMODITIES

Certain currencies are classified as commodity currencies. Not all currencies fit into this classification; however, certain characteristics of currencies cause them to be named a commodity currency. A currency is referred to as a commodity currency if the movement in the price of the currency is linked to movement in the international price of a commodity or a selection of commodities that the country produces and exports (Clements & Fry, 2008; Cashin, Céspedes & Sahay, 2004).

When the production and export of commodities in a country is a large part of total exports, the country is known as a commodity country. Since the country is considered a commodity country, as it is affected by commodities, the currency of the country can therefore be termed a commodity currency. An alternative definition of a commodity currency is a currency whose behaviour is exposed to a substantial extent to the price of the exported commodity (Bova, 2009).

The underlying economic concepts of the law of one price and the law of supply and demand link the prices of commodities to the exchange rates of the countries supplying the commodities. A possible relationship is present between movements in the commodity price and movements in the exchange rates of commodity currencies (Chen, Rogoff & Rossi, 2010).

Cashin, Céspedes and Sahay (2002) explored a selection of currencies to determine whether they met the requirements of being a commodity currency, and the authors found that the South African Rand is not a commodity currency. Commodity currencies show a long run relationship between the real effective exchange rate and real commodity export price of a selected country. The coefficient of the real commodity-export prices in the cointegrating regression was found to be significantly different from zero. South Africa did not show these results.

Conversely, Chen *et al.* (2010) tested multiple currencies to determine whether they met the requirements to be classified as a commodity currency. The results indicated that the South African Rand is a commodity currency. Even though there are mixed results as to the classification of the South African Rand, South Africa still exports a large number of commodities each year. With commodities playing such a significant role as it forms a large part of the South African foreign trade accounts, it is understandable that commodities have an effect on the currency of South Africa (CIA, 2016).

A different view can be taken regarding the link of commodities and the exchange rate of a country. Previously, commodity currency has been identified; however, a different view is linked to currency commodities. Commodity currency is viewed as the effect that commodity prices have on a currency, whereas currency commodities relate to the effect that a currency will have on a commodity price. The difference is related to which variable drives the other. Does the exchange rate cause the change in the commodity price or is it the opposite way around (Clements & Fry, 2008)?

Clements and Fry (2008) explain that with a commodity currency, when a commodity boom is experienced, the appreciation in the currency reduces the impact of the commodity boom in that the increase in domestic currency prices of the country will be lower than the world prices. A further point is that if the country is a large enough producer of a specific commodity, the exports of the country as a result become more expensive and therefore the volume of exports tends to decrease.

Taking into account that the country is a large producer of the commodity, and the export volume decreases, which is seen as a decrease in supply, the price as a result of the law of demand and supply increases the world price being paid for the commodity. When commodity prices are affected by a currency in a similar manner as described for a commodity currency, the currency is referred to as a currency commodity (Clements & Fry, 2008).

A similar concept is the Dutch Disease, which is a term used to define an economy that exhibits a negative relationship between a rise in a commodity price and the competitiveness of other products produced by the economy. A country that produces and exports a large quantity of a specific commodity, will benefit from increased foreign currency inflows, which will in turn lead to currency appreciation. The currency appreciation causes exports of the country to become more expensive, which results in the export market and related products becoming more expensive on the international market (Krugman, 1987; Corden, 1984; Corden & Neary, 1982).

2.4. SOUTH AFRICAN EXCHANGE RATE

The two remaining financial variables included in this study is the South African Rand against the United States Dollar (USD) exchange rate as well as the FTSE/JSE Top 40 Index. These two variables represent the South African financial market in relation to international prices as the commodities included in this study are priced in USD.

An exchange rate is the rate of exchange between two currencies. It is one currency being expressed in terms of a second currency. The exchange rate for the South African Rand is based on a floating exchange rate regime. The law of supply and demand and the resulting demand and supply forces result in changes in the rate. Three different exchange rate classifications exist within the market. The classifications are floating rates, fixed rates and managed floating rates (Copeland, 2008).

The South African Rand has gone through a number of developments over the last five decades. On 14 February 1961, the South African Rand was established as the official currency. Between 1965 and 1995 a dual exchange rate existed, except for a brief period in the early 1980s. The dual exchange rate was made up of the financial rand and the commercial rand. The financial rand was traded at a discount to the commercial rand. The financial rand was available to foreigners only and used for the non-resident capital movement (Roux, 2014).

After the democratic elections in South Africa in 1994, the South African Rand started to change. On 10 March 1995, the dual exchange rate was abolished and became a unified Rand. The exchange rate has gone from a stable rate of around R3.60 to the United States Dollar in 1995 to currently moving between the R14 to R16 mark in 2016 (Roux, 2014).

Figure 2.5 shows the movement of the South African Rand against the United States Dollar from 31 December 1993 to 29 April 2016. The extreme changes in the exchange rate can be seen in the early 2000s as well as between 2007 and 2009. From 2011, the South African Rand has shown a sharp depreciation with no indication of reversing the trend, except for early 2016.



Figure 2.5: South African Rand against the United States Dollar from 1993 to 2016

Source: Thomson Reuters DataStream and Excel.

In the South African market, the exports for 2014 related to agricultural products accounted for 12.5% of merchandise trade and the exports related to fuels and mining products totalled 34.8%. The fuels and mining groups resulted in the commodity exports of South Africa making up 47.3% of merchandise trade (World Trade Organization, 2015).

Ndlovu (2010) has shown that in 2010 South Africa had 42.9% commodity exports which excluded the component for precious metals. Based on this, South Africa is a major commodity exporting country; however, there are mixed results as to whether the South African Rand is a commodity currency.

Figure 2.6 shows the graphical illustration of the comparison of the South African Rand against the S&P GSCI Commodity Total Return Index. Before 2009, the two variables did not show any co-movement as a result of the time-varying correlations, but from 2010 a clearer opposite movement relationship can be seen.

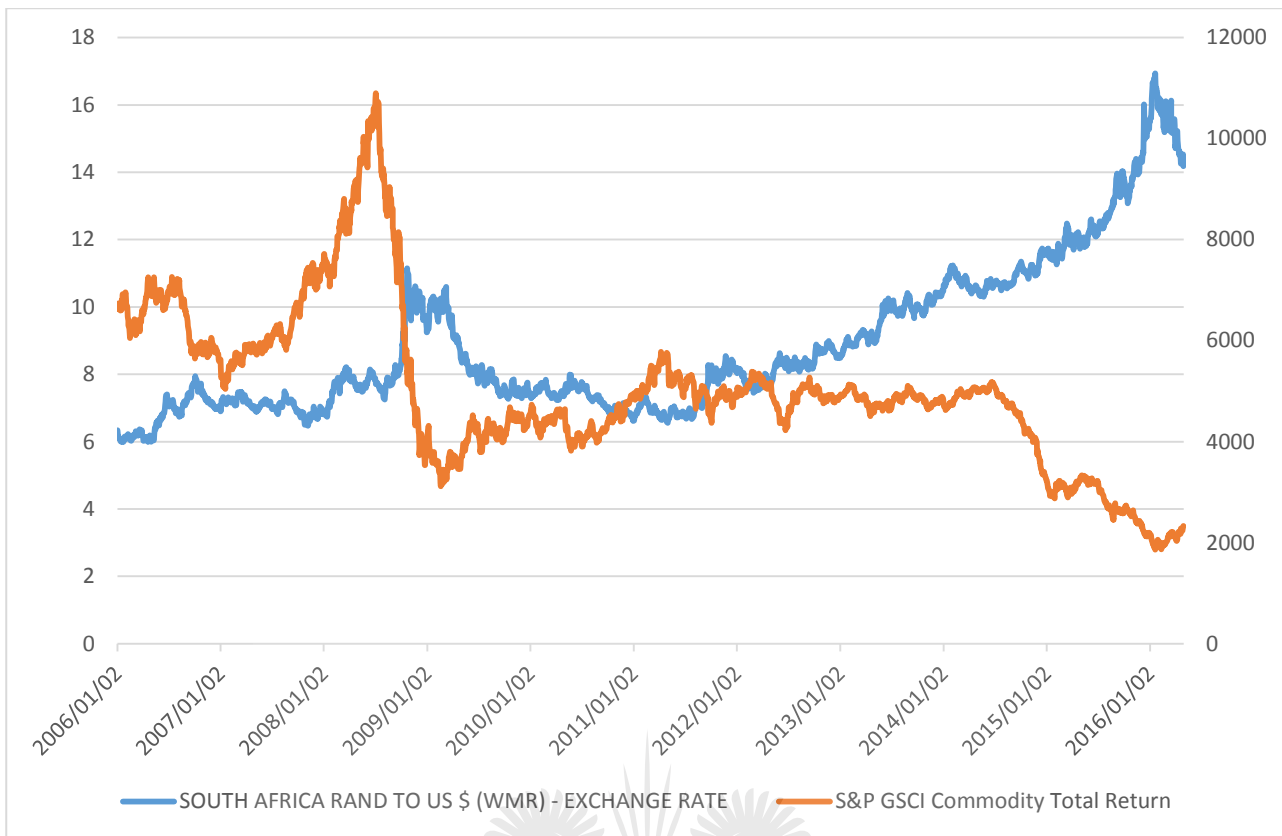


Figure 2.6: ZAR against the S&P GSCI Commodity Total Return Index from 2006 to 2016

Source: Thomson Reuters DataStream and Excel.

The equilibrium real exchange rate of the South African Rand related to commodity prices was explored by MacDonald and Ricci (2003), and Bhundia and Ricci (2005). MacDonald and Ricci (2003) found that a one percent increase in real commodity prices results in an appreciation of 0.5 percent in the real effective exchange rate of the South African Rand. Bhundia and Ricci (2005) found that a one percent decrease in real commodity prices causes the South African Rand to depreciate by 0.5 percent.

2.4.1. Exchange rate regimes

The exchange rate regime that a country uses affects the movements of the country's currency, for example a floating exchange rate regime, a fixed exchange rate regime or a pegged exchange rate regime. Around the world, each country has a currency that is seen as the national currency. In order to participate in international trade, an exchange rate is used to determine the value of an item in a different currency, compared to the local currency of the specific country. An exchange rate is the rate of exchange of one currency in terms of a second currency (Copeland, 2008).

The exchange rate regime adopted by a country is imperative. Exchange rates affect the amount of money generated through goods and services as well as the transfer of capital into and out of a selected country. The choice of exchange regime rate also has an impact of the macroeconomic variables of a country, such as the balance of payments and inflation (Yagci, 2001).

The law of one price and the law of supply and demand are important considerations in exchange rates. The supply of one currency should equate to the demand of a second currency. The relative values of two selected currencies, determined by the supply and demand thereof, are not always equal, as a result of government intervention such as fiscal policies (Copeland, 2008).

The history of exchange rates has gone through a number of different stages over time, with the starting point at the classical gold standard, through the phase of the Bretton Woods system, to the current exchange rate regimes. From 1880 to 1914, the classical gold standard was used, which had a fixed nominal exchange rate to ensure price stability in the long run. The classical gold standard made use of gold as the standard currency and reserve (Garofalo, 2005; Cuddington & Liang, 1998).

The interwar gold-exchange standard and the dirty or managed floating exchange rate regime were used from the beginning of World War I in 1914 to the early 1940s. The exchange rates that were used were an amalgamation of gold-backed and managed floating exchange rates, as gold bullion and foreign exchange were held in the reserves of countries (D'Arista, 2009; Bordo & MacDonald, 2001).

After the interwar gold-exchange standard, the Bretton Woods system was implemented and was in place from 1944 to 1971. The Bretton Woods system pegged the United States Dollar to the gold price, with other countries pegging their currency to the USD. The Bretton Woods system was unlike the gold standard in that pegged exchange rates became adjustable (D'Arista, 2009; Habermeier, Kokenyne, Veyrune & Anderson, 2009).

Three main different exchange rate classification groups are currently used, floating rates, fixed rates, and managed floating rates. Each exchange rate classification has unique characteristics that affect the movement of the exchange rate in terms of another currency (Copeland, 2008). Floating exchange rates started being implemented in the early 1970s, with the *de facto* classification used by the International Monetary Fund (IMF) to identify

different exchange rate regimes, which is currently the system being used around the world (Habermeier *et al.*, 2009).

A floating exchange rate is the most flexible exchange rate regime available. It is free to move with the market forces of supply and demand and has no outside intervention determining its price (Copeland, 2008; Sozovska, 2004; Tobin, 1993). In a floating exchange rate regime, the country's monetary policy functions independently of the floating exchange rate regime (Yagci, 2001).

Fixed exchange rates are different to floating exchange rates in that the currency is not free to move with the forces of supply and demand. Fixed exchange rates are pegged to a specific currency or a selected basket of currencies. The currency or group of currencies that are used as the peg are used to determine the price of the currency being pegged (Copeland, 2008; Sozovska, 2004).

The last main group of exchange rate classification is the managed floating exchange rate regime, also referred to as a dirty floating exchange rate, as it does not meet the characteristics of purely floating or purely fixed, but rather is a combination thereof, as chosen by the authorities of the country (Copeland, 2008; Sozovska, 2004).

The International Monetary Fund (IMF) classifies exchange rates into four main exchange rate classifications with nine different categories. The four main types are hard pegs, soft pegs, floating regimes (market-determined rates), and residual. The category regimes as classified by the IMF are the following: other managed arrangements, no separate legal tender, also referred to as currency boards, soft pegs, conventional pegs, stabilised arrangements, crawl-like arrangements, pegged exchange rate with horizontal bands, floating arrangements, and free floating (International Monetary Fund, 2014).

According to the International Monetary Fund (2014), South Africa is classified as having a floating exchange rate regime. In a floating exchange rate, the exchange rate is largely market determined, without an ascertainable or predictable path for the rate. The intervention related to the foreign exchange market may be direct or indirect, with the objective of moderating the rate of change to prevent any undue fluctuations in the exchange rate. Any policies that are used to target a certain exchange rate are seen as being incompatible with the floating exchange rate regime (International Monetary Fund, 2014).

2.5. SOUTH AFRICAN EQUITY INDEX

The Johannesburg Stock Exchange (JSE) is currently ranked within the twenty largest exchanges in the world, according to market capitalisation. In Africa, the JSE is the largest exchange. In partnership with the FTSE Group, the JSE has two benchmark indices, the FTSE/JSE All Share Index and the FTSE/JSE Top 40 Index.

The FTSE/JSE All Share Index includes 99% of the market capitalisation in South Africa, while the FTSE/JSE Top 40 Index only tracks the top listings by market capitalisation which represent a spread of sectors (JSE, 2016). The FTSE/JSE Top 40 Index will represent the South African equity index in this study as it is deemed to be representative of the market and applicable in this study. The FTSE/JSE Top 40 Index was designed to be used as a performance benchmark, ensuring investability, liquidity and transparency. As of May 2017, the top ten holdings within the index constituted 63.72% of the index, of which two mining companies were listed with a total representation of 11.77%. In July 2017, the top ten holdings increased to 64.40%, with two mining companies representing 12.79%. In September 2016, the two mining companies constituted 12.49% of the index.

The constituents of the FTSE/JSE Top 40 Index in May 2016 are shown in Table 2.3. There are currently 43 constituents, with six constituents in the basic resources industry classification benchmark super sector. Within the other super sectors, as classified by the Industry Classification Benchmark (ICB), commodity based companies are also listed, such as farming and fishing, which is part of consumer goods (JSE, 2016).

Table 2.3: FTSE/JSE Top 40 Index constituents May 2016

| Number | Constituents | Net Market Capitalisation (ZARm) |
|--------|-----------------------------------|----------------------------------|
| 1 | ANGLO AMERICAN PLATINUM LTD | 106335.5 |
| 2 | ANGLO AMERICAN PLC | 194910.6 |
| 3 | ANGLOGOLD ASHANTI LIMITED | 92645.94 |
| 4 | ASPEN PHARMACARE HOLDINGS LIMITED | 147994.7 |
| 5 | BHP BILLITON PLC | 375132.8 |
| 6 | BARCLAYS AFRICA GROUP LTD | 114208.9 |
| 7 | BIDVEST GROUP LIMITED | 121751.6 |
| 8 | BRAIT SE | 79993.94 |
| 9 | BRITISH AMERICAN TOBACCO P.L.C. | 1661031 |
| 10 | CAPITAL & COUNTIES PROPERTIES PLC | 60648.12 |
| 11 | CAPITEC BANK HOLDINGS LIMITED | 64404.19 |
| 12 | RICHEMONT SECS. (JSE) | 504407.9 |
| 13 | DISCOVERY LTD | 79316.38 |

| Number | Constituents | Net Market Capitalisation (ZARm) |
|---------------|---------------------------------------|---|
| 14 | FIRSTRAND LIMITED | 243563.9 |
| 15 | FORTRESS INCOME FUND LTD | 17803.37 |
| 16 | FORTRESS INCOME FUND LTD | 37272.8 |
| 17 | GROWTHPOINT PROPERTIES LIMITED | 67311.94 |
| 18 | INTU PROPERTIES PLC | 84272.25 |
| 19 | INVESTEC LIMITED | 30572.79 |
| 20 | INVESTEC PLC | 65150.04 |
| 21 | MTN GROUP LIMITED | 256800.3 |
| 22 | MEDICLINIC INTERNATIONAL PLC | 138970.4 |
| 23 | MONDI LIMITED | 32666.21 |
| 24 | MONDI PLC | 101138 |
| 25 | MR PRICE GROUP LTD | 44628.01 |
| 26 | NASPERS LIMITED | 849292.8 |
| 27 | NEDBANK GROUP LIMITED | 87014.44 |
| 28 | NETCARE LIMITED | 50392.8 |
| 29 | OLD MUTUAL PLC | 186302.6 |
| 30 | RMB HOLDINGS LIMITED | 76881.31 |
| 31 | RAND MERCHANT INVESTMENT HOLDINGS LTD | 61180.64 |
| 32 | REDEFINE PROPERTIES LIMITED | 58254.34 |
| 33 | REINET INVESTMENTS SCA (DR) | 63386.99 |
| 34 | REMGRO LIMITED | 119646.2 |
| 35 | SABMILLER PLC | 1457644 |
| 36 | SANLAM LIMITED | 143355.3 |
| 37 | SASOL LTD | 286409.3 |
| 38 | SHOPRITE HOLDINGS LIMITED | 96408.5 |
| 39 | STANDARD BANK GROUP LIMITED | 195214.4 |
| 40 | STEINHOFF INTERNATIONAL HOLDINGS NV | 344658.6 |
| 41 | TIGER BRANDS LTD | 64984.88 |
| 42 | VODACOM GROUP | 245289.3 |
| 43 | WOOLWORTHS HOLDINGS LIMITED | 91836.56 |

Source: Thomson Reuters DataStream.

The FTSE/JSE Top 40 Index includes the top forty largest companies according to full market capitalisation. The number of included constituents can exceed forty as certain companies included in the index issue dual listed shares (JSE, 2016).

The allocation among four of the super sectors from 1999 to October 2016 is shown in Figure 2.7 to indicate the change in allocation to resources sector. Since 2008, the allocation to resources has decreased, but there has been a slight increase since 2015.

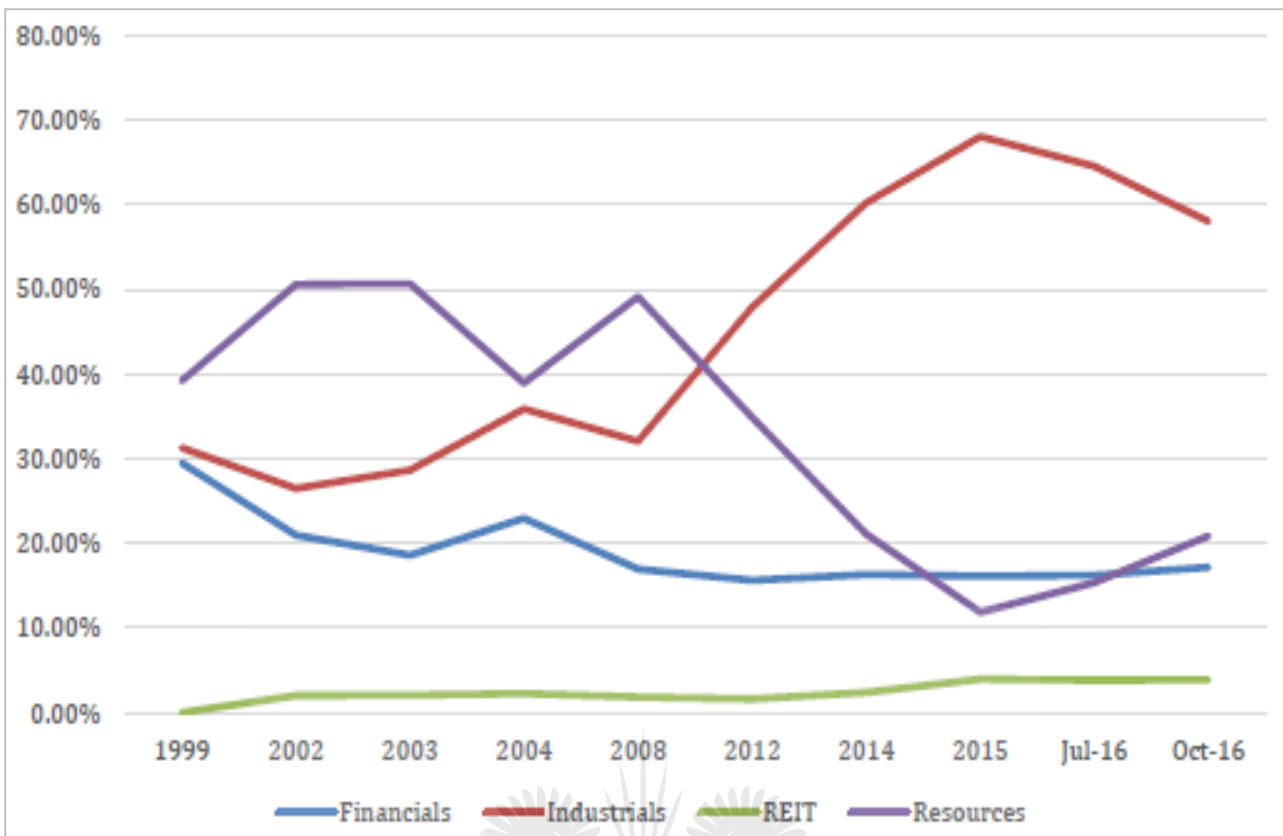


Figure 2.7: FTSE/JSE Top 40 Index super sector allocation from 1999 to 2016

Source: Blount, 2016 (Bayhill Capital).

Figure 2.8 shows the movement of the FTSE/JSE Top 40 Index from 30 June 1995 to 29 April 2016. The trend of the FTSE/JSE Top 40 Index appears similar to the South African Rand shown in Figure 2.5.



Figure 2.8: FTSE/JSE Top 40 Index from 1995 to 2016

Source: Thomson Reuters DataStream and Excel.

In Figure 2.9, the FTSE/JSE Top 40 Index showed a strong increase in value from 2005 to 2008, with a sharp correction as a result of the 2007 financial crisis. From 2009, the index has shown a substantial growth pattern up until 2014, where it has now remained within the 40 000 – 50 000 band for the last two years.

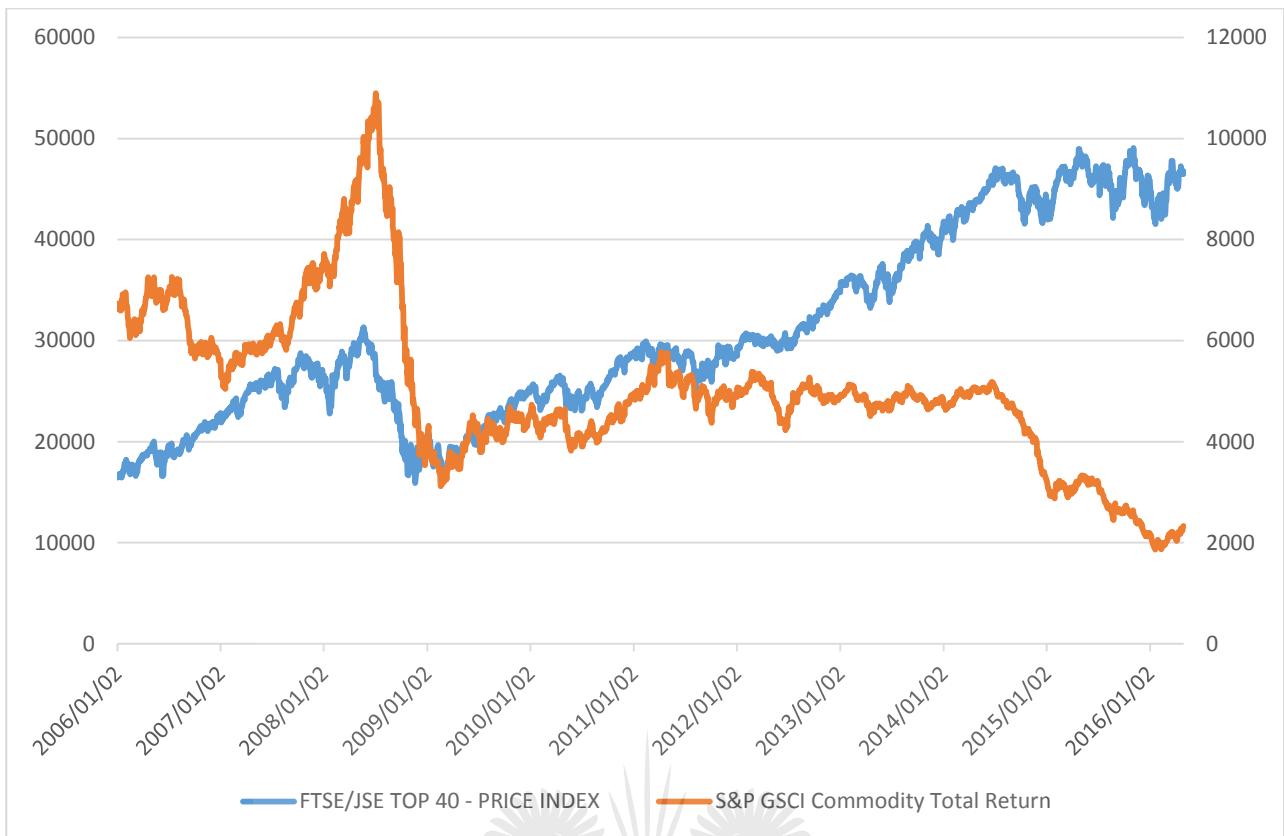


Figure 2.9: FTSE/JSE Top 40 Index against the S&P GSCI Commodity Total Return Index from 2006 to 2016

Source: Thomson Reuters DataStream and Excel.

Like the South African Rand, the FTSE/JSE Top 40 Index has shown signs of co-movement at certain times over the past ten years, as displayed in Figure 2.9. Between 2009 and 2012, the two variables seemed to move in a similar pattern. However, from 2012, the FTSE/JSE Top 40 Index followed an upward trend, where the S&P GSCI Commodity Total Return Index followed a downward trend.

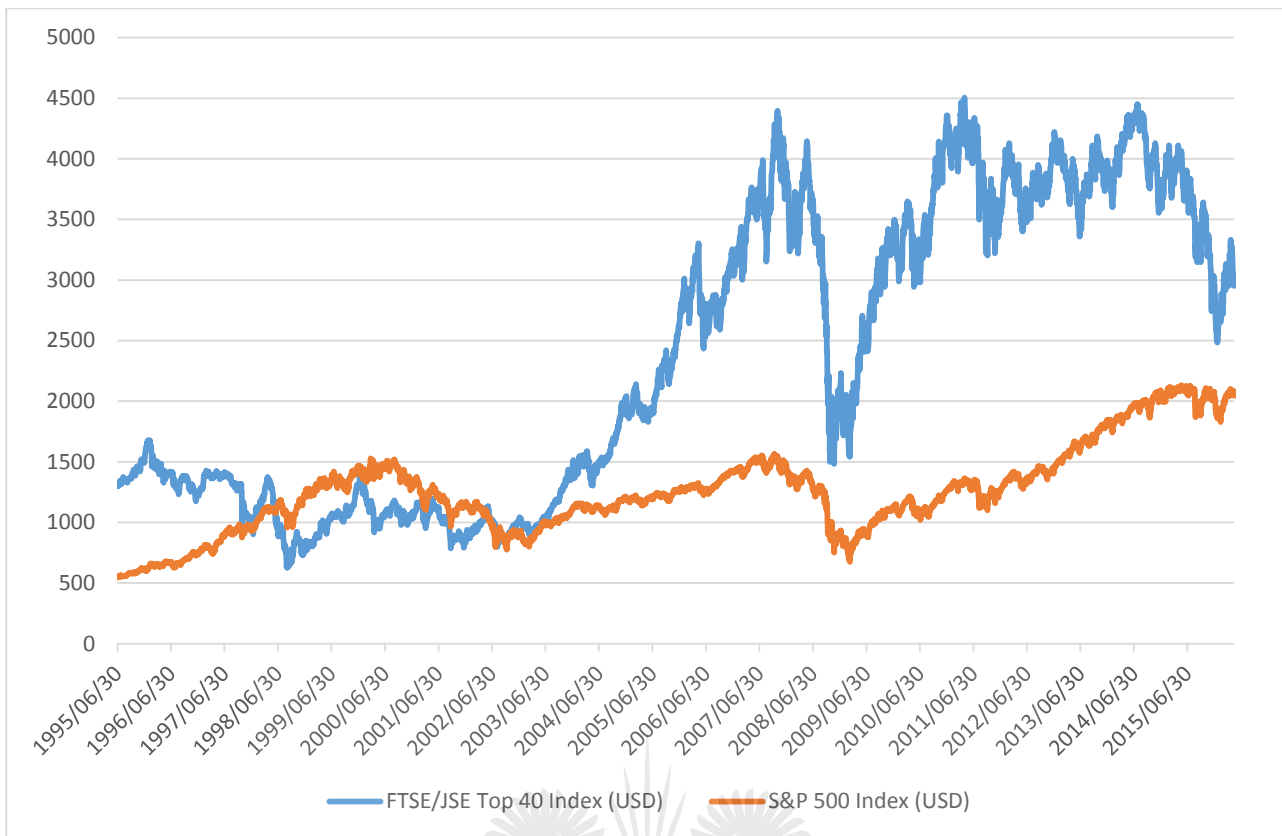


Figure 2.10: FTSE/JSE Top 40 Index (stated in USD) against the S&P 500 Index from 1995 to 2016

Source: Thomson Reuters DataStream and Excel.

The FTSE/JSE Top 40 Index in US Dollar terms is compared to the S&P 500 Index in Figure 2.10. The FTSE/JSE Top 40 shows two strong rally periods as opposed to the S&P 500 Index. The first rally period was from 2003 up until 2007 and the second rally period was from 2009 to 2011. The S&P 500 Index shows periods of growth; however, the growth is at a much steadier pace.

2.6. FINANCIAL CRISIS OF 2007

The financial crises of 2007 were an important separation point as the data period selected for the study is from the beginning of 2010. A financial crisis is defined as a disturbance that occurs in the financial markets which causes a disruption in the capacity of the market to allocate capital required for financial intermediation. The disruption causes investment to slow down or come to a halt (Portes, 1999).

Five distinct stages of the 2007 financial crisis emerged. The stages were: (1) the outbreak of the subprime mortgage crisis; (2) the spread of credit risk, and with the increase of losses of financial institutions; (3) the eruption of liquidity crisis (for example: the run on Bear

Stearns), along with the spread of contagion effects on other investment banks with similar portfolio characteristics (for example: Lehman Brothers); (4) the commodity price bubble; and (5) the ultimate freeze of credit markets accompanied by the massive flight to safety by investors (Orlowski, 2008).

The lack of regulation present within the market was one of the major contributing factors to the 2007 financial crises, which lasted to 2009, with after-effects still being felt. The loss of confidence that occurred in the market resulted in the lending markets being crippled internationally and caused investors to become more aware of risk management requirements (Gorton, 2010; Melvin & Taylor, 2009).

The financial crisis of 2007 was unlike previous financial crises with regard to two characteristics. The first difference was in the availability of investment possibilities, a cause of the crisis was as a result of new and different financial products being developed and offered to the market that provided access to new investment possibilities. The second difference was the linked financial systems due to globalisation as the financial system was at a level of integration much higher compared to previous financial crises (Colander, Föllmer, Haas, Goldberg, Juselius, Kirman, Lux & Sloth, 2009).

2.7. HEDGING RELATIONSHIPS

Hedging is a risk management action where the aim is to reduce or to transfer the risk associated with a specific position or portfolio. Hedging related to investments is a strategy in which the probability of loss from changes in the price of an asset is either limited or offset. The strategy of hedging is similar to buying insurance on the position or portfolio. To hedge a portfolio or position, an equal and opposite position is entered into to reduce the risk of holding the original position. Hedging cannot always be perfect but, as stated, the aim is also to reduce risk, which leads to the concept of cross hedging and optimal hedge ratios related to reducing risk by either limiting it or offsetting it (Poitras, 2002).

Cross hedging is a hedging technique where one variable is hedged with a different variable that is not directly related to the variable being hedged. In a cross hedge, the hedge can be performed effectively, but the risk present is imperfectly shifted as the variables used in the hedge transaction are not the same, based on different factors. In a cross-hedge the relationship between the two variables is not perfect, which means that basis risk exists, as they do not move together (Dinică, 2013; Chen & Sutcliffe, 2012; Hull, 2009).

Baur and Lucey (2010) state that an asset can be utilised as a hedging asset if the correlation between the hedging asset and asset to be hedged is low or negative. This means that if the two variables are uncorrelated or negative correlation exists between the two variables, the one variable can be used as a hedge for the second variable on an average basis. If the two variables are uncorrelated or negatively correlated during periods of turbulence, the asset being used as a hedge is a safe haven asset.

Cross hedging is therefore different to a direct hedge. In a direct hedge, a spot position of a variable is hedged by using a futures contract on the same variable. However, direct hedging is not always possible as futures contracts are standardised. In a direct hedge, basis risk is still present, but can be eliminated. Basis risk is the difference between the spot price and the future price of a variable at a specific date (Chen & Sutcliffe, 2012).

The Dutch Disease concept, whereby an economy that exhibits a negative relationship between a rise in a commodity price and the competitiveness of other products produced by the economy creates opportunity for hedging in that there is price volatility and market shocks that affect the commodities within the economy. The risks that are faced by the participants in the market related to commodity production and consumption create the need for certainty related to the price paid or received for the commodities. Hedging is an option available to the participants present in the commodity market (Chance & Brooks, 2013; Hull, 2009).

Participants utilising the futures market generally fit into three main categories. The categories are divided into speculators, arbitrageurs and hedgers, each with their own purpose and strategy (Hull, 2009). Rutledge (1972) stated that there are three goals to hedging, namely risk minimisation, profit maximisation, and the portfolio approach, taking into account risk and expected return.

Working (1953, 1962) argued that since the cash and futures prices of a variable do not move perfectly in parallel, the opportunity for arbitrage between the two markets arises. Therefore, hedgers are able to profit from fluctuations that occur between the two prices, creating a cash-futures price spread.

Sutcliffe (1993) states that hedging is done for four reasons: (1) to eliminate risk as a result of adverse price fluctuations, (2) to reduce risk as a result of adverse price moves, (3) to profit from basis changes, and (4) to maximise the expected return for a specific level of risk as well as to minimise risk for a given level of return.

In the hedging process, the hedge ratio needs to be determined. In hedging, the hedge ratio (Denoted by h^*) may differ from one as risk is only limited and not completely offset because the change in asset may not change exactly the same in another asset (Witt, Schroeder & Hayenga, 1986). The hedge ratio needs to be empirically tested, which will be discussed in Chapter 3.

Working (1953) introduced the concept of futures trading in commodities, which he defined as “trading conducted under special regulations and conventions, more restrictive than those applied to any other class of commodity transactions, which serve primarily to facilitate hedging and speculation by promoting exceptional convenience and economy of the transaction”. The hedging and speculation was done with the purpose of profit maximisation.

Johnson (1960) first developed the minimum variance hedge ratio in 1960, based on reducing the variance within a portfolio using futures contracts to hedge the spot position. Johnson (1960) and Stein (1961) linked the theory of futures hedging to cash positions first introduced by Working (1953). The optimal hedge ratio, which is also the minimum variance hedge ratio, is referred to as the naïve hedge ratio in the literature due to its assumption that the cash and futures position have similar characteristics. Ederington (1979) furthered the research when a risk-minimising hedge ratio was applied based on constant covariance and hedging effectiveness was measured. The hedge ratio was taken as the covariance between the future price and spot price or the applicable price changes to the variance of futures price (or price changes). Since then, more methods have been and are still being developed to obtain the most optimal hedge ratio that provides hedging effectiveness in the ever-evolving financial markets.

2.7.1. Static hedge ratios

The methods used to determine static optimal hedge ratios based on econometric techniques are the Ordinary Least Square (OLS) regression model, Error Correction Model (ECM), Vector Error Correction Model (VECM) and the Generalised Autoregressive Conditional Heteroscedasticity (GARCH 1,1) with error correction model (ECM-GARCH) (Adams & Gerner, 2012; Dlamini, 2008). Additionally, a review of hedge ratios and their theoretical development is available by Chen, Lee and Shrestha (2003).

The assumption of a perfect hedge or naïve hedge ratio, where the hedge ratio obtained is a negative one, is based on a perfect correlation assumption between two assets. The OLS and more advanced hedge ratio methods are not based on this absolute assumption, but

rather on a more realistic assumption of imperfect correlation between the variables, resulting in basis risk. Furthermore, if a cointegrating relationship exists between two variables, it can be considered when estimating the optimal hedge ratio (Dinică & Armeanu, 2014; Hull, 2009; Sutcliffe, 2006).

In the OLS regression model, the hedge ratio is equal to a slope coefficient of the simple regression line. The hedge ratio obtained from the OLS regression model is only accurate if distribution of asset returns shows constant variance (i.e. no volatility clustering), which is not present in many time series datasets, known as the homoscedasticity assumption (Park & Bera, 1987; Figlewski, 1984; Anderson & Danthine, 1980; Ederington, 1979). A further disadvantage of the OLS methodology used to estimate the hedge ratio is that it ignores the higher moments properties present in financial time series, such as skewness and kurtosis (Brooks, Černý & Miffre, 2012).

The hedge ratio obtained in the OLS regression model is strongly linked to the correlation between two assets. The disadvantage of the OLS method is that it ignores cointegration between two assets, which is later recognised in the ECM model (Chou, Denis & Lee, 1996; Lien, 1996; Castelino, 1992; Engle & Granger, 1987; Fama & French, 1987). The basis of the hedge ratio based on the ECM methodology is linked to cointegration as defined by Granger (1981) and formalised by Engle and Granger (1987), in that the model identifies a stable long run relationship between nonstationary time series (Puhle, 2013; Hull, 2009). Ghosh (1993) and Lien (1996) identified that when a cointegrating relationship exists between the spot and futures prices of selected variables, the hedge ratio obtained will not be optimal and would be smaller than required if cointegration is not taken into account.

Lien (1996, 2004) identified that it is possible that the ECM underestimates the hedge ratio due to the limitation of not identifying the correct number of cointegration equations. This limitation could be overcome by using the VECM model to estimate the hedge ratio. If a larger hedge ratio is obtained using the VECM model, it highlights that the ECM underestimates the hedge ratio and the limitation is valid.

The limitation of the hedge ratio estimation techniques that ignore the higher moments properties present in financial time series, such as skewness and kurtosis, is overcome by the use of the GARCH model. The GARCH model takes into account these moments and estimates conditional covariance and variance of the series to produce a hedge ratio that is unbiased in this nature. The GARCH model also captures the effect of volatility clustering, which is often found in financial time series. The use of the ECM-GARCH method provides

a static hedge ratio value to compare to the other methods as it assumes a constant conditional correlation between the variables being analysed (Kroner & Sultan, 1993; Sephton, 1993a; Cecchetti, Cumby & Figlewski, 1988; Myers & Thompson, 1989; Baillie & Myers, 1991).

Static methods to determine optimal hedge ratios only provide a fixed value for the calculated hedge ratio, which does not take into account the changes that occur as time progresses. Dynamic models assist in including the passage of time in the calculation of the optimal hedge ratio, which produces hedge ratios that are time-varying. The time-varying aspects that are taken into account in dynamic models, but are not included in static methods, are the conditional (time-varying) variances and covariance that exist in financial time series (Fiszeder, 2004; Bollerslev, Engle & Nelson, 1994; Bollerslev, Chou & Kroner, 1992; Myers, 1991).

2.7.2. Dynamic hedge ratios

Time-varying optimal hedge ratios based on econometric techniques are linked to bivariate and multivariate GARCH models as well as ECM including the VECM model. Multivariate GARCH models are based on a variance-covariance matrix, which allows the change in time to be taken into account. ECM models presented take into account the cointegration between two time series in order to determine whether a stochastic trend is present between the variables. Bivariate and multivariate GARCH models have become one of the main methodologies to estimate time-varying hedge ratios in the financial markets (Nia & Naserian, 2015; Lien, 1996; Tong, 1996; Gagnon & Lypny, 1995; Park & Switzer, 1995a; Lien & Luo, 1994; Ghosh, 1993; Kroner & Sultan, 1993; Baillie & Myers, 1991; Myers, 1991; Engle & Granger, 1987).

Time-varying hedge ratios based on a univariate ARCH model were introduced by Engle (1982) and applied by Cecchetti, Cumby and Figlewski (1988). The ARCH model was applied to Treasury bonds and T-bond futures in order to address and correct two problems. The problems identified for standard models were that they only focused on minimising risk and did not take into account time variation changes in the distribution of the spot and future priced variables. In the bivariate GARCH model analysis introduced by Bollerslev (1986), Park and Jei (2010) and Bera, Garcia and Roh (1997) found that the variance of hedge ratios was inversely related to the effectiveness of the hedging relationship. This also applies to the static hedge ratio estimation models where cointegration is ignored as well as taken into account (Lien, 2004).

Bollerslev (1990) proposed the constant conditional correlation GARCH (CCC-GARCH) model, which is a variant part of the family of GARCH models. The CCC-GARCH assumes that the conditional correlation remains constant throughout the period of analysis, which is not a viable assumption in time series analysis of financial data. Bollerslev, Engle and Nelson (1994) presented the matrix diagonal GARCH model as a solution to the constant conditional correlation model. The matrix diagonal GARCH model allowed correlations to be time-varying, which overcame the problem faced with the CCC-GARCH model. A further GARCH model that overcame the problem faced with the CCC-GARCH model was introduced by Engle and Kroner (1995), known as the BEKK-GARCH model. Engle (2002) simplified the model known as the dynamic conditional correlation (DCC) model, which takes into account the time-varying conditional correlation present between two variables.

Evidence of which methodology provides superior results and benefits has not reached consensus yet. When comparing the hedge ratio results, the econometric models used to analyse the data to obtain the hedge ratio provide different results (Lee & Chien, 2010). Evidence of the optimal hedge ratio analysis shows that the OLS regression methodology performs poorly compared to the other static and dynamic hedge ratio methods (Kavussanos & Nomikos, 2000a; Lien & Tse, 1999; Park & Switzer, 1995b; Kroner & Sultan, 1993).

However, evidence is also found where the OLS methodology performs equally well or better, compared to other methods (Alexander and Barbosa, 2007; Moosa, 2003; Bystrom, 2003; Lien *et al.*, 2002). An example is the GARCH method, as it has been found to provide results that are too volatile and therefore cannot be used effectively. In addition, the results indicated that the GARCH models introduce noise into the analysis, which removes the cost-effectiveness of the model (Fan, Li & Park, 2016; Lien, 2008, 2004, 2002; Alexander & Barbosa, 2007; Copeland & Zhu, 2006; Kavussanos & Nomikos, 2000b). Moosa (2003) concluded that the model specification is irrelevant in that it does not provide a significant difference. What does affect the outcome is the correlation between the two variables being evaluated for the hedging relationship.

The correlation coefficient between the spot and future price movement (i.e. returns) analysed still plays a significant role when evaluating hedging effectiveness. Ederington (1979) noted that the model specification is not the determining factor when evaluating hedging effectiveness, but rather the relationship between the variables is important. The relationship between the price movement of a spot and future priced variable plays a vital

role when calculating optimal hedge ratios, more so than the model selected and applied. Should the relationship be weak, then the results obtained and their effectiveness would be lower (Laws & Thompson, 2005; Ghosh & Clayton, 1996). Moosa (2003) highlighted the same results and found no significant difference between the models applied to the data.

2.8. EVIDENCE OF CROSS HEDGING RELATIONSHIPS

The development of hedging and the use of different models to determine the optimal hedge ratio have been undertaken in many studies since the 1960s. Cross hedging relationships and optimal hedge ratio analysis have been widely researched in the foreign exchange market as well as in the equity index markets. The studies were based on a selection of econometric methods to model and forecast hedge ratios based on different variables (Chang & Wong, 2003; Lien & Tse, 1999; Ghosh, 1996; Baillie & Bollerslev, 1994; Benet, 1992; Braga, Martin & Meilke, 1989).

The focus of this section will be on studies done since the mid 2000s to provide a suitable comparison for this study with a larger emphasis on commodity based studies. Prior studies as well as a summary of the relevant literature before the early 2000s are available in the papers by Das and Chakraborty (2015); Vasantha and Mallikarjunappa (2015); Gupta and Singh (2009); and Chen *et al.* (2003).

Lien and Yang (2008) evaluated five methods to obtain the model that provides the most improved hedging performance. The naïve method, OLS, conventional bivariate GARCH (BGARCH), symmetric BGARCH and asymmetric BGARCH models were applied on ten commodities. The commodities included were coffee, copper, corn, cotton, crude oil, heating oil, lean hog, pork belly, silver and soyabeans. Daily data from 1 January 1980 to 31 December 1999 was included to determine whether the asymmetric BGARCH model takes into account basis effect on the time-varying variance-covariance of the returns of the spot and future variables. The results indicated that the asymmetric BGARCH model provided the greatest risk reduction, compared to the other four models.

Dlamini (2008) utilised OLS, ECM, VECM, and ECM-GARCH to estimate static hedge ratios in the South African market. Two variables were considered in the study, the FTSE/JSE Top 40 Index as the spot variable and the associated index futures contract of the FTSE/JSE Top 40 Index as the future variable. A period before the crisis was selected on a daily basis from 2 January 2002 to 28 February 2006. Dlamini (2008) found that the ECM-GARCH model provided the most optimal hedge ratio, while the other three methods of OLS, ECM

and VECM provided lower hedge ratios. This indicates that the hedge ratios obtained from these three methods were underestimated. Dlamini (2008) concluded that the results obtained were similar to results presented by Sephton (1993b) and Floros *et al.* (2004). Dlamini (2008) did not test for hedging effectiveness nor attempt to forecast the hedge ratios, since the objective of the study was to compare the hedge ratios obtained from the four methods.

Kumar, Singh and Pandey (2008) investigated the effectiveness of hedging strategies based on four models, OLS, VAR, VECM and one time-varying model, VAR-MGARCH. Two commodities, namely gold and soyabean, were considered in the Indian market by the use of the S&P CNX Nifty index. Daily closing prices of the S&P CNX Nifty index spot and three futures from 1 January 2004 to 8 May 2008 were included in the analysis. For the commodities, gold spot and two futures from 22 July 2005 to 8 May 2008, and soyabean spot and two futures were included in the analysis from 4 October 2004 to 8 May 2008. The data period included both an in-sample and an out-of-sample period. The out-of-sample periods were from 21 February 2008 to 8 May 2008 for the S&P CNX Nifty Index as well as for gold, whereas 21 February 2008 to 8 May 2008 was used for soyabean. Kumar, Singh and Pandey (2008) found that the time-varying hedge ratios performed better, compared to the static hedge ratios based on variance reduction. Similar results were obtained by Floros and Vougas (2006), Yang (2005), Kavussanos and Nomikos (2000b), Park and Switzer (1995b), Baillie and Myers (1991), and Myers (1991).

Park and Jei (2010) evaluated the time-varying hedge ratios using four specifications of bivariate CCC and DCC models for the spot and nearby future priced agricultural commodities of corn and soyabeans. Daily data from 1 January 1997 to 31 October 2000 constituted the in-sample period followed by the 60 days succeeding 31 October 2000 to 23 January 2001 as the out-of-sample period. Park and Jei (2010) found that certain hedging strategies provided slight improvements when the standard deviations observed were stable and of a low enough level. The slight improvement, however, was not large enough to determine with certainty that the time-varying hedging strategy provides superior results to an OLS hedging strategy.

Degiannakis and Floros (2010) compared the hedge ratios of six models for the FTSE/JSE Top 40 Index and stock index futures on a daily basis from 2 January 2002 to 28 February 2006. Static hedge ratios were estimated using OLS, ECM, VECM, ECM-GARCH and time-varying hedge ratios were estimated using CCC-ARCH and Diag-BEKK ARCH. The ECM-

GARCH and time-varying models provided superior results. Degiannakis and Floros (2010) found that there is no unique model for hedge ratio estimation, but rather that the best performing model needs to be obtained for each market.

Chang, Lai and Chuang (2010) evaluated the hedging effectiveness of eight models in the energy markets (oil and gasoline) during bull and bear markets. The models are OLS, GARCH (MD-GARCH, BEKK-GARCH, CCC-GARCH), ECM (ECM-MD, ECM-BEKK, ECM-CCC), and state space. Daily data from 1 January 1996 to 31 December 2005 was used for the analysis. The in-sample results indicated that the state space model performed the best, whereas the CCC-GARCH and ECM-CCC models performed the best out-of-sample. The asymmetric performance during the two periods highlighted that the choice of model is an important consideration when price-movement patterns are observed.

Hammoudeh, Yuan, McAleer and Thompson (2010) explored the hedging ratios for metal commodities (gold, silver, platinum and palladium) and the US Dollar/Euro exchange rate on a daily basis from 4 January 1999 to 5 November 2007. Vector autoregressive moving average (VARMA)-GARCH and VARMA-DCC was applied in the study and the models provided similar estimates for the hedge ratios.

Chang, McAleer and Tansuchat (2011) calculate the optimal portfolio weights and hedge ratios for crude oil. Four multivariate volatility models are applied, CCC, VARMA-GARCH, DCC and BEKK. Daily spot and future prices for Brent and WTI markets from 4 November 1997 to 4 November 2009 are evaluated. The results indicate that the DCC model performs the best during the period. The hedging effectiveness is based on the adapted method from Ku, Chen and Chen (2007), where conditional volatility is utilised in the original hedging effectiveness formula from Ederington (1979). The hedging effectiveness measure showed that the DCC model provided the most effective results, whereas the BEKK was the worst performing model. Chang, McAleer and Tansuchat (2011) show that the VARMA-AGARCH simplifies into the asymmetric DCC-GARCH model with GJR specification when $m=1$ in a $m \times m$ matrix.

Kumar and Pandey (2011) compared the hedging effectiveness of agricultural and non-agricultural commodities in the Indian market from 2004 to 2008. Two models were applied to compare the static and time-varying hedge ratios and related effectiveness. VECM/VAR was applied where relevant, based on cointegrating relationships, to obtain the static hedge ratios and CCC-MGARCH was applied to obtain the time-varying hedge ratio. Overall,

agricultural commodities provided a higher hedging effectiveness when compared to the non-agricultural commodities, which consisted of metal and energy commodities.

Arouri, Jouini and Nguyen (2011) investigated hedging effectiveness of oil and seven equity segments and selected indices from Europe and United States using four GARCH models, VAR-GARCH, CCC-GARCH, DCC-GARCH and diagonal BEKK-GARCH model. Weekly data from 1 January 1998 to 31 December 2009 was examined in order to compare the models. The VAR-GARCH model outperformed the other models based on the diversification and hedging effectiveness.

Adams and Gerner (2012) explored the cross hedging relationships within the energy commodity group in order to manage jet-fuel spot price exposure. The econometric methods of regression, ECM and ECM-GARCH models were applied in the study, which included Brent oil, WTI oil, gas oil and heating oil forward contracts over different maturity dates ranging from one month to 24 months. The period of analysis focused on June 1995 to June 2010 based on weekly data. The ECM-GARCH model based on gas oil outperformed the other options presented. The results obtained also showed that maturity dates of forward contracts influence the cross hedging capabilities of selected variables.

Dinică (2013) investigates the hedge ratios and hedging effectiveness in the United States wheat market based on weekly prices from 6 November 2002 to 31 October 2012. The static models utilised are the OLS, ECM, whereas the time-varying models are the rolling window OLS, the expanding estimation window OLS, and the bivariate GARCH ECM model. The results indicate that the expanding estimation window OLS performed the best, based on hedging effectiveness.

Dinică and Armeanu (2014) examined the optimal hedging ratio and hedging effectiveness for six non-ferrous metals, aluminium, copper lead, nickel, tin and zinc. OLS, ECM and autoregressive distributed lag (ARDL) model was used to evaluate hedging ratios over different hedging horizons of 1 day to 12 weeks from 3 April 2000 to 30 September 2013. The optimal hedge ratio and hedging effectiveness were found to increase with the hedging horizon, with the more advanced methodologies of ECM and ARDL providing a better hedging effectiveness result. An out-of-sample analysis was done on only two commodities, aluminium and copper. The results indicated that even though the more advanced methodologies were the most effective, the certainty of the results decreased.

The hedging effectiveness of Iranian light crude oil based on different maturity contracts using a selection of multivariate GARCH models and error correction models was investigated by Nia and Naserian (2015). The MD-GARCH, BEKK-GARCH, CCC-GARCH, ECM-MD, ECM-BEKK and ECM-CCC models were applied and compared to determine which strategy would provide the most effective results for data from January 2000 to January 2012. The models based on the ECM provided higher efficiency than the models based on GARCH.

Chkili (2016) explored the dynamic correlations and hedging effectiveness of gold for the stock markets of the BRICS, both based on spot prices (Brazil, Russia, India, China and South Africa). The asymmetric DCC-GARCH model with GJR-GARCH specification was applied on a weekly basis from January 2000 to July 2014. Overall, the combination of gold and the Russian stock index provided the highest hedge ratio as well as the highest hedging effectiveness.

Basher and Sadorsky (2016) evaluated the hedging effectiveness between emerging stock prices, oil, the VIX, gold and bond prices, using three GARCH models (DCC-, ADCC- and Go-GARCH). Daily data from 4 January 2000 to 31 July 2014 was included in the analysis. The ADCC-GARCH model performed the best in most of the combinations, except for the emerging market stock prices and gold combination where Go-GARCH provided the best hedging performance.

2.9. EVIDENCE OF CROSS-MARKET LINKAGES

Studies to determine relationships that involve commodity prices have increased in popularity over the last two decades (Kurihara & Fukushima, 2014; Bhunia, 2013; Nazlioglu & Soytas, 2012; Hassan & Salin, 2011; Saghaian, 2010; Ocran & Biekpe, 2007; Cashin *et al.*, 2004; Chen & Rogoff, 2003). The studies available either test the relationship between commodity prices or alternatively between commodity prices and a financial or economic variable. The methodology used in the majority of the studies is cointegration and the vector error correction model, or slightly altered methodology.

Conclusions reached in previous studies vary depending on which commodity prices and financial or economic variable are included. The date range chosen and methodology followed also contribute to the differences in conclusions reached. The literature review will highlight important studies that focus on relationships between commodities, but the main

focus will be on studies that look at the relationship between commodity prices and financial variables.

The study of Chen and Rogoff (2003) is one of the seminal works exploring the relationships of commodities and whether there is a forecasting relationship between commodity prices and exchange rates. The relationship investigated was between the USD price of commodity exports and the floating real exchange rate of the country exporting the commodity. Chen and Rogoff (2003) found a significant relationship between the commodity prices and the floating real exchange rate of Australia and New Zealand, and specifically that commodity prices influenced the floating real exchange rates.

Cashin *et al.* (2004) investigated the influence of real commodity price changes on the movements of real exchange rates. Fifty-eight commodity-dependent countries were included in the study. They found strong evidence of the potential relationship in only forty percent of the countries. The weaker results related to the relationship identified by Cashin *et al.* (2004) are in contradiction to the findings of the study done by Chen and Rogoff (2003).

A further study linked to Chen and Rogoff (2003) was done by Chen *et al.* (2010), who examined the forecasting relationship further by investigating the power of exchange rates of countries that export significantly large amounts of commodities in forecasting the prices of the commodities exported by that country. Chen *et al.* (2010) again found that certain exchange rates of commodity currencies have a relatively strong forecasting power in forecasting global movements in commodity prices.

Yu, Bessler and Fuller (2006) investigated the long run interdependencies between edible oil prices, which include soyabean, sunflower, rapeseed and palm oil prices. The dynamic relationship between these four edible oil prices and the crude oil price was also explored. Weekly data from the beginning of January 1999 to the end of March 2006 was included in the study. The data was analysed by means of a vector autoregressive model, Johansen cointegration test, directed acyclic graphs mechanism, error correction model, variance decomposition and impulse responses.

The analysis from Yu *et al.* (2006) also included the use of dummy variables in order to test the influence that policies and structural changes in the industry can have on the results. One cointegration relationship was identified, with soyabean resulting in the most changes in other variables. Shocks applied to the crude oil price did not have a significant effect on the edible oil prices.

In South Africa, Ocran and Biekpe (2007) examined whether commodity prices could be used as a signal for informing macroeconomic policy in South Africa. Average gold prices and the IMF's International Financial Statistics metal price index were used as the commodities. The consumer price index, interest rates, money stock and the nominal exchange rate were included as the monetary variables. The variables were based on quarterly data from the first quarter of 1965 to the last quarter of 2004.

Ocran and Biekpe (2007) based their empirical methodology on the methodology applied by Toda and Yamamoto (1995), which used an alternative procedure for conducting the Granger causality test. The null hypothesis of non-causality from commodity prices to macroeconomic variables was tested with the use of an augmented level VAR model so that the loss of long run information was not overlooked as per the traditional Granger causality test procedure. The average gold price showed that it Granger caused interest rates, money supply and the consumer price index. Regarding the metal price index, there was Granger causality from the metal price index to the interest rate, money and exchange rate.

The relationships between the crude oil price and the prices of the four vegetable oils, being palm, soyabean, sunflower and rapeseed oils, were explored by Hameed and Arshad (2009). The study utilised data from January 1983 to March 2008. The results indicated that there was a long run relationship between the crude oil price and the vegetable oil prices. The results were obtained by means of Johansen cointegration tests, Granger causality tests and error correction term, which is the Engle-Granger two-stage estimation procedure. The results were separated into two time periods, before 2006 and after 2006.

The correlation coefficients from the results of Hameed and Arshad (2009) increased drastically to values closer to one in the period after 2006 compared to the before 2006 values, which affirmed the statement that the commodities were moving more together after 2006. The Granger causality test indicated that there was a unidirectional relationship from the crude oil price to the vegetable oil prices, but no feedback relationship was identified. The coefficients of the error correction term measure the speed of adjustment. The coefficients in the study indicated that the speed of correction was relatively low (Hameed & Arshad, 2009).

The relationships between crude oil, natural gas and electricity prices in the United States and European commodity markets were investigated based on a short and long run basis (Bencivenga & Sargenti, 2009). The study period was from October 2001 to March 2009, with the use of daily prices analysed by means of rolling correlation, cointegration, and the

error correction model (ECM). In the short run, a volatile relationship was found; however, in the long run an equilibrium relationship was identified.

Saghaian (2010) investigated the relationships between five commodity prices only. The commodities were corn, soyabean, wheat, crude oil and ethanol. Monthly prices for these five commodities were used from January 1996 to December 2008. The time period included a portion of the financial crises of 2007, which could distort the results. The methodology utilised in the study done by Saghaian (2010) included the use of Johansen cointegration, vector error correction model, pairwise Granger causality tests and directed graphs.

Saghaian (2010) found that the Johansen cointegration test showed a linear relationship between the five commodities. The directed graphs, a visual representation of the causal flow between variables, showed that there was no relationship between the energy and agricultural sectors. The Granger causality tests showed that there were linkages between the two sectors. There was a unidirectional relationship from oil to ethanol, soyabean to ethanol, wheat to ethanol, corn to soyabean, wheat to soyabean, oil to corn, oil to soyabean, and oil to wheat. Bidirectional relationships existed between corn and ethanol as well as between corn and wheat.

From a different perspective, Zhang, Lohr, Escalante and Wetzstein (2010) also explored the relationship between energy and agricultural commodities, but found less conclusive results than Saghaian (2010). Zhang *et al.* (2010) included ethanol, gasoline, oil, corn, rice, soyabeans, sugar and wheat in their analysis. Monthly price data from March 1989 to July 2008 was included in this study. The methodology used in the analysis included Johansen cointegration, vector error correction model, Granger causality tests, and variance decomposition. The analysis indicated that no long run relationship was found between the energy and agricultural commodities combined together, but cointegration relationships were found between commodities in the same sector. A few short run relationships were found between the eight variables. The short run relationship that was found between the two sectors is a unidirectional relationship from sugar to oil.

Esmaili and Shokoohi (2011) examined the relationship between food prices and macroeconomic variables. The food prices included in the study were eggs, meat, milk, oilseeds, rice, sugar and wheat. The macroeconomic variables were crude oil prices, consumer price indices, food production indices, and gross domestic product (GDP) from around the world. Data ranged from 1961 to 2005 in terms of monthly prices. Principal component analysis was used as the methodology, which is different to many of the studies

listed in this chapter. The remainder of the methodology included Granger causality tests. The findings of the study by Esmaeili and Shokoohi (2011) are similar to those of the study done by Zhang *et al.* (2010) in that no long run relationship was found between oil, which is in the energy sector, and the agricultural sector.

A different approach for using commodities was followed by Hassan and Salin (2011), in that commodity prices were used to determine whether they could predict inflation, unemployment and short-term interest rate values in Australia. The authors used similar methodology as per the studies discussed above. The methodology used vector autoregressive model, cointegration and Granger causality test. Monthly data from July 1982 to December 2007 was included for seven variables.

The variables that Hassan and Salin (2011) used were the overall index of commodity prices, the commodity price index for rural commodities, the commodity price index for non-rural commodities, the commodity price for base metal commodities, inflation, unemployment and short-term interest rates. Three of the four commodity price indices, namely the commodity price index for rural commodities, the commodity price index for non-rural commodities, and the commodity price for base metal commodities, showed a causal relationship to inflation. The overall index of commodity prices did not cause inflation and inflation did not cause any of the commodity indices.

Nazlioglu and Soytaş (2012) furthered the research on the relationships between energy and agricultural commodities, but also included the USD. A selection of 24 agricultural commodities as well as oil was used in the research analysis. Monthly data was selected from January 1980 to February 2010. The analysis of the data included panel cointegration and Granger causality tests. The results found that oil prices had a strong impact on the agricultural prices, whereas the USD has an impact on agricultural prices when it is weak.

A study that considered variables similar to the variables included in this thesis was done by Samanta and Zadeh (2012). The variables that Samanta and Zadeh (2012) included in their research were the World Gold Price, World Oil Price, United States Stock Price (Dow-Jones Industrial Index), and the real exchange rate for the USD. The daily closing prices from January 1989 through to September 2009 were included in the study.

Samanta and Zadeh (2012) analysed the variables using Johansen cointegration test, vector autoregression, Stock-Watson's common trend test, Granger causality test and the Diebold and Yilmaz methodology. The results indicated that initially the existence of co-movements

are present between the datasets, but further analysis indicates that the equity price and the gold price tend to move on their own; however, the oil price and exchange rates are affected by other variables.

A study that tests the relationship between the commodity price and the equity market price was done by Bhunia (2013). Bhunia (2013) examined the relationships between three variables in India, namely the world crude index, the Indian gold price and the equity market index of the Bombay stock exchange. The data period for the study was from 2 January 1991 to 31 December 2012 on a daily basis. The data was analysed using Johansen cointegration, and the Granger causality test. A long run relationship was identified in the Johansen cointegration test and three causal relationships were identified as related.

Hussin, Muhammad, Razak, Tha and Marwan (2013) explored the link between oil prices, gold prices and the FTSE Bursa Malaysia Emas Shariah Index, which represents the Islamic equity market in Malaysia. The data was comprised of monthly data from January 2007 to December 2011. The analysis of the data was done by means of a Johansen cointegration test, Granger causality test, impulse response analysis and variance decomposition analysis. The results indicated that the commodities and the Islamic equity returns were not cointegrated, but causality relationships were identified. A bidirectional causality relationship was found between the Islamic equity returns and the oil prices, with no causality relationship between the Islamic equity returns and the gold price.

The cross-market linkages were examined by Chevallier and Ielpo (2013) between commodities, equities and bonds. Chevallier and Ielpo (2013) based their analysis on two previous studies done by Zeng and Swanson (1998) and Büyükşahin, Haigh and Robe (2010). Zeng and Swanson (1998) explored the cointegration relationships present between the S&P 500 Index, treasury bonds, gold and crude oil. The study period was from 1990 to 1995 and error correction model was utilised in the analysis. A cointegration relationship was found between variables.

Büyükşahin *et al.* (2010) also considered the cointegration relationships similar to Zeng and Swanson (1998). They used the S&P 500 Index and the Goldman Sachs Commodity Index from 1991 to 2008 with a sub-period from 1997 to 1999. The results obtained from the analysis indicated that no cointegration relationship was present between the variables. Chevallier and Ielpo (2013) included gold, oil, the Goldman Sachs Commodity Index sub-indices, the S&P 500 Index and the US 10-Year rate treasury bill in their study. The data

period was also more recent, from 1993 to 2011, with two sub-periods, 1993 to 2000 and 2000 to 2011.

Cointegrating relationships were only found between five relationships, firstly between gold, oil, S&P 500 Index and the US 10-Year rate from 1993 to 2011; secondly between one of the Goldman Sachs Commodity Index sub-indices, the Goldman Sachs Commodity Index agricultural and the S&P 500 Index from 1993 to 2011; thirdly between the Goldman Sachs Commodity Index industrial and the S&P 500 Index from 1993 to 2011; fourthly between the Goldman Sachs Commodity Index precious metals and the S&P 500 Index from 1993 to 2011; and lastly between the Goldman Sachs Commodity Index energy and the S&P 500 Index from 1993 to 2011 (Büyükkşahin *et al.*, 2010).

The transmission of monetary policy and the related impact of commodity price fluctuations on the real economy of the BRICS countries (Brazil, Russia, India, China and South Africa) were examined by Mallick and Sousa (2013). Seven macroeconomic variables for each country, namely the commodity price index, the GDP deflator and the real GDP, the central bank rate, the monetary aggregate, the real effective exchange rate, and the equity price index were included in the study.

Mallick and Sousa (2013) used quarterly data from the first quarter of 1990 to the first quarter of 2012 in the study. Econometric time series analysis by means of a Bayesian Structural Vector Auto-Regression (B-SVAR), a Sign-Restrictions VAR and a Panel VAR (PVAR) were applied in the study. The results indicated that shocks to commodity prices caused the real exchange rate to appreciate but no effect on the output was identified.

A study that focused on all three aspects included in this thesis, related to the variables representing commodities, an exchange rate and an equity index, was conducted by Fahami, Haris and Mutalib (2014). The variables included were the crude oil and gold price as well as the exchange rate against the United States Dollar and main equity index for Malaysia, Thailand and Indonesia respectively. The period of study was from 8 November 1993 to 8 November 2013 based on weekly data. The methodology followed included Johansen Juselius Cointegration test and Granger causality test. The results indicated that there was a bidirectional relationship between the equity index and exchange rate for all three countries. A unidirectional relationship exists from the exchange rate of all three countries to crude oil prices.

The relationship between the South African Rand and the gold price volatility was explored by Arezki, Dumitrescu, Freyteg and Quintyn (2014). Prior studies focused on the price time-series data, which is different to the research undertaken by Arezki *et al.* (2014). The authors used monthly data from 1979 to 2010. Johansen cointegration test and vector error correction model was used for the analysis. The analysis indicated that before the capital account in South Africa was liberalised the causality direction was from the South African Rand to the gold price volatility, but the opposite direction afterwards.

From an energy commodity perspective, Frydenberg, Onochie, Westgaard, Midtsund and Ueland (2014) investigated the relationship between futures prices of electricity, natural gas and crude oil for three markets United Kingdom, Germany and Nordic countries. Daily data from 17 July 2006 to 24 September 2012 was included in the study and it was analysed by a cointegration test and the vector error correction model. Cointegration was found between electricity and gas prices in the United Kingdom as well as between electricity and coal prices in the United Kingdom, Germany and the Nordic countries. A weaker cointegration relationship was found between electricity and crude oil prices.

Kohlscheen (2014) explored which fundamental economic factors affect the exchange rate of Brazil, the Brazilian Real over the long run from January 1999 to September 2012. The main economic factors included in the study were commodities in the form of indices, an unweighted commodity price index, a weighted commodity price index and the Commodity Research Bureau price index, all tested against the real effective exchange rate of Brazil. The data was analysed using the Johansen cointegration test and vector error correction coefficients. It was found that commodities play a significant role in the determination of the equilibrium exchange rate in Brazil.

A further study that looked at the relationships between commodity prices, the exchange rate and equity prices was Kurihara and Fukushima (2014). The focus was on Japan and the Euro area from 2001 to 2013 for Japan and 2020 to 2013 for the Euro area based on monthly data. The study included the gold price, Nikkei Average 225, DAX index from Germany, The Japanese Yen against the US Dollar and the Euro against the US Dollar. The methodology applied included the use of the vector autoregressive model, cointegration and Pairwise Granger causality tests. The results indicated that there was a weak relationship between equity prices and the exchange rate. In Japan, there was a significant effect on the commodity prices from the exchange rate, but the same was not found in the Euro area. The commodity prices of both Japan and the Euro area did not impact on equity prices.

In the South African market, Schaling, Ndlovu and Alagidede (2014) examined the commodity currency notion for the South African Rand and also analysed the possible causality relationship between the South African Rand and the non-fuel commodity price index that is published by the International Monetary Fund (IMF) and contains over forty primary commodities traded on various exchanges. Monthly data was used from 1996 to 2010 and the data was analysed using Engle Granger and Johansen tests for cointegration, followed by a vector autoregressive model and vector error correction model. The analysis was concluded with the Granger causality test and the results indicated that a direct relationship exists between the commodity price changes and the exchange rate changes. With regard to the causality test, no causality relationships were found.

2.10. SUMMARY

The literature review chapter has introduced and discussed the major components important to the study and the research question and related objectives. The main research question of this study was to determine what optimal cross hedging relationships are present within the South African financial market context in relation to a selection of commodities.

The main objective:

Investigate optimal cross hedging relationships between the variables.

The sub-objectives to reach the main objective in order to answer the research question were:

- Determine the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index.
- Determine the long run and short run relationships between each commodity price and the ZAR.
- Determine the long run and short run relationships between the FTSE/JSE Top 40 Index and the ZAR.
- Determine the cross hedging opportunities between the variables.
- Determine the co-movement between the variables.

The second component of the literature review was commodities, as these commodities are the core focus of the study and the first major set of variables in the research objective. The third and fourth section discussed in the chapter were the concept of commodity currencies

and currency commodities as the ZAR was the second major variable included as part of the study.

The last major variable included in the study was the FTSE/JSE Top 40 Index and therefore the fifth section of this chapter discusses the South African equity index and its characteristics and relationships with the global commodity index and the S&P 500 Index. An important exclusion related to the time period selected for the study was the exclusion of the 2007 financial crisis, which is briefly discussed in section six of this chapter.

Hedging developments were discussed in section seven, followed by the relationships important to the study in the last two sections. The second last section discussed hedging relationships in order to understand the purpose of hedging as a tool used in investment decisions. The final section discussed evidence of cross-market linkages related to prior studies.

The hedging and market linkages discussed in Sections 2.8 and 2.9 suffer from the problems listed below, which indicates that a gap exists in the literature. This thesis addresses certain of these aspects:

- The studies that have been evaluated and the selected studies included in Chapter 2 highlight that only selected markets, variables, and time periods are explored.
- Most of the studies available focus on a period before the crisis and certain of the studies include the financial crisis of 2007 – 2009. Only a small number of studies are available for a post-crisis period.
- The results of the studies differ from study to study due to the differing markets, variables and time periods.
- The models applied in the studies have evolved over the last two decades (or more) as new techniques were introduced. Many studies only reviewed a small selection of techniques to analyse their data.
- The hedging effectiveness techniques are still developing and no single technique is seen as the best solution to evaluate the hedging strategies.

This thesis addresses a gap in the South African market as well as between international commodity prices based on an extended methodology, lengthened time period as well as a larger selection of commodities.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. INTRODUCTION

In the preceding chapter, an overarching literature review related to the study was provided. Chapters 4 to 7 in this study also each includes a literature review that is related to the respective chapter. This chapter will explain the research methodology that was utilised for the four chapters included as part of this thesis to answer the research question. Chapters 4 to 6 will follow the same research methodology, whereas Chapter 7 follows a slightly different methodology. Both methodologies will be described in this chapter.

Rajasekar, Philominathan and Chinnathambi (2006:2) explain research as

“... a logical and systematic search for new and useful information on a particular topic” which is *“done with the help of student, experiment, observation, analysis, comparison and reasoning”*,

where research methodology is defined as the systematic manner used to solve a problem.

The research question and objectives of the study will be the first section of this chapter, followed by the research strategy and research instrument. The strategy of the sample will be discussed thereafter, followed by the method of data collection. The largest section of this chapter is the data analysis section, which will discuss the process by which the data was analysed related to Chapters 4 to 7. The chapter will conclude with the validity and reliability of the data, the ethical considerations, limitations and the significance of the study.

3.2. RESEARCH QUESTION AND OBJECTIVES

The research question of the study represents the main purpose of the study. The literature review and empirical analysis are used in order to answer the research question and any sub-questions or objectives that are derived.

The main research question of this study was: What optimal cross hedging relationships are present within the South African financial market context in relation to a selection of

commodities? In order to answer the research question regarding relationships, the following objectives needed to be explored in Chapters 4, 5, 6 and 7. The main objective in this study was to:

Investigate optimal cross hedging relationships between the variables.

The sub-objectives to reach the main objective in order to answer the research question were to:

- Determine the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index.
- Determine the long run and short run relationships between each commodity price and the ZAR.
- Determine the long run and short run relationships between the FTSE/JSE Top 40 Index and the ZAR.
- Determine the cross hedging opportunities between the variables.
- Determine the co-movement between the variables.

The research objectives of the study were to investigate the relationships present between the variables included. The relationships were used as a starting point in order to obtain optimal cross hedging relationships using commodities in the South African financial market as well as between the commodities. These objectives were achieved by means of an empirical analysis that will be presented over four chapters.

Chapters 4, 5, and 6 will include a subset of the selection of commodities grouped according to categories of commodities, and Chapter 7 will build on the results of Chapters 4, 5 and 6 to answer the research question stated above. Chapter 7 will investigate cross hedging relationships present between the sixteen variables included in the study

3.3. RESEARCH STRATEGY

Saunders, Lewis and Thornhill (2009) define a research strategy as the framework that is used by a researcher in order to answer the research questions of the study. The research strategy that was utilised in this study was based on secondary data and the financial econometric analysis thereof.

Financial econometrics is the “*application of statistical techniques to problems in finance*” as defined by Brooks (2014:1). Secondary data is data that is already available, therefore existing data.

Secondary data is beneficial as there is a time and cost advantage as new data does not need to be collected. The benefit is limited to availability of the secondary data as well as any errors that are present within the data source. Data sources that are widely used within the market are less likely to contain data errors (Mouton, 2001).

3.3.1. Research paradigm

Patton (1990) describes a research paradigm as the way a researcher views the research problem or the general perspective from which a research problem is approached. This study was approached using a positivism approach with deductive reasoning. Saunders *et al.* (2009) define positivism based on the philosophy where structured models are used by the researcher to observe reality; and define deductive reasoning as the process where a hypothesis is inferred and then tested.

Positivism is linked to the notion that science is the only way to learn about the truth. When undertaking research based on a positivism philosophy, the knowledge gained is through observation, based on data collection and interpretation in an objective and independent manner. Following the positivism philosophy, the findings of the research are observable and quantifiable (Crowther & Lancaster, 2008).

3.3.2. Research method

The study is based on secondary data, which is quantitative in nature. The secondary data that was required to answer the research question was historic time series data. Secondary historical time series data was used as it is required for the econometric analysis that needs to be done in order to interpret the results. The historical time series data was reviewed and analysed in order to arrive at a conclusion and infer implications about the nature of the data and the related interactions between the data which were used to answer the research questions.

Other sources of data that were used in the study included written peer reviewed journal articles which are area-based on sources from all over the world. The time-series data collected was time-based and collected from the Thomson Reuters DataStream database.

3.4. RESEARCH INSTRUMENT

The research instrument is used in order to complete the analysis of the data collected for the study. The instrument that was used in this study was EViews and the related financial econometric tests required to answer the research question and objectives. EViews is an econometric software package that provides statistical, forecasting and modelling tools in order to analyse data.

3.5. SAMPLING STRATEGY

The sampling strategy required for a study is the method that is used to obtain a sample selection. In this study, non-probability purposive or judgemental sampling was used. In purposive sampling, the researcher makes sample selections from the population. This is required in order to answer the research question and meet the related research objectives (Saunders *et al.*, 2009).

3.5.1. Target population

The population available to answer the research question was all financial variables. As the research objectives were focused on commodities (fourteen in total), the FTSE/JSE Top 40 Index and the ZAR, the scope of the research was limited to these variables. The analysis of the data was performed according to the framework in a systematic process in order to identify relevant relationships.

3.5.2. Sample selection

The sample was selected systematically once the research question and objectives were formulated. The sample was divided into three main segments, the commodities, the index to represent the market, and the currency to represent the country. South Africa was the country selected for the study as the researcher is based in South Africa and wanted to identify significant relationships that would be relevant to the South African market. The next step was the selection of the index. The FTSE/JSE Top 40 Index was chosen as the proxy as it is the most representative of the financial markets in South Africa.

The last step was the selection of the commodities, which was a more challenging task. The way the commodities were chosen was based on the availability of data on the Thomson Reuters DataStream database. The benchmark commodity prices available on Thomson Reuters DataStream were the first step in narrowing the selection of commodities. Once the spot price data was obtained, the associated future price data was obtained. The

benchmarks were separated into the different classes of commodities and the analysis in this study was based on those classes. Chapter 4 is based on metals, which include precious metals. Chapter 5 is based on soft commodities, which is focused on agricultural commodities, and Chapter 6 is based on energy commodities.

An additional chapter was considered based on chemical commodities, but the initial analysis done on the chemical commodities caused the researcher to remove chemical commodities because the data available was insufficient. Chapter 7 brings all the commodities together to evaluate the relationships between them. The commodities chosen within each commodity class were based on the commodities that South Africa produces. Additional commodities in each class that were used in the South African market were chosen to identify whether any significant relationships existed outside just the production of a specific commodity which could be used when making future investment decisions.

3.6. DATA COLLECTION METHOD

Data was collected from the Thomson Reuters DataStream database. Thomson Reuters DataStream is widely used around the world in the industry and in academia. Thomson Reuters DataStream “*integrates economic research and strategy with cross-asset, macroeconomic analysis for greater insights and profits*” (Thomson Reuters, 2016).

3.7. DATA ANALYSIS

The data analysis of the study is divided into four chapters and will be discussed in more detail in the sections below, listed in the order of the process followed in order to obtain the necessary financial econometric results. Saunders *et al.* (2009) describe data analysis as the action whereby data is explored and broken down in order to identify and confirm relationships.

3.7.1. Data collected

The data collected for the study was based on secondary time series data. Time series data is data that consists of observations for variables for a selected time frame. The data can consist of one or more variables which form the data set that was used for the study. The frequency of the observations can vary, depending on the requirements of the study. Examples of the frequencies include hourly, daily, weekly, and monthly observations (Asteriou & Hall, 2011).

The daily prices of the following variables were obtained:

- South African Rand against the United States Dollar:
 - ZAR: COMRAN\$ (WM/Reuters)
 - ZAR_F: NYRCS00 (FINEX-US\$/SA RAND CONTINUOUS)
- FTSE/JSE Top 40 Index: JSEAL40 (FTSE):
 - FTSE/JSE40: JSEAL40 (FTSE/JSE TOP 40 - PRICE INDEX)
 - FTSE/JSE40_F: SALCS00 (SAFEX-ALL SHARE 40 INDEX CONT. - SETT. PRICE)
- Aluminium:
 - ALUMINIUM: LAHCASH (LME-Aluminium 99.7% Cash U\$/MT)
 - ALUMINIUM_F: LAHCS00 (LME-ALUMINIUM CONTINUOUS - SETT. PRICE)
- Copper:
 - COPPER: LCPCASH (LME-Copper Grade A Cash U\$/MT)
 - COPPER_F: LCPCS00 (LME-COPPER CONTINUOUS - SETT. PRICE)
- Gold:
 - GOLD: GOLDBLN (Gold Bullion LBM U\$/Troy Ounce)
 - GOLD_F: NGCCS00 (CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE)
- Palladium:
 - PALLADIUM: PALLADM (Palladium U\$/Troy Ounce)
 - PALLADIUM_F: NPACS00 (NYM-PALLADIUM CONTINUOUS - SETT. PRICE)
- Platinum:
 - PLATINUM: PLATFRE (London Platinum Free Market \$/Troy oz)
 - PLATINUM_F: NPLCS00 (NYM-PLATINUM CONTINUOUS - SETT. PRICE)
- Corn:
 - CORN: CORNUS2 (Corn No.2 Yellow U\$/Bushel)
 - CORN_F: CCFCS00 (CBT-CORN COMP. CONTINUOUS - SETT. PRICE)
- Cotton:
 - COTTON: COTTONM (Cotton,1 1/16Str Low -Midl, Memph \$/Lb)
 - COTTON_F: NCTCS00 (CSCE-COTTON #2 CONTINUOUS - SETT. PRICE)
- Soyabean:
 - SOYABEAN: SOYBEAN (Soyabeans, No.1 Yellow \$/Bushel)

- SOYABEAN_F: CS.C.01 (CBT-SOYABEANS TRc1 C.01 - SETT. PRICE)
- Sugar:
 - SUGAR: WSUGDLY (Raw Sugar-ISA Daily Price c/lb)
 - SUGAR_F: NSBCS00 (CSCE-SUGAR #11 CONTINUOUS - SETT. PRICE)
- Wheat:
 - WHEAT: WHEATSF (Wheat No.2,Soft Red U\$/Bu)
 - WHEAT_F: CW.C.01 (CBT-WHEAT C.01 - SETT. PRICE)
- Crude Oil-Brent:
 - BRENT OIL: OILBRNP (Crude Oil-Brent Dated FOB U\$/BBL)
 - BRENT OIL_F: LLCCS00 (ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE)
- Jet Kerosene:
 - JETKEROSENE: JETCIFC U\$ (Jet Kerosene-Cargos CIF NWE U\$/MT)
 - JETKEROSENE_F: None
- Naphtha:
 - NAPHTHA: OILNAPH (Naphtha Europe CIF U\$/MT)
 - NAPHTHA_F: None
- Natural Gas:
 - NATURALGAS: NATGHEN (Natural Gas, Henry Hub U\$/MMBTU)
 - NATURALGAS_F: NNGCS00 (NYM-NATURAL GAS CONTINUOUS - SETT. PRICE)

The futures variables selected for the study were continuously priced variables. The time period included for the abovementioned variables was from 1 January 2000 to 30 June 2007 as well as from 1 October 2009 to 31 December 2016. These dates were chosen as each dataset was active at this time and also to ignore the effects of the 2007 financial crisis. A total of 1954 data points for the period before the 2007-2009 financial crisis and 1892 data points for the period after the 2007-2009 financial crisis were included in the study.

The specific dates were chosen with the aim of excluding the effects of the financial crisis of 2007-2009 for two reasons. Firstly, the price movement of commodities increased substantially before the crisis, followed by a similar substantial drop in prices in 2009. Secondly, commodities display time-varying correlations with other assets and therefore the

effects of the financial crisis were not part of the analysis (Bicchetti & Maystre, 2013; Delatte & Lopez, 2013; Daskalaki & Skiadopoulos, 2011; Büyükhahin *et al.*, 2010).

3.7.2. Data cleaning

The data collected from Thomson Reuters DataStream had the same number of data points for each variable for the dates included in the study, which meant that no data points needed to be removed.

3.7.3. Data handling

The starting point in order to continue with the econometric analysis is the preliminary analysis of the data which is done in order to get a basic understanding of the data. The preliminary analysis is an important step required in order to ensure that further analysis of the data is done in a sound manner. As part of the analysis process the data may need to be transformed and dealt with as the process continues to ensure any time series components that need to be removed are removed to obtain suitable results (Asteriou & Hall, 2011).

The original data was examined to ensure that no omissions of data were identified that could distort the analysis of the data required for the research. The original data with any changes if required were then imported into the applicable data analysis software, which for the purpose of this study was EViews.

3.7.4. Transformation of data

The raw data obtained from the Thomson Reuters DataStream Database needs to be transformed for further analysis requirements. Two major transformations need to be applied to the data for different tests, and are applied as described in this chapter as well as in Chapters 4 to 7. Certain tests require only one transformation and not both transformations applied to the data. The transformations that are required are:

- Logarithmic transformations: Logging the data is done to stabilise the variance present within time series data. A second reason for applying a logarithmic transformation is to linearise the data so that it can be used for the econometric analysis; however, the trend is not removed (Asteriou & Hall, 2011; Osborne, 2002).
- Differencing the data: an important requirement of econometric analysis is to ensure that the data that is used for the analysis process is stationary. Stationary data means

that there is no time series component (i.e. trend) present within the data. The upward and downward movement of the data is removed and changes in the data are based on absolute movements only. If the data is differenced once, it is known as first-order differencing (Asteriou & Hall, 2011).

The transformations of the data were necessary in order to create the graphs required for the visual representation analysis as well as for the required analysis that will be discussed in the following sections.

An important consideration going forward was to determine whether the data was stationary or not and therefore further tests needed to be run, which will be discussed as part of the stationarity subsection.

3.7.5. Stationarity

An important consideration when dealing with financial time-series data is the fact that the data is not stationary. If data that is not stationary is used for the analysis required for the research, the results of the analysis will not be valid and therefore cannot be relied upon as it has no meaning. A further implication of results based on nonstationary data is the notion that the results are spurious, which means the regression results provide the confirmation of a very strong relationship where in fact there is no interrelationship at all. Nonstationary data shows no clear indication of data points returning to a constant value, or alternatively the data points show no clear linear trend (Asteriou & Hall, 2011; Wei, 2006).

Data will be stationary, also known as covariance stationary, if the following three characteristics are present:

- the time series fluctuates around a constant long run mean, which is known as mean reversion.
- the time series has a finite variance.
- the time series exhibits a diminishing theoretical correlogram as the lag length increases (Asteriou & Hall, 2011).

If any of the above three characteristics are violated, the time series is nonstationary. If a shock is applied in a stationary time series, it will have a diminishing effect; however, if a shock is applied in a nonstationary time series, it will persist indefinitely into the future. In order to test for non-stationarity or the existence of unit roots, two main tests are required to

be run. The two tests are the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1981) and the Phillips-Perron (PP) test (Perron, 1989).

The augmented Dickey-Fuller test is based on the original Dickey-Fuller test (Fuller, 1976); however, it corrects the original test in that a violation occurred as the residuals from the regression run were autocorrelated. The augmented Dickey-Fuller test corrected this violation by including lagged differences of the dependent variables as additional independent variables (Dickey & Fuller, 1981; Myers, 1994).

The null hypothesis for the unit root tests is that the variable being tested has a unit root. Unit root testing starts by testing the raw data to determine whether it is stationary or nonstationary. If the data is stationary, the data can be used the way it is for further analysis. If the data is nonstationary, the first difference of the data will be tested for stationarity. This process will continue until the data is found to be stationary and that set of data will need to be used for the analysis that is required for the research process (Asteriou & Hall, 2011; Dickey & Fuller, 1979; Granger & Newbold, 1974).

3.7.6. Visual representations

The initial analysis of the data is done via visual representations in order to understand the data better in the sense of seeing the bigger picture before detailed econometric tests are run. Simple movements in the data can be observed by viewing a line graph of the data showing the historic price movement based on the logged data. A second graph representing the differenced data shows the volatility of the movement of the price data.

The final graph utilised for visual purposes is a histogram showing the distribution characteristics of the data. The visual representations follow the correlation matrix, but will precede the descriptive statistics in order to obtain further initial insights of the relationships between the datasets as well as the characteristics of the dataset respectively.

A line graph can provide a general indication of whether the time series is stationary or not. A time series is stationary if the plot of the graph revolves around the mean. However, a line graph can contain a deterministic trend, which is deceiving as it is similar to a plot that is nonstationary but has a stochastic trend; therefore, further analysis is required in order to determine stationarity (Koop, 2010).

3.7.7. Descriptive statistics

In order to understand the basic characteristics of the variables as well as more accurate information related to the distributions of the variables, descriptive statistics are generated. The descriptive statistics include the results for the mean, median, maximum and minimum values, the standard deviation, skewness, kurtosis, Jacque-Bera, probability, sum, sum square deviation as well as the observations.

The higher moments of skewness and kurtosis of the data are important to understand for commodities as commodities are typically not normally distributed. Skewness relates to the shape of the distribution to identify how the data is distributed. If the data is normally distributed, the skewness will be equal to zero and the data will be symmetric. Kurtosis indicates the degree to which the data is peaked as well as the extent of the fatness of the tails of the distribution. If the kurtosis of a variable is equal to three, it indicates that the variable is normally distributed (Brooks, 2014).

A final addition to the descriptive statistics is the synchronicity of the variables with the South African Rand as well as the FTSE/JSE Top 40 Index in order to evaluate the co-movement present between the variables. Synchronicity is calculated from the R^2 (obtained from squaring the correlation output value) of two variables adjusted as per the methodology ($= \log(R^2/(1- R^2))$) from Morck *et al.* (2000). The synchronicity results indicate that the variables are more synchronised when a higher value is calculated. This implies that if the value is higher, more co-movement exists between the variables.

3.7.8. Correlation

Correlation is a numerical value that indicates the strength of the linear co-movement of two variables (Albright, Winston & Zappe, 2009). The closer the value is to “+1” or “-1” the stronger is the co-movement. If the value is “+1”, it indicates that the two variables being measured move together in a perfectly positive relationship, which means that as the one variable increases by one unit, so does the other variable. The opposite applies for a value at “-1”. As one variable increases by one unit, the other variable decreases by one unit. When the correlation value is zero, it indicates that there is no co-movement between the two variables (Doane & Seward, 2011; Koop, 2010; Leedy & Ormrod, 2010).

Correlation is beneficial when starting to analyse data as it indicates the direction as well as the strength of the co-movement between the selected two variables. However, a correlation

result does not indicate the causal relationship, which is required for further analysis (Doane & Seward, 2011; Lind, Marchal & Wathen, 2010).

The limitations of correlation analysis are:

- Only the linear relationship between two variables is measured in correlation analysis, meaning that the correlation measure is not always reliable (two variables may have a low correlation measure, but have a strong nonlinear relationship).
- When outliers are present in the data series, correlation analysis may be unreliable, as the correlation coefficient is sensitive to outliers.
- Correlation does not suggest a causation relationship, which means that one variable does not cause a change in another variable.
- Correlation analysis can have spurious effects, which means that it could indicate a relationship between the two variables due to a third variable that is incorrect.
- Correlation analysis cannot measure the simultaneous relationship between three or more variables.
- Correlation analysis can only be applied to two continuous variables (Lind *et al.*, 2010; Defusco, McLeavey, Pinto & Runkle, 2007).

Although correlation shows the co-movement between two variables, correlation has a problem as it is a short-term measure and therefore can be unstable over longer time periods. If investment decisions are based purely on the correlation measure it will require the investment portfolio to be rebalanced on a frequent basis. Frequent rebalancing is not realistically practical due to the costs associated with the transactions as well as the capital requirements needed in order to ensure accurate rebalancing (Alexander, 1999).

3.7.9. Vector autoregression model

Once the correlation results are obtained, the vector autoregression (VAR) analysis can commence. A VAR model makes the assumption that all variables are endogenous and therefore handled symmetrically as it is difficult to identify exogenous and endogenous variables. A VAR model is a method in which a structural ordering is placed on the variables. The structural ordering is achieved by the assumption that a recurrent contemporaneous interaction exists between the variables (Sims, 1980).

The VAR model is a simple model as the methodology of ordinary least squares method can be applied and each equation is estimated separately. It measures how one variable responds to shocks and provides a quantification of the contribution of each shock. The VAR model is made up of a system of equations based on the dependent variables lagged values as well as the lagged values of the other variables included in the model (Asteriou & Hall, 2011). The VAR model will provide an indication of the dynamic relationships between the commodities, FTSE/JSE Top 40 Index and the ZAR.

The results of the VAR model will not provide an indication of whether the resulting changes in value of a selected variable has a positive or negative effect on another variable. It also does not indicate the length of time for the effect to be processed. In order to obtain the required information to determine the effect as well as the time period, impulse responses and variance decomposition tests were run (Brooks, 2014).

According to Koop (2010), the VAR model is specified as:

$$Y_t = \alpha_1 + \delta_1 t + \varphi_{11} Y_{t-1} + \dots + \varphi_{1p} Y_{t-p} + \beta_{11} X_{t-1} + \dots + \beta_{1p} X_{t-p} + e_{1t}, \quad [3.1]$$

$$X_t = \alpha_2 + \delta_2 t + \varphi_{21} Y_{t-1} + \dots + \varphi_{2p} Y_{t-p} + \beta_{21} X_{t-1} + \dots + \beta_{2q} X_{t-p} + e_{2t}. \quad [3.2]$$

assuming that only two variables are included in the VAR model, Y_t and X_t , where p is the optimal lag length. The trend variable, $\delta_i t$ for $i = 1$ to number of variables included in the analysis when it is statistically significant.

Advantages of VAR models are:

- All variables are endogenous, therefore no specification of whether the variable is endogenous or exogenous is required.
- VAR models are more flexible as the value of a variable can be based on its own lags as well as other variables' lags.
- The VAR model is based on a simple structure as the ordinary least squares method is used separately for each equation of the model.
- The VAR model forecasts that are produced can be better than the forecasts produced by traditional structural models (Brooks, 2014).

Limitations and problems of VAR models are:

- The model assumes everything causes everything as all variables are endogenous, so VARs are seen as a-theoretical.
- The inclusion of lags causes degrees of freedom to be lost. This causes a problem if the sample size is not large enough.
- The coefficients obtained in the VAR model are difficult to interpret and therefore require further analysis in order to be meaningful (Asteriou & Hall, 2011).

3.7.10. Optimal lag length

The optimal lag length is required in order to proceed with the VAR model. The information is required in order to determine the amount of time that is required in order for a change in a variable to be absorbed and corrected within a system. The optimal lag length is based on the sequential modified LR test statistic (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criterion (HQ). Each of the five tests at a five percent level of significance. The optimal lag length was determined by the results obtained from the five tests and based on which lag periods are significant. These five tests are widely used in literature (Enders, 2010; Luetkepohl, 2005).

3.7.11. Stability

The stability test relates to the inverse roots of the AR characteristic polynomial tests to determine that no root lies outside the unit circle. If no root lies outside the unit circle, then the VAR satisfies the stability condition and the data is stationary. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

3.7.12. Johansen cointegration

Cointegration is defined as the relationship of two or more variables that when combined are stationary, but when viewed individually they are nonstationary (Wei, 2006). The objective of the cointegration test is to determine whether a long run equilibrium relationship exists between variables (Hassan & Salim, 2011). Cointegration is a useful econometric tool in that it can decompose the long-term trends between two or more variables as well as the short-term departures from that trend.

Within the scope of alternative investments and commodities, cointegration is able to identify whether two or more commodities or other variables are linked together in the long run. If

the variables are cointegrated, this creates a reason to further investigate the relationship as there are findings that the variables are linked in some way. Cointegration also provides information to identify whether exogenous effects from the equilibrium can occur (Chevallier & Ielpo, 2013).

When two prices move differently from each other in the short term, but eventually converge towards each other in the long term, the two variables are seen as cointegrated. The differences in the movement could be as a result of policy implications or seasonal factors; however, if the movements cause a drift that is more than the mean reversion behaviour, economic forces tend to cause the convergence (Barrett & Li, 2002; Enders, 1995; Palaskas, 1995).

In order to run the cointegration test, the order of the integration needs to be confirmed, which is done via the stationarity tests. The tests are based on the notion that the prices of the raw time series data with no alternations are considered as nonstationary and therefore integrated of order one which is stated as $I(1)$. This creates the opportunity to investigate whether the time series is stationary at a differenced level. As mentioned, stationarity will be tested by means of the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. The Johansen cointegration test provides two main test results, the maximum eigenvalue statistics and trace statistics.

The cointegration test tests for five possibilities related to the trend of the data. The first and second possibility, the model developed eliminates the trend in the data. The first of these two tests for no intercept or trend, which implies that cointegrating equations are stationary around the mean of zero, and the second possibility tests for an intercept by no trend, which means that the cointegrating equations are stationary around a constant mean.

The third and fourth possibilities include a linear trend of data in the model, with the third possibility assuming an intercept and no trend and the fourth possibility assuming both an intercept and a trend. The fifth possibility uses a quadratic trend assumption with both an intercept and trend, which implies that there are no constraints on the parameters related to the trend. Two test statistics are obtained in the Johansen test procedure, the trace statistics and the maximum eigenvalue statistic, which tests for cointegrating relationships between the data sets. The Johansen cointegration methodology is considered a better model compared to the Engle & Granger model, as it is able to handle more than two variables (Alexander, 1999; Johansen, 1995; Johansen, 1991; Engle & Granger, 1987).

The trace statistic and maximum eigenvalue statistic can yield conflicting results. When conflicting results exist, the interpretability of the cointegrating relationship needs to be considered. Luetkepohl, Saikkone and Trenkler (2001) determined that differences between the two tests are present in small samples, but neither of the tests should be prioritised in practice. Enders (2010) concludes that the maximum eigenvalue statistic is preferred over the trace statistic as the maximum eigenvalue statistic has a sharper alternative hypothesis and is usually preferred to determine the number of cointegrating equations. Johansen and Juselius (1990) also preferred the maximum eigenvalue statistic over the trace statistic, but both statistics need to be carefully examined when conflicting results occur. Cheung and Lai (1993) state that the trace statistic is preferred over the maximum eigenvalue statistic as the trace statistic is more robust to nonnormality.

The Johansen cointegration test is linked to the VAR model and run after the VAR results and optimal lag length is determined.

3.7.13. Granger causality and Toda Yamamoto

Causality is the ability of one variable to cause another. Granger causality test results indicate the causal relationships between the included variables in order to determine the extent of the causal relationship (Stock & Watson, 2001). The Toda Yamamoto test tests for causality without testing for cointegration first (Toda & Yamamoto, 1995), which is why both tests are included to identify the differences.

A variable is not Granger caused by another variable included in the set of two variables if the optimal predictor of the variable in question does not use information from the other variable (Patterson, 2000). There are four main states available in causality relationships.

The four states are:

- Variable 1 causes variable 2, but variable 2 does not cause variable 1; this is a unidirectional feedback relationship.
- Variable 2 causes variable 1, but variable 1 does not cause variable 2; this is a unidirectional feedback relationship.
- Variable 1 causes variable 2, and variable 2 causes variable 1; this is a bi-directional feedback relationship.
- Variable 1 does not cause variable 2, and variable 2 does not cause variable 1, these two variables are independent of each other (Asteriou & Hall, 2011).

The analysis in this study included the Granger causality test, which was developed by Clive Granger in 1969 (Granger, 1969). Granger causality tests for short run predictability between variables (Hassan & Salim, 2011).

The Granger causality test is preferred as it takes into account the possibility of a two-way causation relationship (Quartey & Prah, 2008). However, two points of criticism exist for the test. The first criticism is that the test is dependent on the number of lags chosen causing the direction of the causality change based on the lags. In the event that the lag selected for the test is different from the lag that exists in the market, the results of the model become inaccurate, with regard to being biased and inefficient (Majid, 2007). The second criticism is related to the stationarity of variables. If nonstationary variables are included in the test, the results could be misleading (Wooldridge, 2006).

According to Koop (2010), the Granger causality equation is:

$$Y_t = \delta t + \varphi_1 Y_{t-1} + \dots + \varphi_p Y_{t-p} + \beta_1 X_{t-1} + \dots + \beta_q X_{t-q} + e_{1t} \quad [3.3]$$

if the β_i for $i = 1$ to q are statistically significant, then X_t Granger causes Y_t .

The Granger causality results will be shown before the VAR analysis in Chapters 4 to 6 as the results apply to all variables included; however, the Granger causality specifications were based on the results of the VAR results.

The Toda Yamamoto test is an adapted Granger causality test where the optimal lag lengths are determined, followed by the updated VAR model in order to run the Granger non-causality test. The test is run based on logged prices (Toda & Yamamoto, 1995).

3.7.14. Vector error correction model

In the vector error correction model (VECM), the objective of the model is to specify the short run dynamics of each variable. The model is based on a framework which is linked to the cointegration relationship. The VECM provides the results that indicate the movements away from the long run equilibrium (Gujarati and Porter, 2009). A VECM is a restricted VAR model. Within the VECM, cointegration conditions are included in the model in order to restrict the long run behaviour of the endogenous variable, but allowing for the short run movements.

The cointegration term that is obtained from the VECM results is known as the error correction term. The error correction term is named as such as the deviance away from the long run equilibrium is gradually corrected by a series of partial short run adjustments. The

error correction term shows the long run causality and the lagged explanatory variables show the short run causality. The short run causality as discussed is tested using the Block exogeneity Wald test. The long run causality based on the error correction term is accepted if it is significantly different from zero.

According to Koop (2010), the equation for VECM can be specified as:

$$\Delta Y_t = \theta_1 + \delta_1 t + \rho_1 e_{1t-1} + \gamma_{11} \Delta Y_{t-1} + \dots + \gamma_{1p} \Delta Y_{t-p} + \omega_{11} \Delta X_{t-1} + \dots + \omega_{1p} \Delta X_{t-p} + \varepsilon_{1t} \quad [3.4]$$

$$\Delta X_t = \theta_2 + \delta_2 t + \rho_2 e_{2t-1} + \gamma_{21} \Delta Y_{t-1} + \dots + \gamma_{2p} \Delta Y_{t-p} + \omega_{21} \Delta X_{t-1} + \dots + \omega_{2p} \Delta X_{t-p} + \varepsilon_{2t} \quad [3.5]$$

where p is the optimal lag length and where e_{1t-1} and e_{2t-1} are the error terms from the VAR model.

3.7.15. Block exogeneity

The Block exogeneity Wald test tests the short run causality, which is linked to the VECM. The block exogeneity Wald test provides the results in order to determine the Cholesky ordering that will be used in the variance decomposition test. The Cholesky ordering provides the information to determine the order of variables from the least endogenous, therefore the most exogenous to the most endogenous. The most exogenous implies that the variable is the most independent and that none of the shocks applied to the other variables has a contemporaneous effect on the most exogenous variable (Sims, 1980).

3.7.16. Impulse responses

Impulse responses defined by Brooks (2014:299) “*traces out the responsiveness of the dependent variables in the VAR to shocks to each of the variables*”. Each variable is shocked separately by the other variables in order to determine the effect of the shock on the dependent variable. Impulse response diagrams illustrate the effect of a shock in a variable on another variable (Gujarati & Porter, 2009). Sims (1980) explains that the impulse responses provide the time path of the shocks applied on the variables. The impulse response analysis as well as the variance decomposition that will be discussed next are referred to as innovation accounting methods (Plasmans, 2006).

3.7.17. Variance decomposition

In the variance decomposition analysis, the method examines the contribution that the dependent variable has on itself as well as the contribution change that other variables have

on the dependent variable (Sims, 1980). Variance decomposition indicates how every variable included in the test accounts for the variance in another variable over a selected time period. The variables in the variance decomposition were ordered according to the Cholesky ordering. The Cholesky ordering places the variables in order from most exogenous to most endogenous. Therefore, variables that are least influential in the selection of variables are placed last in the order of variables and the variables that have the most influence over other variables are placed first (Brooks, 2014).

3.7.18. Chapter 7 – Optimal cross hedging relationships

The analysis that needs to be done for Chapter 7 is different from that for Chapters 4 to 6, except for the inclusion of correlation and Granger causality. The hedge ratios based on different methodologies will be presented to determine the optimal hedge ratios between the sixteen variables. The optimal hedge ratios along with the empirical analysis from Chapters 4, 5 and 6 will be utilised to determine whether underlying relationships between commodities exist that can be used for further research purposes.

The OLS, ECM, VECM, ECM-GARCH as well as the time-varying bivariate ADCC-GARCH method will be applied to obtain hedge ratios between the variables. Thereafter, the most effective methods will be identified, based on the variables as well as the data periods included to determine whether a difference has arisen since the 2007-2009 financial crisis.

The static risk-minimising hedge ratio (h^*) can be written as an element of covariance and variance, such that:

$$h^* = \frac{-cov_{sf}}{\sigma_f^2} \quad [3.6]$$

where $-cov_{sf}$ is the covariance between the spot and future price variable and σ_f^2 is the variance of the futures price variable with itself.

3.7.18.1. OLS methodology

Using the ordinary least squares method to calculate the minimum-variance hedge ratio, the regression equation that is obtained is (Coakley, Dollery & Kellard, 2008):

$$\Delta c_t = \beta_0 + \beta_1 \Delta f_t + \varepsilon_t \quad [3.7]$$

where the estimated value of β_1 is the minimum variance hedge ratio. β_0 is assumed to be zero as the cash position is initially equal to zero. The futures variable is not considered as an endogenous variable in this context (Kumar *et al.*, 2008).

In order to calculate the hedge ratio, minimum variance hedge ratio (h) is also the beta coefficient (β) and is calculated as:

$$h = \rho \frac{\sigma_i}{\sigma_j} \quad [3.8]$$

where ρ is the correlation coefficient between the returns of i and j and σ_i and σ_j are the standard deviations of returns of i and j respectively which is similar to h being expressed in terms of covariance (Howard & D'Antonio, 1984; Johnson, 1960).

The OLS regression will be based on logged returns (logged first differenced data) in order to obtain a hedge ratio between spot and future price variables. The spot logged returns represent the dependent variable and the future logged returns represent the independent variable. The beta or slope estimate of the regression equation provides the estimate for the hedge ratio based on the OLS methodology (Degiannakis & Floros, 2010; Butterworth & Holmes, 2000).

This method was based on the classical approach of taking into account only the short run fluctuations between two time series in order to obtain the hedge ratio. The OLS method ignores conditioning information (Myers & Thompson, 1989); time-varying aspects of the two series (Cecchetti, Cumby & Figlewski, 1988); as well as the covariance between the two variables (Kumar *et al.*, 2008).

3.7.18.2. ECM methodology

The OLS does not test for the cointegrating relationship therefore the ECM methodology is applied in order to include any possible cointegrating relationships. Cointegration will be based on the Engle and Granger (1987) cointegration and not the Johansen cointegration as the relationship is a bivariate model and not a multivariate model. Engle and Granger (1987) have the objective of finding a linear combination between nonstationary time series variables that when combined form a stationary time series. It is therefore possible to identify stable long run relationships between stationary time series. In the case of this study, it was between prices.

In order to determine the hedge ratios based on ECM, the classical hedge ratio from OLS was compared by taking into account the long run stable relationship between the two time series. The analysis is based on the Engle and Granger two-step estimation technique (Engle & Granger, 1987). The initial step in the Engle and Granger two-step estimation technique is to test for a unit root or non-stationarity by means of the augmented Dickey-Fuller test (Dickey & Fuller, 1981). The unit root test was verified by the Phillips-Perron test (Puhle, 2013; Alexander, 1999; Perron, 1989).

Following on, a relationship of non-stationarity is required, therefore the null hypothesis of non-stationarity should not be rejected. The next step would be to estimate the static equilibrium model and test the residuals for a stationary time series by means of the unit root test, augmented Dickey-Fuller test. The critical values used to determine if the null hypothesis is rejected or not rejected are based on the Engle and Yoo (1987) critical values as the series is now an estimated one. In this step we aim to reject the null hypothesis of non-stationarity to obtain two cointegrated variables (Puhle, 2013; Alexander, 1999).

According to Alexander (1999), if there are two cointegrated log price series X and Y , the ECM takes the form:

$$\Delta X_t = \alpha_1 + \sum_{i=1}^{m_1} \beta_{2i} \Delta X_{t-i} + \sum_{i=1}^{m_2} \beta_{2i} \Delta Y_{t-i} + \gamma_1 z_{t-1} + \varepsilon_{1t} \quad [3.9]$$

$$\Delta Y_t = \alpha_2 + \sum_{i=1}^{m_3} \beta_{3i} \Delta X_{t-i} + \sum_{i=1}^{m_4} \beta_{4i} \Delta Y_{t-i} + \gamma_2 z_{t-1} + \varepsilon_{2t} \quad [3.10]$$

where Δ denotes the first difference operator, z is the cointegrating vector $X - \alpha Y$, and the lag lengths and coefficients are determined by the ordinary least squares regression (Alexander, 1999).

Chou, Denis and Lee (1996) estimated the hedge ratio with the ECM as follows:

$$\Delta S_t = c + a \hat{\varepsilon}_{t-1} + b \Delta F_t + \theta_1 \Delta F_{t-1} + \phi_1 \Delta S_{t-1} + u_t \quad [3.11]$$

where $\hat{\varepsilon}_{t-1} = S_{t-1} - (\hat{c}_0 + \hat{b}_0 F_{t-1})$. The slope coefficient b in Equation 3.11 represents the hedge ratio, and ΔS_t and ΔF_t represent spot and futures price changes.

Once two cointegrated variables are obtained, the Error-Correction Model (ECM) will be estimated based on the Autoregressive Distributed Lag (ARDL) cointegration model, which was proposed by Pesaran (1997) and adapted by Chen, Lee and Shrestha (2004). The ARDL model includes lags for the dependent and independent variables in order to obtain the optimal lag selection (Greene, 2008). The logged returns will be used for the ECM

methodology, and the coefficient obtained for the slope of the futures returns with no lag therefore provides the hedge ratio based on the ECM model using the ARDL methodology. The ECM is a dynamic model in that it looks at how the system returns to its static equilibrium as well as how long it takes to return to the static equilibrium. The ECM methodology is mainly utilised for short-term forecasts, as the correction back to equilibrium in the long term is moderately slow (Scutaru, 2011).

3.7.18.3. VECM methodology

The VECM methodology is similar to the methodology applied in Chapters 4, 5 and 6 and requires the VAR process to be followed in that two variables, one spot and one future will be analysed within a VAR based on logged prices, cointegration results obtained from the ECM model, and VECM model testing based on logged returns. The starting point for this methodology is to determine the appropriate lag length required in order to obtain the applicable VAR model that leads into the VECM testing, if applicable based on the cointegration results, in order to obtain the hedge ratio results similar to Equation 3.8. Equation 3.8 is specified in terms of the standard deviation of the asset returns, whereas the VECM hedge ratio is calculated using the standard deviation of the residuals. The inputs for the equation are obtained from the VECM outputs as well as the correlation coefficient and standard deviations of the residuals of the two variables.

The hedge ratio obtained from the VECM methodology is based on the following form (Ghosh, 1993; Lien, 1996):

$$\Delta S_t = a_s \hat{\varepsilon}_{t-1} + \theta_{11} \Delta F_{t-1} + \phi_{11} \Delta S_{t-1} + u_{s,t} \quad [3.12]$$

$$\Delta F_t = a_f \hat{\varepsilon}_{t-1} + \theta_{12} \Delta F_{t-1} + \phi_{12} \Delta S_{t-1} + u_{f,t}. \quad [3.13]$$

3.7.18.4. ECM-GARCH methodology

The ECM-GARCH methodology is similar to the ECM methodology, but takes into account the volatility clustering present within the variables in order to determine the hedge ratio. If volatility clustering is present, tested by means of the Lagrange Multiplier test, also known as the autoregressive conditional heteroscedasticity (ARCH) LM test, a univariate GARCH model will be applied in order to obtain the hedge ratio. The value of the coefficient of the futures returns represents the hedge ratio in the ECM-GARCH (1,1) model.

The ECM-GARCH method extends the ECM model from Chou *et al.* (1996) in that the hedge ratio obtained from the ECM with GARCH is as follows (Bollerslev & Wooldridge, 1992):

$$\Delta S_t = c + a\hat{\varepsilon}_{t-1} + b\Delta F_t + \theta_1\Delta F_{t-1} + \phi_1\Delta S_{t-1} + u_t \quad [3.11]$$

where $u_t = \sigma_t z_t$; and $\sigma_t^2 = a_0 + a_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$.

The logged prices are used to obtain the residual series for the first part of the analysis. The second part of the analysis is based on the logged returns as well as the generated residual series.

3.7.18.5. Asymmetric DCC-GARCH methodology

The bivariate asymmetric dynamic conditional correlation (DCC) GARCH model with multivariate normal error distribution will be utilised to obtain the time-varying hedge ratios between the spot and future variables before and after the crisis. The asymmetric DCC-GARCH model is based on the Glosten, Jagannathan, and Runkle (GJR)-GARCH specification in order to model the conditional correlations, variances and covariances. This model is used as asymmetry in the time series is taken into account within the estimation process (Chkili, 2016; Cappiello, Engle & Sheppard, 2006; Glosten, Janannathan & Runkle, 1993).

The Capiello *et al.* (2006) asymmetric DCC-GARCH model, referred to as the ADCC-GARCH model based on the DCC model as well as the asymmetric GARCH model developed by Glosten *et al.* (1993) takes the following form for the univariate case:

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \hat{\varepsilon}_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 + d_i \hat{\varepsilon}_{i,t-1}^2 I(\varepsilon_{t-1}) \quad [3.14]$$

where $I = 1$ if $\varepsilon_t < 0$ and otherwise 0.

The asymmetric DCC-GARCH model of Cappiello, Engle and Sheppard (2006) takes the following form:

$$H_t = D_t R_t D_t \quad [3.15]$$

where H_t is a 2×2 diagonal matrix of time varying standard deviations ($\sigma_{i,t}$) when modelled by the univariate GJR-GARCH model, and R_t is the time-varying correlation matrix.

Cappiello *et al.* (2006) explain that the time varying covariance matrix is estimated using a two-step procedure. Initially, the univariate GARCH model is fitted to each set of asset returns. The second step is to estimate the correlation matrix using the asset returns when transformed by the estimated standard deviations.

When applied to hedge ratios, H_t is given by

$$H_t = \begin{bmatrix} \sigma_{s,t}^2 & \sigma_{sf,t} \\ \sigma_{sf,t} & \sigma_{f,t}^2 \end{bmatrix} \quad [3.16]$$

where σ_{sf} is the time varying covariance of the spot and futures returns obtained from the ADCC-GARCH model. The set of time varying hedge ratios (h_t^*) is then easily obtained using

$$h_t^* = \frac{\sigma_{sf,t}}{\sigma_{f,t}} \quad [3.17]$$

where $\sigma_{f,t}$ is the time varying variance of the futures price obtained from the GJR-GARCH model.

3.7.18.6. Hedging effectiveness and tail risk measures

The variance of hedge ratios and the effectiveness of the hedging relationship are important considerations when selecting the optimal hedge ratio based on different models. Hedging effectiveness takes into account the variance reduction that the hedge ratio estimation model provides. The variance reduction is based on the decrease in the conditional variance of the spot and future combination portfolio as compared to the spot variable where no hedging is taken into account (Park & Jei, 2010).

To determine which hedge ratio estimation model provides the most efficient results, hedge effectiveness needs to be considered. The most common tool utilised is the variance reduction method, which compares the hedged variance against the unhedged variance which takes the form of:

$$\text{Variance reduction} = 1 - \frac{\text{Var}R^p}{\text{Var}R^s} \quad [3.18]$$

$$\text{Var}R^p = \sigma_s^2 + h^2\sigma_F^2 - 2h\sigma_{s,F} \quad [3.19]$$

where the ($\text{Var}R^p$) represents the variance of the portfolio which is the hedged variance and ($\text{Var}R^s$) is the spot variable only, which is the unhedged variance. In addition, σ_s and σ_F are

the standard deviation of the spot returns and future returns and $\sigma_{S,F}$ is the covariance between the two assets.

Hedging effectiveness is calculated from the hedged variance and unhedged variance, such that (Liu, Geaun & Lei, 2001; Ederington, 1979; Heifner, 1972; Johnson, 1960):

$$\text{Hedging Effectiveness } (E) = \frac{(\text{Var}R^S - \text{Var}R^P)}{\text{Var}R^S}. \quad [3.20]$$

Equation 3.18 and 3.20 provide the same results. The hedging effectiveness of the OLS methodology is obtained from the R^2 of the regression equation, whereas the remainder of the models apply Equation 3.18 and 3.19 in order to calculate the hedging effectiveness (Das & Chakraborty, 2015; Kumar *et al.*, 2008).

The hedging effectiveness calculation determines what percentage of variance in the unhedged portfolio is removed by means of hedging with a second variable. The model that provides the highest hedging effectiveness value provides the most effective hedging option for the spot variable (Dinică & Armeanu, 2014).

Lien (2005) stated that the hedging effectiveness measure from Ederington (1979) is not an appropriate measure to use when comparing methods to OLS strategy as it considers only unconditional variance and in most cases leads to the incorrect conclusion that OLS is the best performing strategy. However, Lien (2009) states that the conventional hedge ratio which is measured by the hedging effectiveness measure from Ederington (1979) is preferred above other heading strategies since the unconditional variance is considered.

Hedging effectiveness has a disadvantage in that it does not take into account deviations from the normal distribution. To overcome this disadvantage, tail risk measures of Value at Risk (Jorion, 2006) and Expected Shortfall (Artzner, Delnaen, Eber & Heath, 1999) are utilised to assess the hedging performance in addition to the hedging effectiveness measure from Ederington (1979).

Value at Risk (VaR) estimates the size of the worst expected loss a portfolio can experience at selected confidence intervals, whereas Expected Shortfall, also known as conditional VaR (ES or CVaR), takes into account the expectation of all events less than the VaR at selected confidence intervals. Expected Shortfall is a coherent risk measure whereas Value at Risk is not (Jorion, 2006; Artzner *et al.*, 1999). When institutions model and forecast VaR, the Basel Accord allows them to specify their own model. The Basel II and III Accord therefore requires firms to backtest their models to compare the predicted losses from the VaR model

to the actual losses experienced during the period (Zhang & Zhang, 2016; Sharma, 2012). Two tests are used to backtest the models, the Kupiec unconditional coverage test (Kupiec, 1995) and the Christoffersen and Pelletier's duration based test of independence (Christoffersen & Pelletier, 2004). This thesis is not attempting to predict losses, but rather to obtain an understanding of the relationships between the variables of which VaR and CVaR are used as part of the hedging effectiveness measure and optimal cross hedging relationships done in Chapter 7.

Lien, Lee, Yang and Zhou (2015) provide an analysis of effectiveness of different strategies and allude to the development of alternative effectiveness measures linked to tail risk, such as VaR and CVaR. VaR and CVaR measures are used to minimise the conditional value that is at risk, but Lien *et al.* (2015) state that when comparing hedging strategies, it is the unconditional value at risk that is important.

Drawdown is also included in Chapter 7 as an indication of the peak to trough decline in a financial time series showing the value that is at risk over time. The maximum drawdown measure provides an indication of the percentage value that has been lost over a specific period of time (Zabarankin, Pavlikov & Uryasev, 2014).

The original hedging effectiveness from Ederington (1979) will be compared to the hedging effectiveness based on VaR and expected shortfall. The maximum drawdown and mean-variance analysis (a classical method which involves comparing different portfolios in mean-variance space) will be used as accompanying measures to evaluate the optimal cross hedging relationships. The analysis will be done to determine the best performing methods and combination of variables both before and after the crisis.

The VaR hedging effectiveness measure is based on the calculation from McNeil, Frey and Embrechts (2015):

$$VaR_{\alpha} = \mu + \sigma\phi^{-1}(\alpha) \text{ and } VaR_{\alpha}^{mean} = \sigma\phi^{-1}(\alpha) \quad [3.21]$$

where ϕ represents the standard normal density function and $\phi^{-1}(\alpha)$ is the α -quantile of ϕ . The mean is represented by μ , standard deviation by σ and $\alpha \in (0,1)$. This measure is also applied to Expected Shortfall. McNeil *et al.* (2015) show that when returns are assumed to be normally distributed, the formula for expected shortfall is given by:

$$S_{\alpha} = \mu + \sigma \frac{\phi(\Phi^{-1}(\alpha))}{1-\alpha}, \quad [3.22]$$

where Φ^{-1} denotes the inverse of the cumulative distribution function of the standard normal distribution. Expected shortfall gives an indication of the expected loss, given that the loss is greater than VaR (Equation 3.21).

3.7.18.7. Optimal relationships

The final analysis will be done to determine which future variable is the best cross hedging variable based on different measures. The measures that will be used are mean-variance analysis to identify the lowest risk and highest return risk-return profile, maximum drawdown, Value at Risk and Expected Shortfall. The last three measures will be based on the smallest value obtained for the spot variable from all future variables included.

3.8. VALIDITY AND RELIABILITY OF DATA

The validity and the reliability of the data are extremely important in a research study. The source from where data is obtained is a vital consideration and cannot be problematic or disputed. The quality of the data is just as important as the source as poor quality data will provide inaccurate research results. If the source and/or the quality of the data is not at the correct standard it will nullify the research results.

3.8.1. Validity of measurement

The measurement or analysis instrument used in a research study to analyse the data has an effect of the validity. If the analysis instrument measures what it is anticipated to measure, then it is viewed as valid (Leedy & Ormrod, 2010; Saunders *et al.*, 2009). The measurement instruments that were used in this study were VAR, Cointegration, VECM, ECM, ECM-GARCH, ADCC-GARCH, VaR, ES, drawdown and mean-variance analysis from EViews, R and Excel. These are credible tools used in econometric analysis.

3.8.2. Reliability

The data collected for this study was collected using the Thomson Reuters DataStream database. The tool and method used should produce findings that are the same when compared to another reliable source. A second aspect of reliability is whether the analysis of this research can be duplicated and repeated by another researcher. The methodology applied in this thesis is based on financial econometric methods which have been applied in other literature, examples of which have been discussed in Chapter 2 as well as in Chapters 4 to 7 (Leedy & Ormrod, 2010; Saunders *et al.*, 2009).

3.9. ETHICAL CONSIDERATIONS

Ethical considerations are vital in research. If any component of research is conducted in an unethical manner it creates an opportunity for the research to be questioned, which can affect many aspects in the research study. In this study, the data needed to be collected and analysed ethically. To ensure that an ethical process was followed, data was collected from a reliable data source based on benchmark data.

A further ethical consideration is the use of references in the study. The necessary permissions would need to be obtained if required and the sources would need to be referenced correctly without plagiarising any work done by another person. If references are used that have not been peer-reviewed, these would need to be evaluated for accuracy to ensure that no false information is used.

3.10. LIMITATIONS

Limitations to the study are created by the variables used as well as the literature available on the specific research question and objectives. The first limitation is the data sets that were used in the study. Not all commodity data sets were included in the study and only selected commodity benchmarks were chosen to represent each commodity class included in the study. The second limitation is based on the currency selected as well as the index selected. A final limitation is that the study ignores transaction costs, taxation and investments in other securities.

The knowledge and understanding available on commodity markets is limited to the analysis that has been done based on the types of commodities that were part of the study, the time frame included in the study as well as the method of analysis. This study was limited to a time frame, namely a selected period before and after the financial crisis of 2007, but the commodities included in the study, metal, soft and energy commodities, were chosen with the aim of being broad. The methodology applied to the data was formal analysis procedures based on the financial econometrics aimed to identify both long and short run relationships present between the variables. The relationships were further analysed to determine investable opportunities that market participants and academics apply.

South Africa was the country of focus and therefore the South African Rand was the selected currency. A number of indices were available in the South African financial market and only one index was selected to represent the market. The index was chosen as the most representative of the South African financial market.

The analysis of the data was based on accepted econometric standards and on other peer-reviewed research. A limitation on this concept occurs if other methods of analysis would be applied to the same data sets. This difference could result in different research findings and conclusions.

3.11. SIGNIFICANCE OF THE STUDY

This study is important for fellow academics who conduct research in similar fields and for market participants who are interested in having a better understanding of the relationships present between the data sets. Any findings within this study are likely to add to the current body of literature available on this topic by expanding on the sample size with regard to the variables included and the time period selected. Commodity price movement changes continuously, with market implications of commodity price movements affecting many aspects of the financial markets. The aim of the research was to contribute to the field of commodities as an alternative asset.

Both traditional assets and alternative assets are traded in the financial market, with traditional assets widely researched and understood. The research available on alternative assets is limited in scope and time as alternative assets are a continuously developing field. The financialisation of commodity markets only started gaining momentum in the last ten to fifteen years. Commodities have emerged as an investable asset class for institutional investors holding larger quantities as diversification benefits are sought outside traditional assets (Büyüksahin & Robe, 2014; Singleton, 2014; Basak & Pavlova, 2013).

Market participants who can benefit from information obtained from this study are financial institutions that deal with commodities such as banks, asset managers, policymakers, economists, trading houses. Other market participants include institutions that work with the financial aspects of commodities.

3.12. SUMMARY

The research methodology chapter has discussed the method that was used to analyse the data and the considerations associated with the research method. The main methods used in Chapters 4 to 6 include correlation, VAR model, Granger causality, Johansen cointegration, VECM, impulse responses and variance decomposition. Chapter 7 uses correlation, Granger causality test, OLS, ECM, VECM, ECM-GARCH, asymmetric DCC-GARCH with GJR specification, hedging effectiveness combined with more advanced hedging effectiveness methods, drawdown, mean variance analysis, VaR and ES.

The overall research question of the study was to determine what optimal cross hedging relationships exist within the South African financial market context in relation to a selection of commodities. In order to achieve the overall research question, the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index, between each commodity price and the ZAR, and between the FTSE/JSE Top 40 Index and the ZAR needed to be determined so that the interrelationships between the variables were understood.

Chapters 4 to 6 will include a subset of the selection of commodities grouped according to categories of commodities. Chapter 4 is based on metals, which include precious metals. Chapter 5 is based on soft commodities, focused on agricultural commodities, and Chapter 6 is based on energy commodities.

The relationships were used as a starting point in order to obtain optimal hedging relationships and ratios using commodities in the South African financial market, which will be finalised in Chapter 7. These objectives were achieved by means of an empirical analysis described over four chapters, from Chapters 4 to 7. Chapter 7 will build on the results of the Chapters 4, 5, and 6 in order to answer the research question stated above. Chapter 7 will investigate optimal cross hedging relationships present between the sixteen variables included in the study.

The research strategy utilised in this study was based on secondary data and the financial econometric analysis thereof. The secondary data required to answer the research question was historic time series data. The research instrument used in this study was EViews, R, Excel and the related financial econometric tests required to answer the research question and objectives.

In order to address the research objectives in Chapters 4 to 6 the research methodology of Chapters 4 to 6 was identical in the tests performed. The analysis that were performed were stationarity tests, visual representations, descriptive statistics, correlation, vector autoregression, Johansen cointegration, Granger causality and Toda Yamamoto causality test, vector error correction model, block exogeneity, impulse responses, and variance decompositions.

Chapter 7 used correlation, Granger causality test, OLS, ECM, VECM, ECM-GARCH, asymmetric DCC-GARCH with GJR specification, hedging effectiveness combined with

more advanced hedging effectiveness methods, drawdown, mean variance analysis, VaR and ES.

The significance of the study is that research available on commodities is limited in scope and time as commodities are a continuously developing field. The financialisation of commodity markets has only started gaining momentum in the last ten to fifteen years. Therefore, commodities have emerged as an investable asset class that investors are looking at as they are looking for diversification opportunities outside traditional investment strategies and assets. The overall aim of the research is to contribute to the field of commodities as an alternative asset.



CHAPTER 4

ESSAY 1: METAL COMMODITIES

4.1. INTRODUCTION

“A pessimist sees the difficulty in every opportunity; an optimist sees the opportunity in every difficulty” (Bio: Churchill, 2014).

Opportunities in the investment environment are present in many different forms and manners and are limited only by the amount of knowledge an individual has about the asset classes and their related characteristics. The speed with which market events affect investment opportunities has increased over the last number of years as a result of developments in technology and the way that technology is utilised in the financial markets. The speed factor reduces traditional investment opportunities available to investors. The need for alternative investment opportunities creates the need for alternative investments in order to search for alpha (Mulvey, 2012).

Alpha is the risk-adjusted return available to an investor. It is the return received by an investor over and above the return as a result of the risk-free rate and the market risk premium. In alternative investment classes, the search for alpha is cast over a wider opportunity set as compared to traditional asset classes. The search for alpha is not reliant on the investment class only, but also on the strategy used within and between asset classes (Anson, Chambers, Black & Kazemi, 2012).

One type of investment related strategy in the financial industry is cross hedging. To hedge is a means of protection or defence against a financial loss (Merriam-Webster, 2014). When taking an offsetting position in an alternative instrument or good with similar movements in price, a cross hedge action is entered into. A cross hedge is necessary as there could be an instance where no direct alternative is available to hedge an instrument which leads to the concept of analysing other instruments to identify possible significant relationships (Powers, 1991).

In order to investigate cross hedging relationships, the relationship between various variables needs to be explored in order to determine the nature of relationships that exist.

The movement of variables provides the opportunity for cross hedging if the correct combinations of instruments are chosen.

The combination of variables selected for this chapter are five metal commodities, namely aluminium, copper, gold, palladium, and platinum; the FTSE/JSE Top 40 Index; and the South African Rand (ZAR) against the United States Dollar. The five above-mentioned commodities were selected as they are produced in South Africa and exported internationally. South Africa is the second largest producer of platinum and palladium in the world, and the sixth largest producer of gold in the world. The production of aluminium and copper are ranked lower, but are still important commodities for South Africa (USGS Minerals Resources Program, 2016).

The FTSE/JSE Top 40 Index and the ZAR were chosen as the comparative datasets as the FTSE/JSE Top 40 Index is representative of the majority of companies that trade on the JSE and the ZAR is included as the commodities are exported for use around the world. The FTSE/JSE Top 40 Index was designed to be used as a performance benchmark, ensuring investability, liquidity and transparency. As of May 2017, the top ten holdings within the index constitute 63.72% of the index, of which two mining companies are listed with a total representation of 11.77%.

The objective of the study was to investigate the possible long and short run significant relationships between five commodities against the FTSE/JSE Top 40 Index and between the ZAR, FTSE/JSE Top 40 Index and the five commodities. The sample includes data points on a daily basis from before as well as after the 2007-2009 financial crisis, which will be split in the analysis section in order to compare the two periods. In addition, the variables are represented by spot as well as future prices of all seven variables, which will also be compared against each other. Once the initial relationships have been determined between the seven variables by means of correlation, causality will be discussed in order to understand the causal relationships present between the variables. The Pairwise Granger causality test and Toda Yamamoto test apply to all fourteen variables included in the study. The Toda Yamamota test tests for causality without testing for cointegration first (Toda & Yamamota, 1995), which is why both tests are included to identify the differences. The analysis will then be divided into two main sections.

The first section will test the relationship between the commodities and the FTSE/JSE Top 40 Index both spot and future as well as before and after the crisis. The second section will test the relationship between commodities and the FTSE/JSE Top 40 Index against the ZAR

again both spot and future as well as before and after the crisis. The first part of each section will include the VAR analysis to validate the linear interdependencies among multiple time series to determine significant relationships.

The next section will include Johansen cointegration, which will be run to determine the long run relationship. If cointegration relationships are found in the Johansen cointegration test, then the short run dynamics can be done in the last part of each section. The short run dynamics will be tested by means of a VECM and the innovation accounting methods of impulse responses and variance decomposition. Should cointegration relationships not be found in the Johansen cointegration test, then VECM will not be included, but innovation accounting methods will be included.

The remainder of the chapter is structured in the following format. Part 2 provides a review of the current literature available. Part 3 explains the methodology used in the study. Part 4 provides an explanation of the data. Part 5 explains and interprets the results and findings of the study. Lastly, part 6 provides the conclusions drawn from the results of the study.

4.2. REVIEW OF THE LITERATURE

In the traditional investment strategy of buying and selling equities, it has become extremely difficult to consistently outperform the market, specifically in the short term, based on the efficient market hypothesis. The amount of information presented to the market and the speed of processing the information has increased substantially over the last two decades (Stout, 1997).

Traditional investment strategies are influenced by market efficiency behaviour which in turn influences the related return opportunities. With the growing size of the participants in the financial markets environment the opportunities for above-market return generation or alpha are diminished as supply of return is limited, but there is an always increasing demand (Anson *et al.*, 2011).

A method of creating an opportunity for alpha is by means of alternative assets and alternative investment strategies. Alternative investment opportunities are part of modern financial developments and extend beyond the range of traditional investment instruments and traditional investment strategies. Examples of alternative investment assets are hedge funds, commodities and structured products. Alternative investment strategies are the ways in which the investments in alternative asset instruments and traditional assets instruments

are traded, such as event driven, emerging markets focused, or sector driven (Amenc, Martellini & Vaissie, 2003).

Commodities are separated into two main subclasses, namely hard and soft commodities. Hard commodities include metals such as gold, silver, and platinum; soft commodities include agricultural products such as maize and corn. Commodities can be traded by purchasing the commodity at a spot price via the actual commodity or via purchasing a commodity linked company share; or alternatively for a future date via a derivative contract such as a future or forward contract (Le Roux & Els, 2013).

Various studies have been undertaken to investigate what type of relationship commodity prices have to prices of other instruments, such as exchange rates, equity prices and monetary policy instruments. Garcia-Herrero and Thornton (1997) did a comparison of world commodity prices to retail prices of products in the United Kingdom, as a forecasting tool. The study showed inconclusive results that commodity prices can be used to forecast changes in retail prices. The authors used cointegration and Granger causality techniques to identify any forecasting possibilities.

Saghaian (2010) investigated the possible relations and simultaneous causal structures between energy and commodity datasets. The study indicated that there is a strong correlation between oil and commodity prices, but the causal relation between oil and commodity prices showed mixed results. Cointegration and Granger causality were used to present the empirical results.

A study on equity prices and exchange rates in Australia with emphasis on commodity prices was done by Groenewold and Paterson (2013). The authors found that the short run relationship indicated that the exchange rate had a significant effect on commodity prices and that the commodity prices influence equity prices. In the long run, however, the effect of commodity prices on equity prices is weak. A further study was done to explore the relationship between the exchange rate and commodity prices. The exchange rate had a strong effect on commodity prices, but commodity prices did not have a strong effect on the exchange rate. Cointegration, the vector error correction model and Granger causality were used in the study.

Kurihara and Fukushima (2014) explored the relationships between the exchange rates, equity prices and commodity prices in Japan and the Euro area. The study showed that there was a weak relationship between equity prices and the exchange rate. In Japan, there

was a significant effect on the commodity prices from the exchange rate, but the same was not found in the Euro area. The commodity prices of both Japan and the Euro area did not impact on equity prices. The authors used VAR, cointegration and Pairwise Granger causality tests as part of the empirical analysis.

Vala (2013) explored the link between commodity prices and monetary policy in India. The results showed that commodity price indices can predict GDP and inflation. Time-series econometric models were used in this study. The models and tests used were Johansen cointegration, the vector error correction model and Granger causality.

The main focus of this chapter will be on commodities and the significant relationships that are present. The analysis can lead to further research on whether these commodities can be used as a cross hedging instrument for both traditional and alternative investment asset classes. The results can be used to identify any relationships which can be utilised for investment purposes.

4.3. METHODOLOGY

The research strategy implemented for this study was of a quantitative nature based on historical time-series data. The research objective of this study was to explore the relationships present between the seven variables included in the study. In order to explore the relationships a number of econometric tests needed to be applied to the data.

The relationships that were investigated are:

1. Movements in the commodity price against movements in the FTSE/JSE Top 40 Index and vice-versa;
2. Movements in the commodity price against movements in the ZAR and vice-versa;
3. Movements in the FTSE/JSE Top 40 Index against movements in the ZAR and vice-versa.

The relationships investigated included a correlation matrix as part of the initial analysis, followed by the Pairwise Granger causality test and the Toda Yamamoto test. The empirical analysis was split into two sections, each starting with the VAR results, following by the Johansen cointegration test in order to determine the long run relationship. The short run dynamics concluded the testing of relationships present between the variables by means of

a VECM and innovation accounting methods, which included impulse responses and variance decomposition (Asteriou & Hall, 2011; Luetkepohl, 2011; Watson, 1994).

The combination of the econometric tests is required to identify any relationships that are of interest to the research in order to locate interdependencies between the variables which can form the basis for cross hedging in the South African financial market.

4.4. DATA

A selection of five metal commodities was chosen to use in this study, namely aluminium, copper, gold, palladium, and platinum. The daily spot and future prices of these five commodities were compared to the daily spot and future price of the FTSE/JSE Top 40 Index respectively. The spot and future price of the South African Rand (ZAR) against the United States Dollar (USD) was also utilised in this chapter to investigate any relationship between the ZAR and the FTSE/JSE Top 40 Index and the five commodities.

The daily prices were obtained from the Thomson Reuters DataStream database. The sample selected to be used in this chapter was from 1 January 2000 to 30 June 2007 as well as from 1 October 2009 to 31 December 2016. These dates were chosen as each dataset was active at this time and to ignore the effects of the 2007 financial crisis. A total of 1954 data points for the period before the 2007-2009 financial crisis and 1892 data points for the period after the 2007-2009 financial crisis were included in the study. The data points were cleaned by removing any data that had no value in any of the datasets from all datasets. The data was analysed using financial econometric techniques in EViews.

The empirical results are referenced as follows (the code represents the daily spot price followed by the daily future price):

- South African Rand against the United States Dollar: ZAR and ZAR_F
- FTSE/JSE Top 40 Index: FTSE/JSE40 and FTSE/JSE40_F
- Aluminium: ALUMINIUM and ALUMINIUM_F
- Copper: COPPER and COPPER_F
- Gold: GOLD and GOLD_F
- Palladium: PALLADIUM and PALLADIUM_F
- Platinum: PLATINUM and PLATINUM_F.

In the analysis, there are instances where the above codes are preceded by the letters “L” and “DL”. When the analysis includes the codes with the letter “L” in front of the code, the

logged data was utilised within the test. If the letters “DL” precede the code, then the first differenced logged data was used. The different data transformations are used to ensure that the results of the analysis are reliable.

4.5. EMPIRICAL RESULTS

The empirical results included the initial analysis, Pairwise Granger causality test results, Toda Yamamoto test results, VAR results, long run relationship analysis and the short run dynamics results in order to determine the relationships present between the seven variables included in this study. The variables include spot and future prices analysed before and after the 2007–2009 financial crisis.

4.5.1. Initial analysis

In order to view the data graphically, the data needs to be transformed accordingly. When exploring the relationship between time series data a risk that is present is that the data is not stationary. The unit root tests, namely the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are run to determine whether the time series is stationary or not. The null hypotheses of the two unit root tests are:

- ADF test: variable has a unit root
- PP test: variable has a unit root.

The two tests mentioned above were used to test for unit roots and the results are shown in Table 4.1. The order of the tests started by testing for stationarity at level with intercept only as well as trend and intercept, followed by first difference of the intercept only, and trend and intercept for the ADF and PP test respectively.

Table 4.1: Unit root test using the Augmented Dickey-Fuller and Phillips-Perron method

| ADF before crisis | Level | | 1st Difference | |
|-------------------|-----------|---------------------|----------------|---------------------|
| | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| ALUMINIUM | -0.392 | -2.264 | -47.663* | -47.682* |
| ALUMINIUM_F | -0.342 | -2.241 | -47.605* | -47.626* |
| COPPER | 0.633 | -1.519 | -48.311* | -48.366* |
| COPPER_F | 0.811 | -1.477 | -48.758* | -34.852* |
| GOLD | 0.165 | -2.591 | -45.329* | -45.346* |
| GOLD_F | 0.085 | -2.674 | -46.136* | -46.152* |

| ADF before crisis | Level | | 1st Difference | |
|--------------------------|------------------|----------------------------|-----------------------|----------------------------|
| PALLADIUM | -1.298 | -1.459 | -16.970* | -16.969* |
| PALLADIUM_F | -1.255 | -1.387 | -17.656* | -17.654* |
| PLATINUM | -0.213 | -2.130 | -37.112* | -37.112* |
| PLATINUM_F | -0.367 | -2.541 | -46.173* | -46.170* |
| FTSE_JSE40 | 1.790 | -0.508 | -44.278* | -44.403* |
| FTSE_JSE40_F | 1.716 | -0.561 | -43.871* | -43.986* |
| ZAR | -1.439 | -1.970 | -43.834* | -43.841* |
| ZAR_F | -1.534 | -2.038 | -43.495* | -43.499* |
| PP before crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| ALUMINIUM | -0.133 | -2.122 | -48.580* | -48.806* |
| ALUMINIUM_F | -0.089 | -2.085 | -48.535* | -48.765* |
| COPPER | 0.545 | -1.591 | -48.272* | -48.325* |
| COPPER_F | 0.567 | -1.549 | -48.743* | -48.795* |
| GOLD | 0.148 | -2.623 | -45.314* | -45.330* |
| GOLD_F | 0.113 | -2.663 | -46.101* | -46.120* |
| PALLADIUM | -1.356 | -1.524 | -41.103* | -41.093* |
| PALLADIUM_F | -1.322 | -1.491 | -42.058* | -42.048* |
| PLATINUM | -0.496 | -2.391 | -49.714* | -49.656* |
| PLATINUM_F | -0.333 | -2.414 | -46.176* | -46.173* |
| FTSE_JSE40 | 2.475 | -0.119 | -44.664* | -45.364* |
| FTSE_JSE40_F | 2.572 | -0.082 | -44.551* | -45.530* |
| ZAR | -1.399 | -1.942 | -43.856* | -43.864* |
| ZAR_F | -1.524 | -2.029 | -43.489* | -43.499* |
| ADF after crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| ALUMINIUM | -1.855 | -3.570 | -45.128* | -45.122* |
| ALUMINIUM_F | -1.829 | -3.617 | -45.227* | -45.222* |
| COPPER | -1.503 | -3.323 | -44.593* | -44.600* |
| COPPER_F | -1.524 | -3.307 | -44.468* | -44.474* |
| GOLD | -1.906 | -2.433 | -43.604* | -43.642* |
| GOLD_F | -1.900 | -2.425 | -44.721* | -44.759* |
| PALLADIUM | -3.169 | -2.919 | -42.673* | -42.696* |
| PALLADIUM_F | -3.228 | -3.032 | -40.831* | -40.848* |
| PLATINUM | -0.770 | -3.530 | -41.355* | -41.386* |

| ADF before crisis | Level | | 1st Difference | |
|--------------------------|------------------|----------------------------|-----------------------|----------------------------|
| PLATINUM_F | -0.859 | -3.582 | -41.343* | -41.369* |
| FTSE_JSE40 | -1.509 | -2.904 | -33.594* | -33.598* |
| FTSE_JSE40_F | -1.489 | -3.010 | -33.467* | -33.469* |
| ZAR | -0.601 | -2.950 | -42.591* | -42.584* |
| ZAR_F | -0.563 | -2.901 | -41.684* | -41.677* |
| PP after crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| ALUMINIUM | -1.830 | -3.546 | -45.110* | -45.104* |
| ALUMINIUM_F | -1.789 | -3.601 | -45.215* | -45.211* |
| COPPER | -1.425 | -3.262 | -44.651* | -44.667* |
| COPPER_F | -1.418 | -3.217 | -44.577* | -44.582* |
| GOLD | -1.896 | -2.419 | -43.610* | -43.654* |
| GOLD_F | -1.880 | -2.407 | -44.719* | -44.764* |
| PALLADIUM | -3.169 | -2.919 | -42.667* | -42.692* |
| PALLADIUM_F | -3.174 | -2.954 | -40.774* | -40.801* |
| PLATINUM | -0.929 | -3.653 | -41.427* | -41.444* |
| PLATINUM_F | -0.955 | -3.671 | -41.333* | -41.356* |
| FTSE_JSE40 | -1.443 | -2.494 | -45.224* | -45.245* |
| FTSE_JSE40_F | -1.410 | -2.588 | -45.611* | -45.630* |
| ZAR | -0.415 | -2.725 | -43.282* | -43.284* |
| ZAR_F | -0.438 | -2.765 | -41.991* | -41.991* |

Notes: The critical values for the Augmented Dickey-Fuller (Trend and Intercept) tests are -3.959, -3.410, and -3.127 at the 1%, 5% and 10% significance levels.

The critical values for the Augmented Dickey-Fuller (Intercept only) tests are -3.431, -2.861, and -2.567 at the 1%, 5% and 10% significance levels.

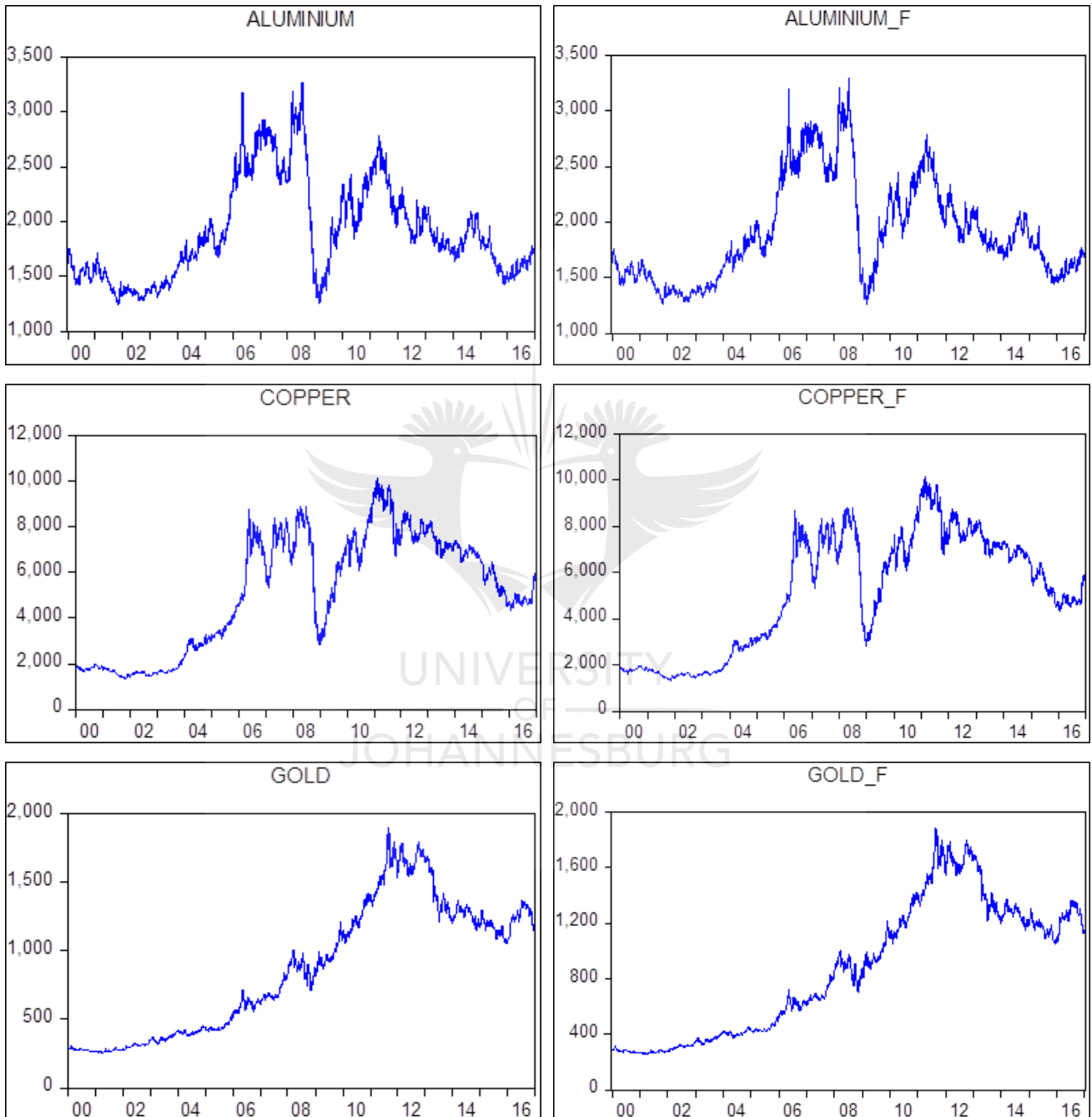
An asterisk (*) indicates that the null hypothesis of a unit root is rejected (at a 1% significance level).

Source: Thomson Reuters DataStream and EViews.

The unit root tests indicate that all the variables are stationary at first difference at a 1% significance level, therefore we conclude that the variables are integrated of order one. Therefore, the Johansen cointegration test is appropriate since all variables have the same order of integration. It is also appropriate to use the logged data within the VAR model for further analysis that is required after VAR model.

An initial evaluation of the data by means of a graphical representation illustrated in Figures 4.1 and 4.2 shows movements between the spot and future datasets, from the daily price on the line graph as well as on the log differenced graphs illustrating the volatility present.

The global financial crisis of 2007-2009 was not included in the dataset in order to remove the effects of the crisis on the commodities, index and currency. However, the graphs in Figures 4.1 and 4.2 include the entire data period from 2000 to 2016. The line graphs which display the variables included in the study show that the data seems to be trended. The log differenced graphs show signs of volatility clustering throughout the data period.



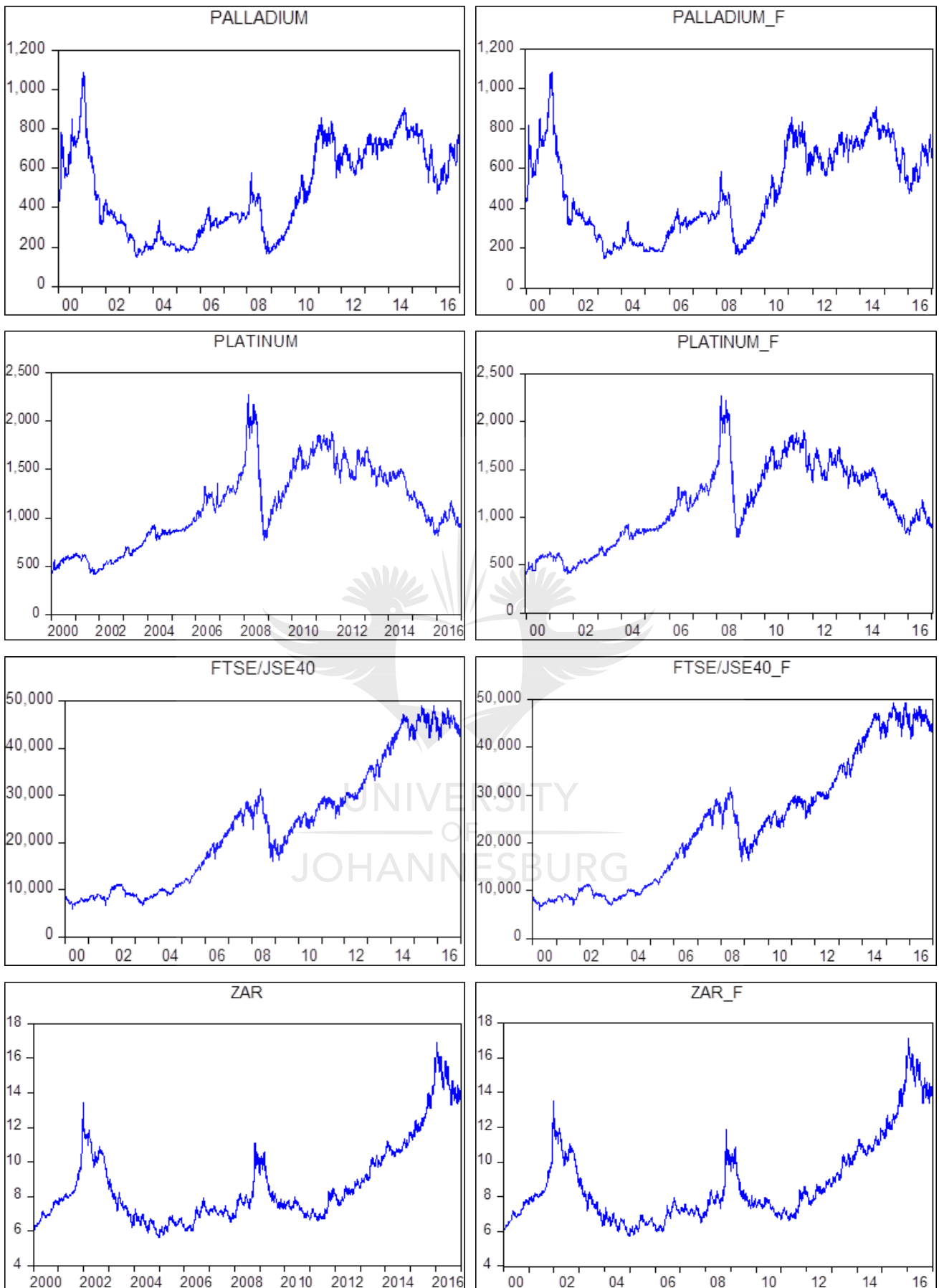
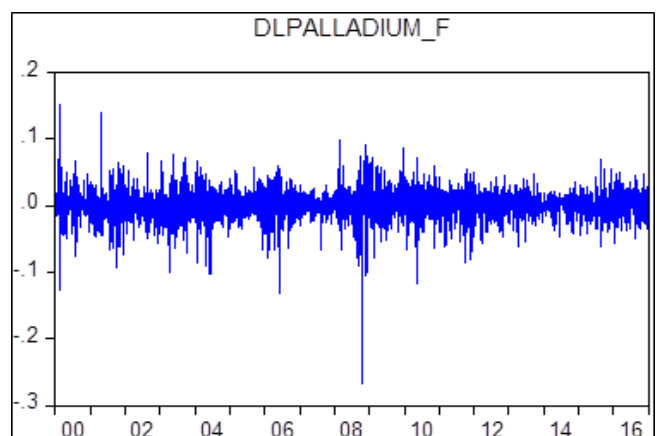
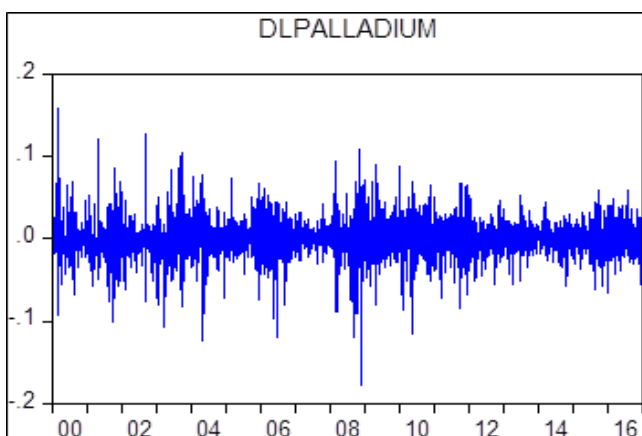
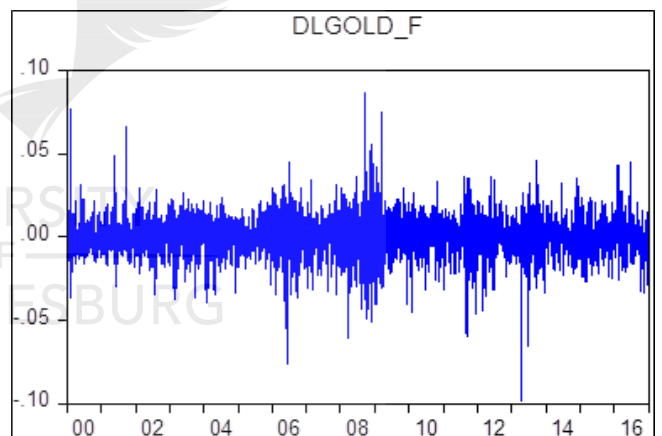
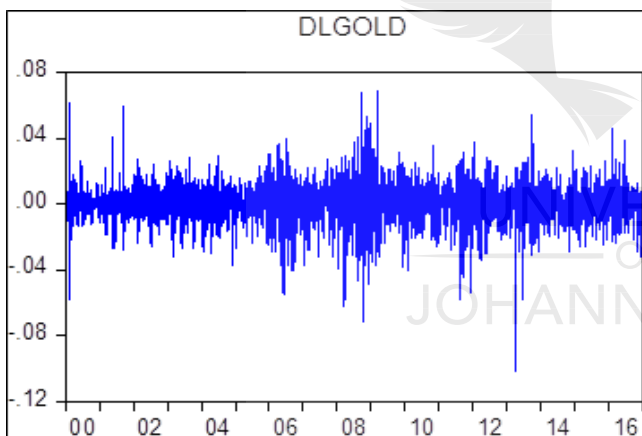
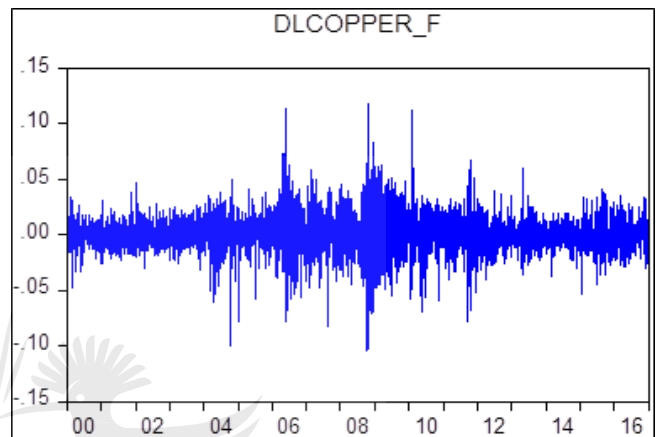
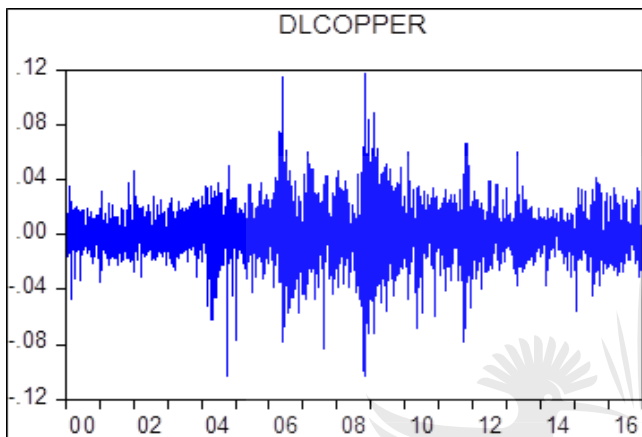
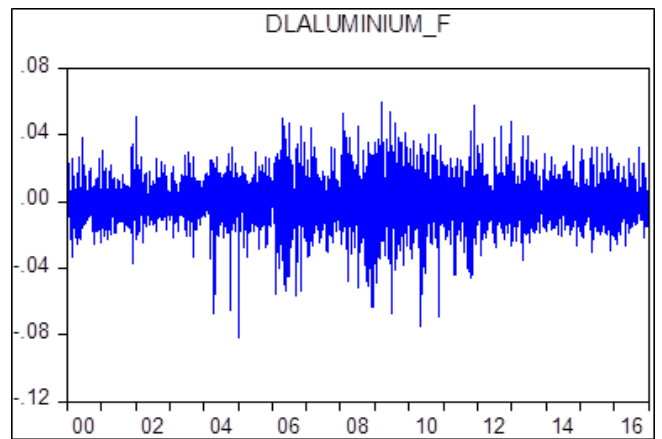
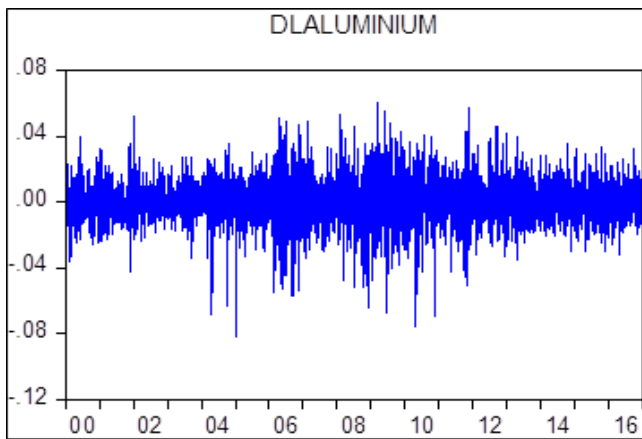


Figure 4.1: Price movement in the seven datasets

Source: Thomson Reuters DataStream and EViews.



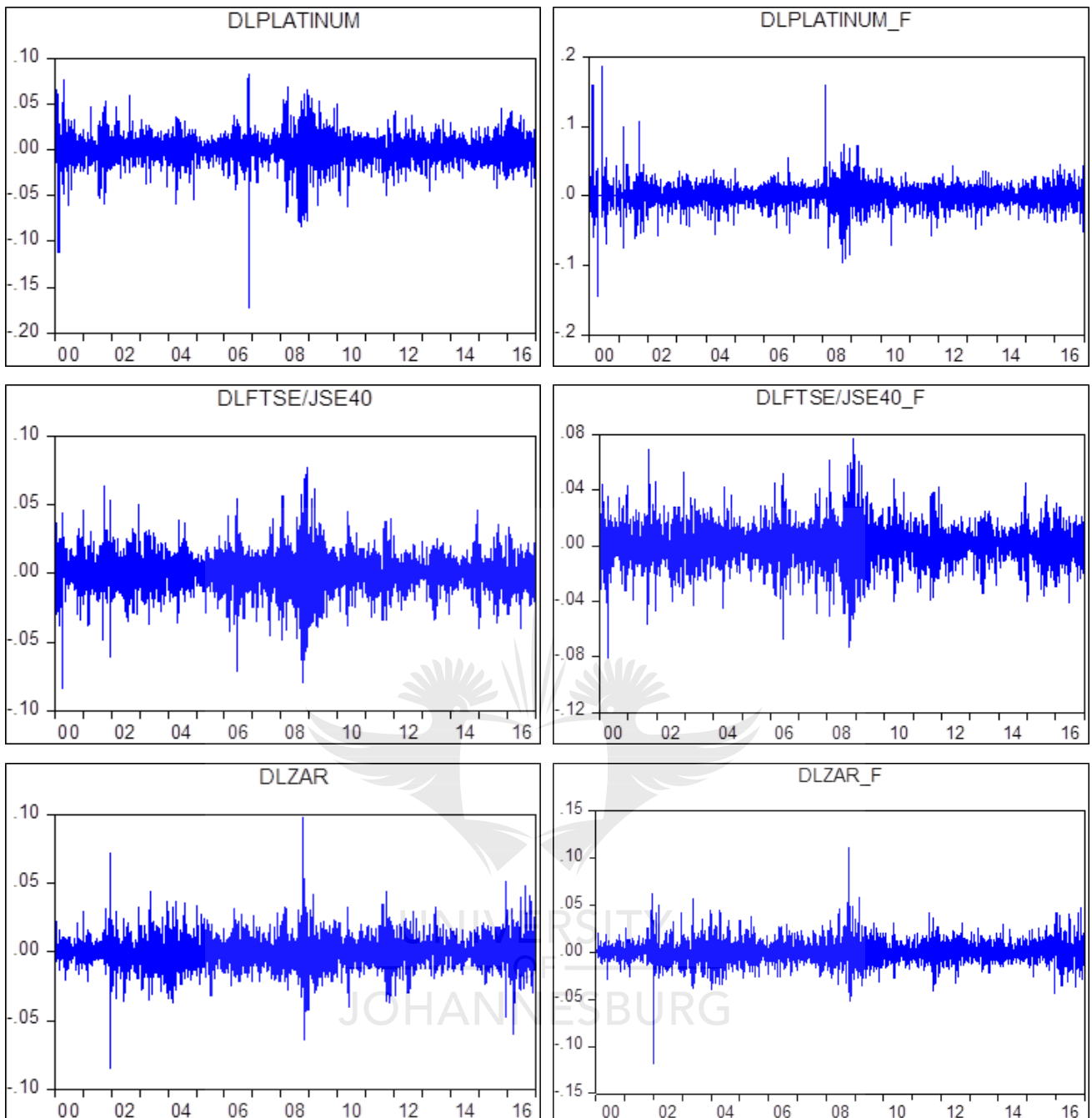
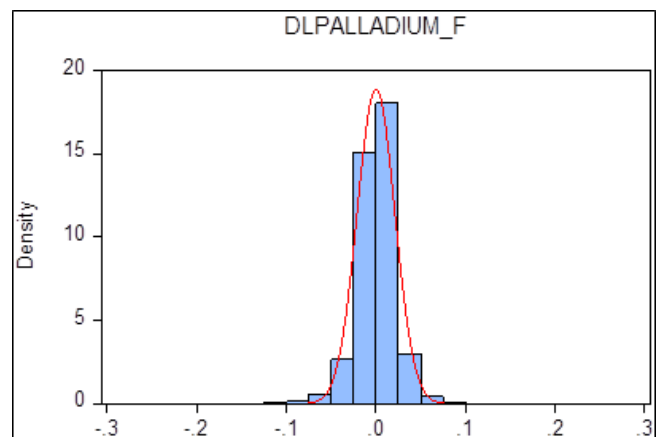
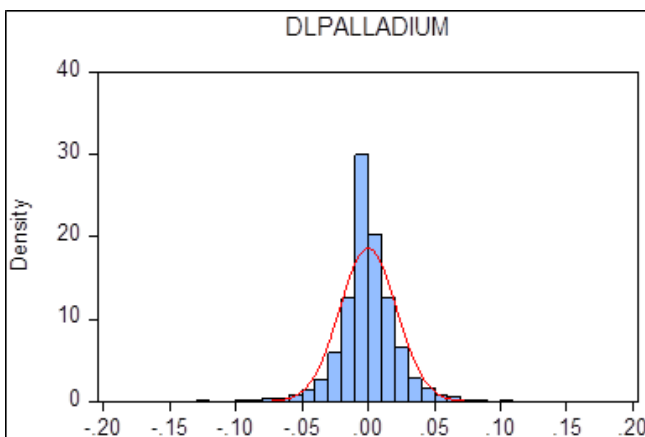
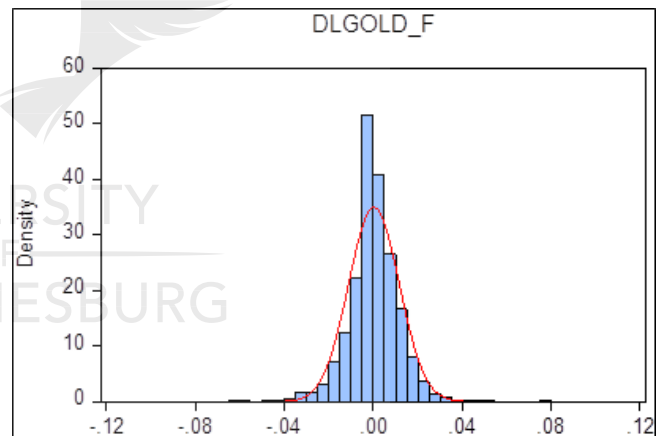
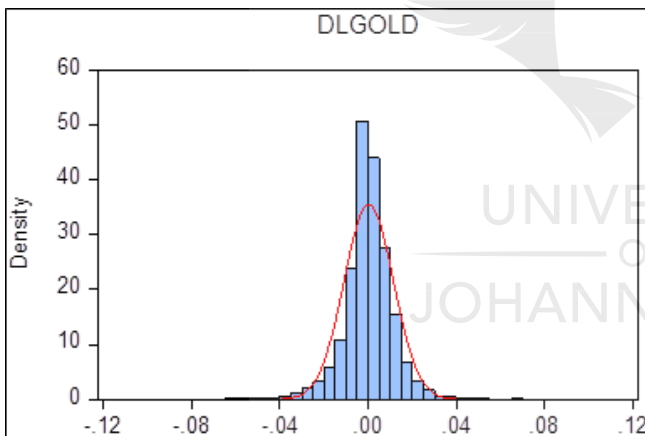
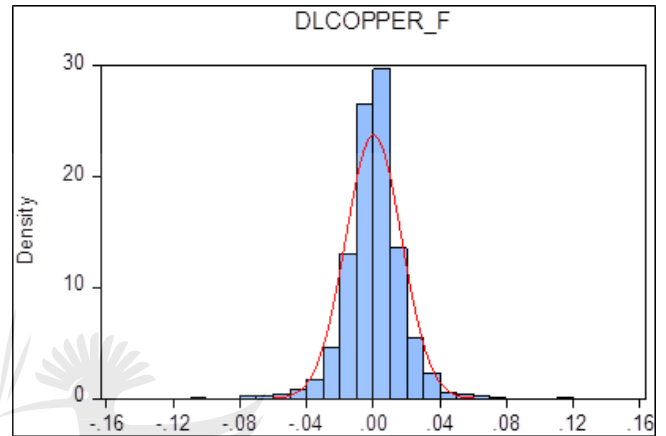
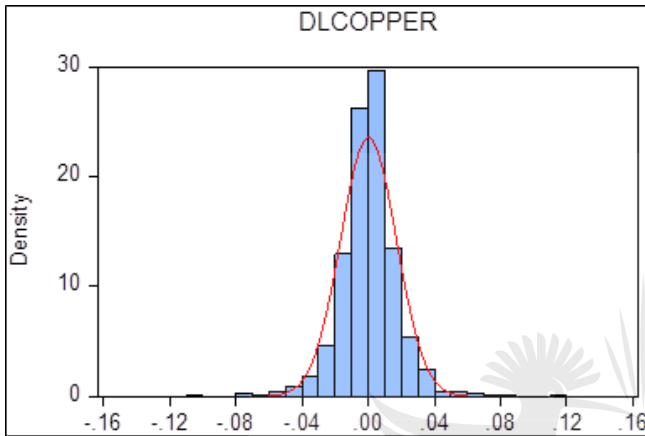
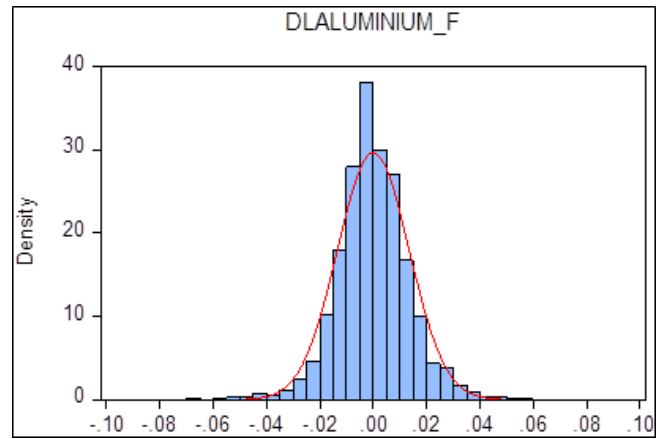
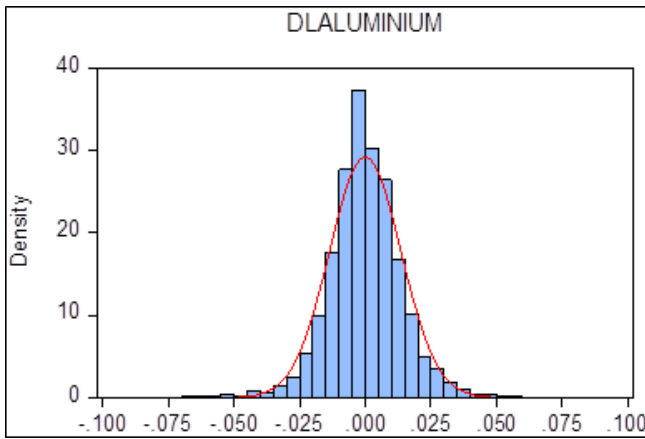


Figure 4.2: Volatility movement in the seven datasets

Source: Thomson Reuters DataStream and EViews.

Histograms graphically illustrating the distribution of the data as well as the skewness and kurtosis of the data are shown in Figure 4.3. When comparing the histograms against the normal distribution (red line), the log returns (i.e. first differencing) of the data are not normally distributed. The data also shows signs of leptokurtosis.



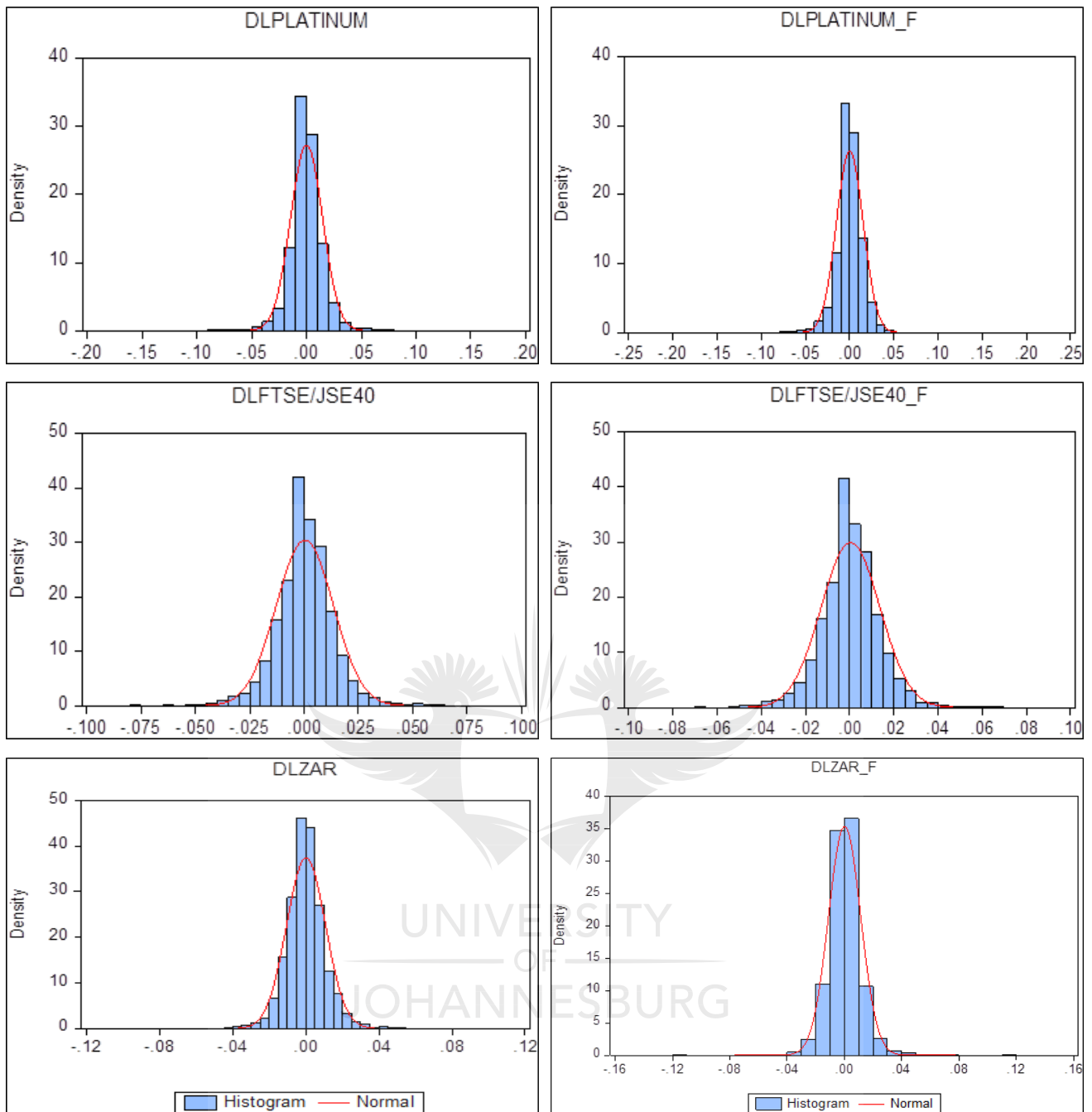


Figure 4.3: Histograms of the log returns of the seven datasets

Source: Thomson Reuters DataStream and EViews.

Table 4.2 shows the descriptive statistics of the seven datasets. A total of 3846 observations are included for all seven variables, spot and future, before and after the crisis. The descriptive statistics confirm that the log returns of the variables included are not normally distributed and are leptokurtic as seen on the histograms. In addition, the skewness indicates that the majority of the variables are slightly negatively skewed. The table also includes the synchronicity or co-movement of the variables with the ZAR and the FTSE/JSE Top 40 Index on a spot and future basis. Synchronicity in Table 4.2 is based on the R^2 of

two variables adjusted as per the methodology ($= \log(R^2/(1- R^2))$) from Morck *et al.* (2000). The higher the value of the synchronicity results, the more synchronised or co-movement exists between the variables. Platinum and palladium show the highest synchronicity with the ZAR and the FTSE/JSE Top 40 Index for spot and future over the entire period. Gold future and ZAR future show the high synchronicity as well for the FTSE/JSE Top 40 Index future.

Table 4.2: Descriptive statistics

| Before crisis spot | DLALUMINIUM | DLCOPPER | DLFTSE/JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
|---|---------------|------------|----------------|----------|---------------|--------------|----------|
| Mean | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.052 | 0.116 | 0.064 | 0.062 | 0.158 | 0.084 | 0.072 |
| Minimum | -0.083 | -0.104 | -0.084 | -0.058 | -0.124 | -0.173 | -0.085 |
| Std. Dev. | 0.013 | 0.016 | 0.012 | 0.010 | 0.022 | 0.014 | 0.010 |
| Skewness | -0.366 | -0.079 | -0.214 | -0.190 | 0.056 | -1.207 | 0.097 |
| Kurtosis | 6.489 | 8.202 | 6.303 | 7.770 | 8.668 | 21.753 | 8.201 |
| Jarque-Bera | 1034.548 | 2204.984 | 902.985 | 1864.402 | 2616.926 | 29106.330 | 2205.554 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.497 | 1.420 | 1.186 | 0.804 | -0.218 | 1.051 | 0.142 |
| Sum Sq. Dev. | 0.313 | 0.471 | 0.303 | 0.185 | 0.977 | 0.387 | 0.204 |
| Observations | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 |
| After crisis spot | DLALUMINIUM | DLCOPPER | DLFTSE/JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.058 | 0.067 | 0.047 | 0.054 | 0.089 | 0.051 | 0.052 |
| Minimum | -0.075 | -0.078 | -0.040 | -0.102 | -0.117 | -0.062 | -0.060 |
| Std. Dev. | 0.013 | 0.014 | 0.011 | 0.011 | 0.019 | 0.012 | 0.010 |
| Skewness | -0.101 | -0.079 | -0.142 | -0.769 | -0.263 | -0.114 | 0.191 |
| Kurtosis | 4.813 | 5.524 | 4.409 | 9.769 | 5.695 | 4.392 | 5.891 |
| Jarque-Bera | 262.303 | 504.366 | 162.920 | 3798.876 | 594.273 | 156.742 | 670.581 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | -0.085 | -0.107 | 0.678 | 0.144 | 0.824 | -0.360 | 0.590 |
| Sum Sq. Dev. | 0.314 | 0.390 | 0.210 | 0.217 | 0.657 | 0.286 | 0.184 |
| Observations | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 |
| Synchronicity with ZAR - full period | -3.455 | -3.593 | -3.533 | -2.286 | -4.897 | -4.685 | N/A |
| Synchronicity with FTSE/JSE40 - full period | -3.021 | -2.748 | N/A | -3.654 | -4.372 | -5.333 | -3.533 |
| Before crisis future | DLALUMINIUM_F | DLCOPPER_F | DLFTSE/JSE40_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F | DLZAR_F |
| Mean | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.051 | 0.114 | 0.070 | 0.077 | 0.153 | 0.187 | 0.063 |
| Minimum | -0.082 | -0.100 | -0.081 | -0.076 | -0.132 | -0.144 | -0.119 |
| Std. Dev. | 0.012 | 0.015 | 0.013 | 0.010 | 0.022 | 0.015 | 0.011 |
| Skewness | -0.410 | -0.074 | -0.139 | -0.141 | -0.113 | 1.063 | -0.117 |

| Before crisis spot | DLALUMINIUM | DLCOPPER | DLFTSE/JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
|---|---------------|------------|----------------|----------|---------------|--------------|----------|
| Kurtosis | 6.628 | 8.254 | 5.604 | 8.582 | 7.901 | 30.754 | 12.415 |
| Jarque-Bera | 1126.052 | 2249.135 | 558.316 | 2543.079 | 1960.081 | 63080.910 | 7221.459 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.497 | 1.413 | 1.167 | 0.794 | -0.198 | 1.090 | 0.152 |
| Sum Sq. Dev. | 0.299 | 0.459 | 0.322 | 0.206 | 0.929 | 0.427 | 0.238 |
| Observations | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 |
| After crisis future | DLALUMINIUM_F | DLCOPPER_F | DLFTSE/JSE40_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F | DLZAR_F |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.058 | 0.113 | 0.049 | 0.046 | 0.087 | 0.045 | 0.048 |
| Minimum | -0.075 | -0.078 | -0.041 | -0.098 | -0.117 | -0.071 | -0.044 |
| Std. Dev. | 0.013 | 0.015 | 0.011 | 0.011 | 0.019 | 0.013 | 0.010 |
| Skewness | -0.040 | 0.139 | -0.102 | -0.776 | -0.409 | -0.282 | 0.236 |
| Kurtosis | 4.853 | 7.152 | 4.422 | 9.347 | 5.529 | 4.485 | 4.807 |
| Jarque-Bera | 271.070 | 1365.380 | 162.658 | 3365.785 | 557.038 | 199.040 | 275.121 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | -0.096 | -0.108 | 0.676 | 0.132 | 0.827 | -0.363 | 0.604 |
| Sum Sq. Dev. | 0.309 | 0.402 | 0.221 | 0.224 | 0.657 | 0.309 | 0.183 |
| Observations | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 |
| Synchronicity with ZAR_F - full period | -3.824 | -3.959 | -4.101 | -2.440 | -4.482 | -4.588 | N/A |
| Synchronicity with FTSE/JSE40_F - full period | -2.920 | -2.691 | N/A | -4.692 | -4.153 | -4.412 | -4.101 |

Source: Thomson Reuters DataStream and EViews.

The correlation results based on the log returns (first differencing) of the data are shown in Table 4.3 to determine the initial relationships present between the variables.

Table 4.3: Correlation matrix

| Spot before crisis | DLALUMINIUM | DLCOPPER | DLFTSE_JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
|--------------------|--------------|--------------|--------------|--------|--------------|--------------|--------|
| DLALUMINIUM | 1.000 | 0.726 | 0.216 | 0.264 | 0.130 | 0.135 | -0.175 |
| DLCOPPER | 0.726 | 1.000 | 0.245 | 0.308 | 0.126 | 0.161 | -0.164 |
| DLFTSE_JSE40 | 0.216 | 0.245 | 1.000 | 0.159 | 0.112 | 0.069 | 0.169 |
| DLGOLD | 0.264 | 0.308 | 0.159 | 1.000 | 0.270 | 0.322 | -0.304 |
| DLPALLADIUM | 0.130 | 0.126 | 0.112 | 0.270 | 1.000 | 0.484 | -0.086 |
| DLPLATINUM | 0.135 | 0.161 | 0.069 | 0.322 | 0.484 | 1.000 | -0.096 |
| DLZAR | -0.175 | -0.164 | 0.169 | -0.304 | -0.086 | -0.096 | 1.000 |
| Spot after crisis | DLALUMINIUM | DLCOPPER | DLFTSE_JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
| DLALUMINIUM | 1.000 | 0.689 | 0.348 | 0.256 | 0.307 | 0.317 | -0.327 |
| DLCOPPER | 0.689 | 1.000 | 0.419 | 0.305 | 0.362 | 0.331 | -0.377 |
| DLFTSE_JSE40 | 0.348 | 0.419 | 1.000 | 0.127 | 0.355 | 0.295 | -0.283 |
| DLGOLD | 0.256 | 0.305 | 0.127 | 1.000 | 0.362 | 0.531 | -0.295 |
| DLPALLADIUM | 0.307 | 0.362 | 0.355 | 0.362 | 1.000 | 0.690 | -0.319 |
| DLPLATINUM | 0.317 | 0.331 | 0.295 | 0.531 | 0.690 | 1.000 | -0.329 |
| DLZAR | -0.327 | -0.377 | -0.283 | -0.295 | -0.319 | -0.329 | 1.000 |

| Spot before crisis | DLALUMINIUM | DLCOPPER | DLFTSE_JSE40 | DLGOLD | DLPALLADIUM | DLPLATINUM | DLZAR |
|----------------------|---------------|--------------|----------------|--------------|---------------|--------------|---------|
| Future before crisis | DLALUMINIUM_F | DLCOPPER_F | DLFTSE_JSE40_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F | DLZAR_F |
| DLALUMINIUM_F | 1.000 | 0.699 | 0.226 | 0.275 | 0.215 | 0.182 | -0.146 |
| DLCOPPER_F | 0.699 | 1.000 | 0.252 | 0.309 | 0.215 | 0.193 | -0.137 |
| DLFTSE_JSE40_F | 0.226 | 0.252 | 1.000 | 0.095 | 0.124 | 0.109 | 0.128 |
| DLGOLD_F | 0.275 | 0.309 | 0.095 | 1.000 | 0.320 | 0.356 | -0.283 |
| DLPALLADIUM_F | 0.215 | 0.215 | 0.124 | 0.320 | 1.000 | 0.398 | -0.106 |
| DLPLATINUM_F | 0.182 | 0.193 | 0.109 | 0.356 | 0.398 | 1.000 | -0.100 |
| DLZAR_F | -0.146 | -0.137 | 0.128 | -0.283 | -0.106 | -0.100 | 1.000 |
| Future after crisis | DLALUMINIUM_F | DLCOPPER_F | DLFTSE_JSE40_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F | DLZAR_F |
| DLALUMINIUM_F | 1.000 | 0.678 | 0.365 | 0.271 | 0.431 | 0.411 | -0.282 |
| DLCOPPER_F | 0.678 | 1.000 | 0.420 | 0.316 | 0.497 | 0.444 | -0.346 |
| DLFTSE_JSE40_F | 0.365 | 0.420 | 1.000 | 0.103 | 0.382 | 0.295 | -0.196 |
| DLGOLD_F | 0.271 | 0.316 | 0.103 | 1.000 | 0.469 | 0.699 | -0.261 |
| DLPALLADIUM_F | 0.431 | 0.497 | 0.382 | 0.469 | 1.000 | 0.701 | -0.343 |
| DLPLATINUM_F | 0.411 | 0.444 | 0.295 | 0.699 | 0.701 | 1.000 | -0.363 |
| DLZAR_F | -0.282 | -0.346 | -0.196 | -0.261 | -0.343 | -0.363 | 1.000 |

Source: Thomson Reuters DataStream and EViews

The correlation matrix in Table 4.3 shows that there is a strong positive correlation (0.55 and above) between the following dataset combinations:

- Aluminium and copper (before and after the crisis for both spot and future)
- Palladium and platinum (before and after the crisis for future only)
- Gold and platinum (after the crisis for future only)

The strong positive relationships between the metal commodities are expected, especially the palladium and platinum relationship, considering the commodities fall within the same commodity category. Notably, gold and platinum show a strong positive correlation after the crisis only, whereas aluminium and copper move closely together before and after the crisis.

Baur and Lucey (2010) state that an asset can be utilised as a hedging asset if the correlation between the hedging asset and asset to be hedged is low or negative, meaning that if the two variables are uncorrelated or negative correlation exists between the two variables, then the one variable can be used as a hedge for the second variable on an average basis. The remainder of the correlation values shows low or negative correlation values.

The relationship between commodities and share indices is mixed, depending on which commodity is being compared to a selected share index, with copper showing the highest correlation value for both the spot and future after the crisis, even though it is still low. The

changes in business cycles, the macroeconomic environment as well as market sentiments influence the correlations between commodities, exchange rates and share indices. The time period included for the analysis is also an important consideration as commodities show time-varying correlations with equity returns (Rossi, 2012; Büyükkşahin *et al.*, 2010; Gorton & Rouwenhorst, 2006).

4.5.2. Granger causality

The Pairwise Granger causality tests and the Toda Yamamoto test show which variables cause another variable. If one variable causes another variable, then the past values of the first variable should be able to assist in predicting the future values of the variable being caused. The causality tests are only run once the VAR tests are completed, but it will be shown before the VAR results as the causality results apply to all the variables in the study.

The full Pairwise Granger causality test results and Toda Yamamoto test results are included in Appendix A.1 for all seven variables before and after the crisis as well as both spot and future. These apply to the next section of analysis, which includes only six variables, as well as the last section of analysis that includes all seven variables. The Pairwise Granger causality test is applied to the log differenced data as all variables were found to be of order 1, $I(1)$. The Toda Yamamoto test is applied to the logged data.

Appendix A.1 indicates that the following datasets have a feedback or bilateral causal relationship at a 10% level of significance:

- Gold and aluminium: spot before crisis for Toda Yamamoto test only, future before crisis for Toda Yamamoto test only
- Platinum and palladium: spot before crisis for both tests
- Palladium and aluminium: spot after crisis for both tests
- Gold and copper: future before crisis for Toda Yamamoto test only
- Platinum and copper: future before crisis for both tests
- Platinum and gold: future before crisis for Toda Yamamoto test only
- FTSE/JSE Top 40 Index and gold: future before crisis for both tests
- FTSE/JSE Top 40 Index and palladium: future before crisis for Toda Yamamoto test only

The following datasets have a unidirectional causal relationship at a 10% level of significance:

- From aluminium to FTSE/JSE Top 40 Index: spot before crisis for both tests, future before crisis for both tests
- From aluminium to copper: spot after crisis for both tests, future after crisis for both tests
- From aluminium to gold: spot before crisis for Pairwise Granger causality test only
- From aluminium to palladium: spot before crisis for both tests, future before crisis for Toda Yamamoto test only
- From aluminium to platinum: spot before crisis for both tests, spot after crisis for both tests, future before crisis for both tests
- From copper to FTSE/JSE Top 40 Index: spot before crisis for both tests, spot after crisis for both tests, future before crisis for both tests, future after crisis for both tests
- From copper to gold: spot before crisis for both tests
- From copper to palladium: spot before crisis for both tests, spot after crisis for both tests
- From copper to platinum: spot before crisis for both tests, spot after crisis for both tests
- From FTSE/JSE Top 40 Index to gold: spot before crisis for both tests
- From FTSE/JSE Top 40 Index to palladium: spot before crisis for Toda Yamamoto test only, spot after crisis for both tests
- From FTSE/JSE Top 40 Index to platinum: spot after crisis for both tests, future before crisis for both tests
- From gold to copper: future before crisis for Toda Yamamoto test only, future after crisis for Pairwise Granger causality test only
- From gold to palladium: spot before crisis for both tests, spot after crisis for both tests, future after crisis for both tests
- From gold to platinum: spot before crisis for both tests, spot after crisis for both tests, future after crisis for both tests
- From ZAR to aluminium: spot after crisis for both tests, future after crisis for both tests
- From ZAR to copper: spot after crisis for Pairwise Granger causality test only
- From ZAR to gold: spot before crisis for both tests, spot after crisis for Toda Yamamoto test only, future after crisis for both tests
- From ZAR to palladium: spot before crisis for Pairwise Granger causality test only, spot after crisis for both tests, future before crisis for Pairwise Granger causality test only, future after crisis for both tests

- From ZAR to platinum: spot before crisis for both tests, spot after crisis for both tests, future after crisis for both tests
- From ZAR to FTSE/JSE Top 40 Index: spot after crisis for both tests, future after crisis for both tests
- From platinum to gold: future before crisis for Pairwise Granger causality test only
- From platinum to aluminium: future after crisis for both tests
- From platinum to FTSE/JSE Top 40 Index: future after crisis for Pairwise Granger causality test only
- From palladium to platinum: future before crisis for both tests
- From palladium to FTSE/JSE Top 40 Index: future before crisis for Pairwise Granger causality test only, future after crisis for both tests
- From palladium to aluminium: future after crisis for both tests.

The unidirectional relationships between the commodities are expected as the commodities fall within the same commodity category and spill-over between the commodities in line with expectations. The unidirectional relationship between the FTSE/JSE Top 40 Index to palladium, the FTSE/JSE Top 40 Index and platinum, and the ZAR to palladium and platinum is consistent as platinum and palladium are one of the most produced commodities in South Africa with a number of companies producing and exporting these two commodities.

Copper and aluminium to the FTSE/JSE Top 40 Index is one of the outliers as copper and aluminium are not among the largest commodities produced and exported in South Africa. It is outranked by gold, platinum and palladium, but constituents that are included in the FTSE/JSE Top 40 Index produce and export copper. The most notable omission from the results is that gold is not caused or causing the FTSE/JSE Top 40 Index after the crisis. However, ZAR does cause gold at spot before crisis for both tests, spot after crisis for Toda Yamamoto test only, and future after crisis for both tests. A possible reason for the independence of gold is that gold production in South Africa has decreased year on year for the 25 years. In 1980, gold made up 67 percent of all mineral sales in South Africa. In 2014, the gold sales only amounted to 12.5 percent. Even though South Africa is one of the top producers and exporters of gold, the amount of gold exported has decreased drastically (StatsSA, 2016). A possible second reason is that gold is a store of value and therefore not traded in the same way as other metal commodities are.

A summary of the number of variables that each variable causes as well as the number that a variable is caused by the other variables respectively is listed below:

- Aluminium:
 - Spot before crisis: 4 (both tests) and 1 (Toda Yamamoto test)
 - Spot after crisis: 3 (both tests) and 2 (both tests)
 - Future before crisis: 4 (2 both tests and 2 Toda Yamamoto tests) and 1 (Toda Yamamoto test)
 - Future after crisis: 1 (both tests) and 3 (both tests)
- Copper:
 - Spot before crisis: 4 (both tests) and 0
 - Spot after crisis: 3 (both tests) and 1 (both tests)
 - Future before crisis: 3 (2 both tests and 1 Toda Yamamoto test) and 2 (1 both tests and 1 Toda Yamamoto test)
 - Future after crisis: 1 (both tests) and 3 (2 both tests and 1 Pairwise Granger causality test)
- Gold:
 - Spot before crisis: 3 (2 both tests and 1 Toda Yamamoto test) and 4 (both tests)
 - Spot after crisis: 2 (both tests) and 1 (both tests)
 - Future before crisis: 4 (1 both tests and 3 Toda Yamamoto tests) and 4 (2 both tests and 2 Toda Yamamoto tests)
 - Future after crisis: 3 (2 both tests and 1 Pairwise Granger causality test) and 1 (both tests)
- Palladium:
 - Spot before crisis: 1 (both tests) and 6 (4 both tests, 1 Pairwise Granger causality test and, 1 Toda Yamamoto test)
 - Spot after crisis: 1 (both tests) and 5 (both tests)
 - Future before crisis: 2 (2 both tests) and 3 (1 Pairwise Granger causality test and 2 Toda Yamamoto tests)
 - Future after crisis: 2 (both tests) and 2 (both tests)
- Platinum:
 - Spot before crisis: 1 (both tests) and 5 (both tests)
 - Spot after crisis: 0 (both tests) and 5 (both tests)
 - Future before crisis: 2 (2 both tests) and 5 (4 both tests and 1 Toda Yamamoto test)
 - Future after crisis: 2 (1 both tests and 1 Pairwise Granger causality test) and 2 (both tests)
- FTSE/JSE Top 40 Index:

- Spot before crisis: 2 (1 both tests and 1 Toda Yamamoto test) and 2 (both tests)
- Spot after crisis: 2 (both tests) and 2 (both tests)
- Future before crisis: 3 (2 both tests and 1 Toda Yamamoto test) and 4 (both tests)
- Future after crisis: 0 and 4 (3 both tests and 1 Pairwise Granger causality test)
- ZAR:
 - Spot before crisis: 3 (2 both tests and 1 Pairwise Granger causality test) and 0
 - Spot after crisis: 5 (4 both tests and 1 Toda Yamamoto test) and 0
 - Future before crisis: 1 (1 Pairwise Granger causality test) and 0
 - Future after crisis: 6 (both tests) and 0

Therefore, aluminium, copper, gold and the ZAR cause the most variables to change and palladium and platinum are caused to move the most by the other variables. A possible reason that aluminium and copper cause the most variables is the amount that is produced of each of the commodities. In relative terms, a substantially higher amount of aluminium and copper is produced as compared to platinum and palladium (USGS Minerals Resources Program, 2016).

The remaining variables do not have statistically significant causal relationships, which implies independence.

The results for the relationship between the FTSE/JSE Top 40 Index and the five commodities before and after the crisis as well as both spot and future will be shown and discussed first, followed by the results for the relationship between the FTSE/JSE Top 40 Index and five commodities against the ZAR before and after the crisis as well as both spot and future.

4.5.3. VAR results between commodities and the FTSE/JSE Top 40 Index

The long run relationship and short run dynamics analysis starts with the VAR model, which requires the optimal lag length to be determined and the output is shown in Table 4.4. The VAR analyses for all four data sets are included in Appendix A.2.

Table 4.4 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model estimated using two lags and results in 25 significant relationships in the VAR results. Spot after crisis is three lags, and 35 significant relationships exist. Future before crisis is two lags and 15 significant relationships exist. Future after crisis is two lags and 15 significant relationships exist.

Table 4.4: VAR lag order selection criteria of the FTSE/JSE Top 40 Index and the five commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|----------------------|-----|-----------|---------|--------|----------|---------|----------|
| Spot before crisis | 2 | 34721.350 | 149.831 | 0.000* | -35.586* | -35.363 | -35.504* |
| Spot after crisis | 3 | 35425.730 | 81.653* | 0.000* | -37.327* | -36.993 | -37.204 |
| Future before crisis | 2 | 34462.150 | 107.878 | 0.000* | -35.320* | -35.097 | -35.238 |
| Future after crisis | 2 | 35591.940 | 104.548 | 0.000* | -37.541* | -37.313 | -37.457 |

* 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: Thomson Reuters DataStream and EViews.

The estimated VAR that is obtained in the analysis will be stable, otherwise known as stationary, if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 4.4, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

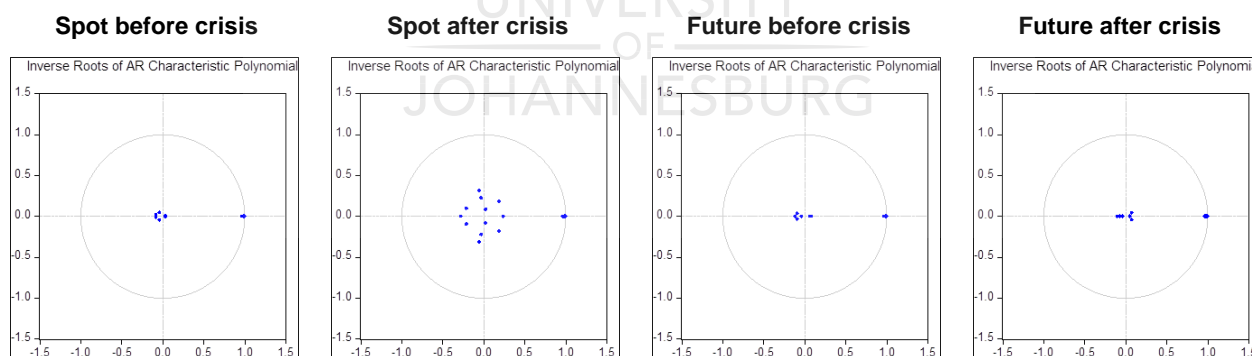


Figure 4.4: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

4.5.4. Long run relationship between commodities against the FTSE/JSE Top 40 Index

The investigation of the relationships between the datasets leads to the determination of whether the six variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done in order to determine which relationships are

present between the variables. To identify whether the variables are cointegrated, the Johansen cointegration test was done. The long run relationship analysis was followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required in order to determine if an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables both showing a common stochastic drift. A stochastic drift is the change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once (Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

The Johansen cointegration test in Table 4.5 shows there is a cointegrating relationship when the data is not linear, testing intercept no trend, as well as when the data is linear, testing intercept no trend, and intercept and trend and lastly, when the data is quadratic, testing intercept and trend.

Table 4.5: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 1 | 1 | 0 | 2 | 2 |
| Spot before crisis: Max-Eig | 1 | 1 | 0 | 2 | 2 |
| Spot after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Spot after crisis: Max-Eig | 0 | 1 | 1 | 0 | 0 |
| Future before crisis: Trace | 1 | 0 | 0 | 1 | 2 |
| Future before crisis: Max-Eig | 1 | 0 | 0 | 1 | 2 |
| Future after crisis: Trace | 0 | 1 | 0 | 0 | 0 |
| Future after crisis: Max-Eig | 0 | 1 | 1 | 0 | 1 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred as all the variables have trends that are stochastic. The Johansen cointegration test indicates that only spot after crisis and future after crisis have

one cointegrating relationship. The remainder of the results indicate the variables are not cointegrated and therefore no VECM results were included. When cointegration exists, it implies that Granger causality exists in at least one direction between the included variables, which was discussed in an earlier section. The Pairwise Granger causality test and Toda Yamamoto test indicated that causality was found between a number of variables. The vector error correction model (VECM) identified the short and long run dynamics of the included variables based on one cointegration relationship for spot after crisis and future after crisis.

Table 4.6 reports the maximum eigenvalue statistics and trace statistics as allowance for an intercept and no trend in the data was made. The table illustrates that only the null hypothesis based on the maximum eigenvalue of no cointegrating equations can be rejected. Therefore, if the max-eigenvalue is considered, cointegration is present within this set of variables, indicating a long run relationship.

Table 4.6: Maximum eigenvalue statistics and trace statistics

| Hypothesized number of Cointegrating Equations | Eigen-value | Trace Statistic | 5% Critical Value | Prob** |
|--|-------------|-------------------|-------------------|--------|
| Spot after crisis: None | 0.022 | 94.242 | 95.754 | 0.063 |
| Future after crisis: None | 0.022 | 95.491 | 95.754 | 0.052 |
| Hypothesized number of Cointegrating Equations | Eigen-value | Max-Eig Statistic | 5% Critical Value | Prob** |
| Spot after crisis: None* | 0.022 | 41.292 | 40.078 | 0.036 |
| Future after crisis: None* | 0.022 | 42.918 | 40.078 | 0.023 |

Spot after crisis:

Trace test indicates no cointegration at the 0.05 level

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

Future after crisis:

Trace test indicates no cointegration at the 0.05 level

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

**MacKinnon-Haug-Michelis (1999) p-values

Source: Thomson Reuters DataStream and EViews.

4.5.5. Short run dynamics between commodities against the FTSE/JSE Top 40 Index

The VECM further investigates the long run and short run dynamics of the variables. It is a restricted VAR designed for use with nonstationary series that are known to be cointegrated.

Table 4.7 is linked to the results from the Johansen cointegration test based on one cointegrating relationship.

Table 4.7: Cointegration equation – normalised for the FTSE/JSE Top 40 Index

| Cointegrating Eq: | LFTSE/JSE40(-1) | LALUMINIUM(-1) | LCOPPER(-1) | LGOLD(-1) | LPALLADIUM(-1) | LPLATINUM(-1) |
|----------------------------------|-------------------|------------------|---------------|-------------|------------------|-----------------|
| Spot after crisis: CointEq1 | 1.000 | 0.679 | 0.695 | 0.113 | -0.876 | -0.147 |
| | | (0.168) | (0.192) | (0.100) | (0.060) | (0.164) |
| | | [4.039] | [3.620] | [1.133] | [-14.496] | [-0.894] |
| | LFTSE_JSE40_F(-1) | LALUMINIUM_F(-1) | LCOPPER_F(-1) | LGOLD_F(-1) | LPALLADIUM_F(-1) | LPLATINUM_F(-1) |
| Future after crisis: CointEq1 | 1.000 | 0.620 | 0.732 | 0.120 | -0.872 | -0.144 |
| | | (0.168) | (0.185) | (0.097) | (0.059) | (0.159) |
| | | [3.702] | [3.958] | [1.234] | [-14.781] | [-0.905] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

In Table 4.7, when the cointegrating equation (normalised for the FTSE/JSE Top 40 Index) is considered for spot after crisis as well as future after crisis, it is evident that aluminium, copper, and palladium are statistically significant variables when the FTSE/JSE Top 40 Index is the dependent variable in the long run. Palladium is the most significant variable with the highest t-statistic of absolute value of 14.495 and 14.781 for spot and future respectively. Aluminium and copper have a negative relationship with the FTSE/JSE Top 40 Index of 0.679 and 0.695 units respectively for spot after the crisis and 0.620 and 0.732 units respectively for future after the crisis. The coefficient obtained in the results is inverted, therefore a positive value results in a negative relationship. Palladium has a positive relationship with the FTSE/JSE Top 40 Index of one unit.

Table 4.8: Vector Error Correction Model (VECM) short run

| Error Correction: | D(LFTSE_JSE40) | D(LALUMINIUM) | D(LCOPPER) | D(LGOLD) | D(LPALLADIUM) | D(LPLATINUM) |
|----------------------------------|------------------|-----------------|--------------|------------|-----------------|----------------|
| Spot after crisis: CointEq1 | -0.006 | -0.005 | -0.005 | 0.006 | 0.028 | 0.013 |
| | (0.003) | (0.004) | (0.005) | (0.003) | (0.006) | (0.004) |
| | [-1.617] | [-1.190] | [-1.171] | [1.736] | [4.713] | [3.369] |
| | D(LFTSE_JSE40_F) | D(LALUMINIUM_F) | D(LCOPPER_F) | D(LGOLD_F) | D(LPALLADIUM_F) | D(LPLATINUM_F) |
| Future after crisis: CointEq1 | -0.006 | -0.005 | -0.009 | 0.004 | 0.023 | 0.011 |
| | (0.004) | (0.004) | (0.005) | (0.004) | (0.006) | (0.004) |
| | [-1.833] | [-1.193] | [-1.945] | [1.200] | [3.852] | [2.620] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

When the short run dynamics are considered, as shown in Table 4.8, palladium and platinum are statistically significant, as the *t-statistics* are above 1.96 for both spot after crisis and future after crisis. However, the error correction coefficients of both variables are positive. This implies that if a shock occurs the variables move away from equilibrium. However, FSTE/JSE Top 40 Index and copper for future after the crisis are entering the cointegrating equation significantly (on a 90% confidence level) with a negative sign indicating it will adjust towards equilibrium over time. Although the adjustment will be very slow since the coefficients are small, the future after crisis becomes significant but the spot after crisis is only significant on 80% level.

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities and the FTSE/JSE Top 40 Index are displayed in Table 4.9.

Table 4.9: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|---------|----|--------|
| Spot before crisis | DLFTSE/JSE40 | All | 25.183 | 10 | 0.005* |
| Spot before crisis | DLALUMINIUM | All | 11.843 | 10 | 0.296 |
| Spot before crisis | DLCOPPER | All | 11.094 | 10 | 0.350 |
| Spot before crisis | DLGOLD | All | 44.532 | 10 | 0.000* |
| Spot before crisis | DLPALLADIUM | All | 60.853 | 10 | 0.000* |
| Spot before crisis | DLPLATINUM | All | 47.260 | 10 | 0.000* |
| Spot after crisis | DLFTSE/JSE40 | All | 26.224 | 15 | 0.036 |
| Spot after crisis | DLALUMINIUM | All | 12.462 | 15 | 0.644 |
| Spot after crisis | DLCOPPER | All | 29.858 | 15 | 0.012 |
| Spot after crisis | DLGOLD | All | 26.631 | 15 | 0.032 |
| Spot after crisis | DLPALLADIUM | All | 116.047 | 15 | 0.000* |
| Spot after crisis | DLPLATINUM | All | 141.717 | 15 | 0.000* |
| Future before crisis | DLFTSE/JSE40_F | All | 20.600 | 10 | 0.024 |
| Future before crisis | DLALUMINIUM_F | All | 12.001 | 10 | 0.285 |
| Future before crisis | DLCOPPER_F | All | 8.113 | 10 | 0.618 |
| Future before crisis | DLGOLD_F | All | 21.448 | 10 | 0.018 |
| Future before crisis | DLPALLADIUM_F | All | 4.430 | 10 | 0.926 |
| Future before crisis | DLPLATINUM_F | All | 22.721 | 10 | 0.012* |
| Future after crisis | DLFTSE/JSE40_F | All | 29.474 | 10 | 0.001* |
| Future after crisis | DLALUMINIUM_F | All | 15.015 | 10 | 0.132 |
| Future after crisis | DLCOPPER_F | All | 33.317 | 10 | 0.000* |

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|---------------------|--------------------|----------|--------|----|-------|
| Future after crisis | DLGOLD_F | All | 11.416 | 10 | 0.326 |
| Future after crisis | DLPALLADIUM_F | All | 19.784 | 10 | 0.031 |
| Future after crisis | DLPLATINUM_F | All | 17.378 | 10 | 0.066 |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: FTSE/JSE Top 40 Index, gold, palladium and platinum
- Spot after crisis: Palladium and platinum
- Future before crisis: Platinum
- Future after crisis: FTSE/JSE Top 40 Index and copper

The null hypothesis can be rejected for the remainder of the variables. This confirms the significant variables from the VECM, where gold and aluminium did not enter the cointegrating equation significantly. The variables ranked from the most exogenous to the most endogenous are indicated by Chi-square value. A higher Chi-square value indicates that the variable is more exogenous.

Appendix A.3 shows the response of the FTSE/JSE Top 40 Index when one of the other variables experiences an innovation. The impulse response when five periods on a daily basis are included, indicates whether the FTSE/JSE Top 40 Index increases or decreases and whether this effect is likely to be permanent. As shown by the impulse response, a rapid increase in a commodity price will cause an initial increase in the FTSE/JSE Top 40 Index. Thereafter, it seems to decrease slowly to equilibrium. This confirms the results from the VECM where the FTSE/JSE Top 40 Index entered the cointegrating equation significantly (but not very high) with a negative sign, indicating adjustment towards equilibrium, although at a slow rate. On average, it takes two to three days for the FTSE/JSE Top 40 Index to move back to equilibrium.

The variance decomposition of the six variables is displayed in Appendix A.3 to indicate that the percentage value of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals.

The variance decomposition of the FTSE/JSE Top 40 Index illustrates that at period 1, most of the movement is explained by its own variance. Aluminium explains the second highest amount of the movement after the crisis at above 12%.

The results for the relationship between the ZAR and the FTSE/JSE Top 40 Index and five commodities before and after the crisis as well as both spot and future are shown below in the remainder of the section.

4.5.6. VAR results between commodities, FTSE/JSE Top 40 Index and ZAR

The long run relationship and short run dynamics analysis for the relationship between the commodities and the FTSE/JSE Top 40 Index against the ZAR begins with the VAR model, which requires the optimal lag length to be determined, and the output is shown in Table 4.10. The VAR analyses for all four datasets are included in Appendix A.4.

Table 4.10: VAR lag order selection criteria of the ZAR, FTSE/JSE Top 40 Index and the five commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|-----------------------------|-----|-----------|----------|--------|----------|---------|---------|
| Spot before crisis | 2 | 41089.140 | 165.844 | 0.000* | -42.100* | -41.799 | -41.989 |
| Spot after crisis | 3 | 41760.420 | 106.800* | 0.000* | -43.981* | -43.530 | -43.815 |
| Future before crisis | 2 | 40625.490 | 121.842 | 0.000* | -41.624* | -41.323 | -41.513 |
| Future after crisis | 2 | 41705.790 | 142.771 | 0.000* | -44.162* | -43.853 | -44.048 |

* 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: Thomson Reuters DataStream and EViews.

Table 4.10 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model is estimated using two lags and results in 27 significant relationships in the VAR results. Spot after crisis is three lags, and 42 significant relationships exist. Future before crisis is two lags and 17 significant relationships exist. Future after crisis is two lags and 30 significant relationships exist.

The estimated VAR that is obtained in the analysis will be stable or stationary if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning

that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 4.5, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

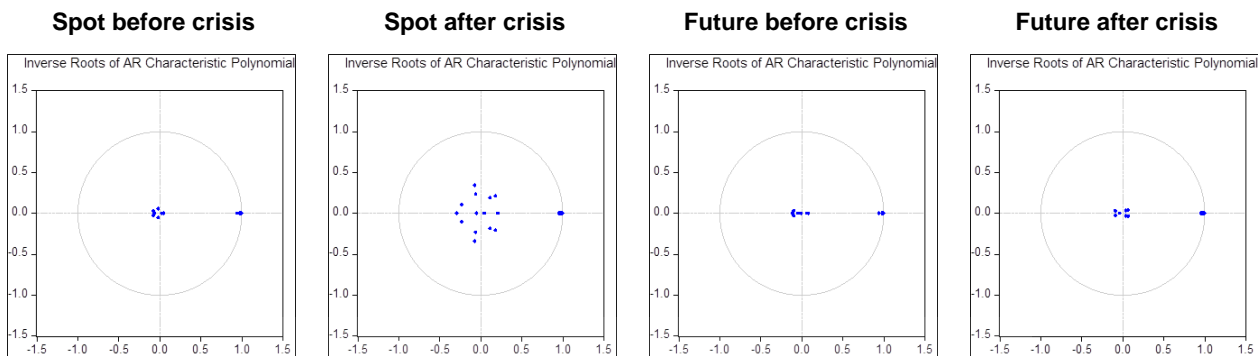


Figure 4.5: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

4.5.7. Long run relationship between commodities and the FTSE/JSE Top 40 Index against the ZAR

The examination of the relationships between the variables leads to the objective of whether the seven variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done to determine which relationships are present between the variables. To identify whether the variables are cointegrated, the Johansen cointegration test was done. The long run relationship analysis was followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required in order to determine whether an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables both showing a common stochastic drift. A stochastic drift is the change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once (Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

Table 4.11: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 1 | 1 | 1 | 2 | 2 |
| Spot before crisis: Max-Eig | 1 | 1 | 1 | 2 | 2 |
| Spot after crisis: Trace | 1 | 1 | 1 | 0 | 1 |
| Spot after crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Future before crisis: Trace | 1 | 1 | 1 | 2 | 2 |
| Future before crisis: Max-Eig | 1 | 1 | 1 | 2 | 2 |
| Future after crisis: Trace | 1 | 2 | 1 | 1 | 1 |
| Future after crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The Johansen cointegration test in Table 4.11 shows there are cointegrating relationships at the following sets:

- No trend in the data, not testing intercept and trend
- No trend in the data, testing intercept and not trend
- Data is linear, testing intercept and not trend
- Data is linear, testing intercept and trend
- Data is quadratic, testing intercept and trend.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred, as all the variables have trends that are stochastic. The Johansen cointegration test indicates that all four data sets – spot before crisis, spot after crisis, future before crisis, and future after crisis – have one cointegrating relationship. When cointegration exists, it implies that Granger causality exists in at least one direction between the included variables, which was discussed in an earlier section. The Pairwise Granger causality test and Toda Yamamoto test indicated that causality was found between a number of variables. The vector error correction model (VECM) identified the short and long run dynamics of the included variables based on one cointegration relationship for all four data sets – spot before crisis, spot after crisis, future before crisis, and future after crisis.

Table 4.12: Maximum eigenvalue statistics and trace statistics

| Hypothesized number of Cointegrating Equations | Eigen-value | Trace Statistic | 5% Critical Value | Prob** |
|--|-------------|-------------------|-------------------|--------|
| Spot before crisis: None* | 0.029 | 143.271 | 125.615 | 0.003 |
| Spot after crisis: None* | 0.022 | 133.385 | 125.615 | 0.015 |
| Future before crisis: None* | 0.029 | 140.319 | 125.615 | 0.005 |
| Future after crisis: None* | 0.022 | 137.146 | 125.615 | 0.008 |
| Hypothesized number of Cointegrating Equations | Eigen-value | Max-Eig Statistic | 5% Critical Value | Prob** |
| Spot before crisis: None * | 0.029 | 58.354 | 46.231 | 0.002 |
| Spot after crisis: None | 0.022 | 42.559 | 46.231 | 0.118 |
| Future before crisis: None* | 0.029 | 58.367 | 46.231 | 0.002 |
| Future after crisis: None | 0.022 | 42.968 | 46.231 | 0.108 |

Spot before crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates no cointegration at the 0.05 level

Spot after crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates no cointegration at the 0.05 level

Future before crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

Future after crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates no cointegration at the 0.05 level

** denotes rejection of the hypothesis at the 0.05 level*

***MacKinnon-Haug-Michelis (1999) p-values*

Source: Thomson Reuters DataStream and EViews.

Table 4.12 reports the maximum eigenvalue statistics and trace statistics as allowance for an intercept and no trend in the data was made. According to the trace test and Max-eigenvalue test, cointegration is present within the combination of variables, which indicates a long run relationship.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend.

4.5.8. Short run dynamics between commodities and the FTSE/JSE Top 40 Index against the ZAR

The VECM will identify the short and long run dynamics of the included time series variables. The VECM is a restricted VAR that is intended to use with nonstationary series that are

known to be cointegrated. Table 4.13 is based on the results from the Johansen cointegration test based on one cointegrating relationship.

In Table 4.13, the FTSE/JSE Top 40 Index, aluminium and palladium are statistically significant variables when the ZAR is the dependent variable in the cointegrating relationship (normalised for the ZAR) in the long run both before and after the crisis for spot and future. Gold was statistically significant for spot and future before the crisis only.

Table 4.13: Cointegration equation – normalised for the ZAR

| Cointegrating Eq | LZAR(-1) | LALUMINIUM(-1) | LCOPPER(-1) | LGOLD(-1) | LPALLADIUM(-1) | LPLATINUM(-1) | LFTSE_JSE40(-1) |
|-----------------------------------|------------|------------------|---------------|-------------|------------------|-----------------|-------------------|
| Spot before crisis: CointEq1 | 1.000 | 2.509 | 0.277 | -1.600 | -0.463 | -0.019 | -0.720 |
| | | (0.305) | (0.152) | (0.281) | (0.060) | (0.176) | (0.116) |
| | | [8.230] | [1.817] | [-5.685] | [-7.767] | [-0.109] | [-6.228] |
| Spot after crisis: CointEq1 | 1.000 | -0.949 | -0.737 | -0.295 | 1.497 | 0.459 | -2.236 |
| | | (0.334) | (0.348) | (0.179) | (0.260) | (0.294) | (0.318) |
| | | [-2.844] | [-2.120] | [-1.645] | [5.762] | [1.563] | [-7.042] |
| | LZAR_F(-1) | LALUMINIUM_F(-1) | LCOPPER_F(-1) | LGOLD_F(-1) | LPALLADIUM_F(-1) | LPLATINUM_F(-1) | LFTSE_JSE40_F(-1) |
| Future before crisis: CointEq1 | 1.000 | 2.633 | 0.161 | -1.647 | -0.455 | 0.158 | -0.726 |
| | | (0.315) | (0.155) | (0.271) | (0.059) | (0.156) | (0.109) |
| | | [8.362] | [1.037] | [-6.079] | [-7.672] | [1.016] | [-6.662] |
| Future after crisis: CointEq1 | 1.000 | -0.542 | -0.492 | -0.249 | 1.084 | 0.408 | -1.773 |
| | | (0.255) | (0.260) | (0.136) | (0.194) | (0.220) | (0.235) |
| | | [-2.125] | [-1.894] | [-1.840] | [5.592] | [1.854] | [-7.530] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

For the spot and future before the crisis results, aluminium was the most significant variable when the ZAR was the dependent variable. Aluminium has a positive coefficient, which implies a negative relationship with the ZAR of 2.509 and 2.633 units spot and future respectively. A positive coefficient implies it is not of the correct sign for the VECM results. Palladium has a positive relationship with the ZAR of 0.463 and 0.455 units spot and future respectively and is of the correct sign. For spot and future after the crisis, FTSE/JSE Top 40 was the most significant variable when the ZAR was the dependent variable.

Table 4.14: Vector Error Correction Model (VECM) short run

| Error Correction: | D(LZAR) | D(LALUMINIUM) | D(LCOPPER) | D(LGOLD) | D(LPALLADIUM) | D(LPLATINUM) | D(LFTSE/JSE40) |
|--------------------------------|-----------|-----------------|-----------------|-----------------|-----------------|-----------------|------------------|
| Spot before crisis: CointEq1 | -0.001 | -0.012 | -0.014 | 0.006 | 0.009 | 0.006 | 0.006 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.005) | (0.003) | (0.003) |
| | [-0.252] | [-4.309] | [-4.162] | [3.085] | [1.897] | [1.991] | [2.273] |
| Spot after crisis: CointEq1 | -0.002 | 0.001 | 0.001 | -0.003 | -0.016 | -0.008 | 0.004 |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) | (0.002) | (0.002) |
| | [-1.255] | [0.473] | [0.444] | [-1.343] | [-4.618] | [-3.452] | [1.799] |
| | D(LZAR_F) | D(LALUMINIUM_F) | D(LCOPPER_F) | D(LGOLD_F) | D(LPALLADIUM_F) | D(LPLATINUM_F) | D(LFTSE_JSE40_F) |
| Future before crisis: CointEq1 | -0.001 | -0.014 | -0.014 | 0.006 | 0.006 | 0.003 | 0.006 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.005) | (0.003) | (0.003) |
| | [-0.499] | [-4.993] | [-4.247] | [2.457] | [1.273] | [0.797] | [1.978] |
| Future after crisis: CointEq1 | -0.004 | 0.000 | 0.003 | -0.002 | -0.017 | -0.008 | 0.005 |
| | (0.002) | (0.003) | (0.004) | (0.003) | (0.005) | (0.003) | (0.003) |
| | [-1.813] | [-0.034] | [0.707] | [-0.806] | [-3.753] | [-2.671] | [1.955] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

When the short run dynamics are considered as shown in Table 4.14, aluminium, copper, gold, platinum and the FTSE/JSE Top 40 Index are statistically significant for spot before the crisis as the *t-statistics* are significant on a 95% confidence level (critical value = 1.96). Future before the crisis only aluminium, copper and gold are statistically significant, whereas palladium and platinum are statistically significant for both spot and future after the crisis.

For spot before the crisis aluminium and copper have a negative error correction coefficient and therefore will move back to the long run equilibrium if there are short-term shocks. The coefficients for aluminium and copper are close to zero, which implies that the move back to the equilibrium will be slow. The FTSE/JSE Top 40 Index has a significant (95% confidence) positive error correction coefficient, indicating a move away from equilibrium after a shock; however, the coefficient is very small. Palladium is entering the cointegrating equation significantly at a 90% confidence level and adjusting to the equilibrium after a shock; however, the coefficient is close to zero and there will be a slow adjustment towards equilibrium.

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities, FTSE/JSE Top 40 Index, and the ZAR are displayed in Table 4.15.

Table 4.15: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|---------|----|--------|
| Spot before crisis | DLZAR | All | 6.120 | 12 | 0.910 |
| Spot before crisis | DLFTSE/JSE40 | All | 26.902 | 12 | 0.008* |
| Spot before crisis | DLALUMINIUM | All | 12.973 | 12 | 0.371 |
| Spot before crisis | DLCOPPER | All | 12.506 | 12 | 0.406 |
| Spot before crisis | DLGOLD | All | 53.806 | 12 | 0.000* |
| Spot before crisis | DLPALLADIUM | All | 62.008 | 12 | 0.000* |
| Spot before crisis | DLPLATINUM | All | 48.551 | 12 | 0.000* |
| Spot after crisis | DLZAR | All | 15.921 | 18 | 0.598 |
| Spot after crisis | DLFTSE/JSE40 | All | 35.052 | 18 | 0.009* |
| Spot after crisis | DLALUMINIUM | All | 22.393 | 18 | 0.215 |
| Spot after crisis | DLCOPPER | All | 40.710 | 18 | 0.002* |
| Spot after crisis | DLGOLD | All | 30.415 | 18 | 0.034 |
| Spot after crisis | DLPALLADIUM | All | 126.904 | 18 | 0.000* |
| Spot after crisis | DLPLATINUM | All | 168.465 | 18 | 0.000* |
| Future before crisis | DLZAR_F | All | 5.785 | 12 | 0.927 |
| Future before crisis | DLFTSE/JSE40_F | All | 25.419 | 12 | 0.013 |
| Future before crisis | DLALUMINIUM_F | All | 15.116 | 12 | 0.235 |
| Future before crisis | DLCOPPER_F | All | 9.424 | 12 | 0.666 |
| Future before crisis | DLGOLD_F | All | 25.734 | 12 | 0.012 |
| Future before crisis | DLPALLADIUM_F | All | 7.791 | 12 | 0.801 |
| Future before crisis | DLPLATINUM_F | All | 28.863 | 12 | 0.004* |
| Future after crisis | DLZAR_F | All | 14.587 | 12 | 0.265 |
| Future after crisis | DLFTSE/JSE40_F | All | 47.481 | 12 | 0.000* |
| Future after crisis | DLALUMINIUM_F | All | 31.482 | 12 | 0.002* |
| Future after crisis | DLCOPPER_F | All | 49.704 | 12 | 0.000* |
| Future after crisis | DLGOLD_F | All | 20.787 | 12 | 0.054 |
| Future after crisis | DLPALLADIUM_F | All | 40.228 | 12 | 0.000* |
| Future after crisis | DLPLATINUM_F | All | 43.410 | 12 | 0.000* |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: FTSE/JSE Top 40 Index, gold, palladium and platinum
- Spot after crisis: FTSE/JSE Top 40 Index, copper, palladium and platinum
- Future before crisis: Platinum
- Future after crisis: FTSE/JSE Top 40 Index, aluminium, copper, palladium and platinum

This shows robustness of the results since adding the ZAR to the combination of variables has only slightly changed the dynamics from the previous analysis. The null hypothesis can be rejected for the remainder of the variables. The variables ranked from the most exogenous to the most endogenous are determined by the Chi-square value indicating that the variable with the highest Chi-square value is more exogenous.

In Appendix A.5 the response of the ZAR when one of the other variables experiences a shock is shown. The impulse response when five periods are included indicates whether the ZAR increases or decreases and whether this effect is likely to be permanent. The response of the FTSE/JSE Top 40 Index is opposite to the response obtained for the ZAR as the response of the ZAR is in upward sloping, starting from a negative base, except before the crisis. On average, the move back to the equilibrium is between two and three days. The ZAR shows an opposite reaction to the FTSE/JSE Top 40 Index, as the flow of funds related to international trade is different between the currency and the equity index. With the ZAR against the USD, two currencies are being affected, the ZAR and the USD. With the FTSE/JSE Top 40 Index, only the index is involved and not two currencies (Rossi, 2012; Chaban, 2009).

The variance decomposition of the seven variables is displayed in Appendix A.5 to indicate how much of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the ZAR and FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals. The variance decomposition of the ZAR shows that most of the movement is explained by itself.

The FTSE/JSE Top 40 Index illustrates that most of the movement is explained by its own variance. Copper explains between 6% and 9% of the FTSE/JSE Top 40 Index movement before the crisis for both spot and future, whereas aluminium explains between 7% and 10% of the FTSE/JSE Top 40 Index movement after the crisis for both spot and future.

The VECM results where only the FTSE/JSE Top 40 Index and the five commodities were included showed that in the long run, aluminium, copper and palladium were statistically significant when the FTSE/JSE Top 40 Index was the dependent variable. In the short run, palladium and platinum were statistically significant, with a small positive error correction coefficient at a 95% confidence level. The FTSE/JSE Top 40 Index entered the cointegrating

equation significantly with a small negative error correction coefficient at a 90% confidence level for spot after crisis. The FTSE/JSE Top 40 Index and copper entered the cointegrating equation significantly with a small negative error correction coefficient at a 90% confidence level, which shows that movement back to the equilibrium will occur, but at a slow rate.

The VECM results, where all seven variables were included, showed that the FTSE/JSE Top 40 Index, aluminium, and palladium were statistically significant variables when the ZAR was the dependent variable. Considering the short run dynamics, the VECM results showed that palladium, platinum and the FTSE/JSE Top 40 Index were statistically significant. Palladium and platinum had a small negative error correction coefficient for both spot and future after the crisis, but the FTSE/JSE Top 40 Index had a small positive error correction coefficient. The Cholesky ordering for both relationships was similar, which implies that the ordering is correct.

4.6. CONCLUSION

Overall, the empirical results show that there are significant relationships in the long run and short run of the included variables. The objectives addressing the movement relationships between the variables were the main focus of this chapter. The correlation analysis showed that seven sets of variables moved together in a positive manner. The variables that moved together were: Aluminium and copper (before and after the crisis for both spot and future), palladium and platinum (before and after the crisis for future only); and gold and platinum (after the crisis for future only).

The synchronicity results showed that platinum and palladium had high synchronicity with the ZAR and the FTSE/JSE Top 40 Index for spot and future over the entire period. Gold future and ZAR future showed high synchronicity with the FTSE/JSE Top 40 Index future.

From the Granger causality results, a number of bilateral causal relationships exist, with majority before the crisis, but after the crisis, the only relationship is between spot palladium and spot aluminium for both tests. The unidirectional relationships found between a commodity, the FTSE/JSE Top 40 Index and the ZAR were: from aluminium, copper, platinum and palladium to the FTSE/JSE Top 40 Index, from the FTSE/JSE Top 40 Index to gold, palladium and platinum, from the ZAR to all the commodities, and lastly from the ZAR to the FTSE/JSE Top 40 Index. Only gold, palladium and platinum showed being Granger caused by the FTSE/JSE Top 40 Index and the ZAR.

After the crisis, the following unidirectional relationships related to the ZAR and the FTSE/JSE Top 40 Index exist:

- From copper to FTSE/JSE Top 40 Index: spot and future (both tests)
- From FTSE/JSE Top 40 Index to palladium: spot (both tests)
- From FTSE/JSE Top 40 Index to platinum: spot (both tests)
- From ZAR to aluminium: spot and future (both tests)
- From ZAR to copper: spot (Pairwise Granger causality test)
- From ZAR to gold: spot (Toda Yamamoto test) and future (both tests)
- From ZAR to palladium: spot and future (both tests)
- From ZAR to platinum: spot and future (both tests)
- From ZAR to FTSE/JSE Top 40 Index: spot and future (both tests)
- From platinum to FTSE/JSE Top 40 Index: future (Pairwise Granger causality test)
- From palladium to FTSE/JSE Top 40 Index: future (both tests)

The remainder of the analysis focused on VAR, Johansen cointegration, VECM and innovation accounting methods. The analysis indicates that there are numerous significant relationships between the seven variables.

The VECM results were split into the two main relationships being investigated. The first relationship of the FTSE/JSE Top 40 Index and the five commodities indicated that when considering the cointegrating relationship, aluminium, copper and palladium were statistically significant when the FTSE/JSE Top 40 Index was the dependent variable for both spot and future after the crisis. The cointegrating equation normalised for the ZAR indicated the following:

- Spot and future before crisis: aluminium, gold, palladium, and the FTSE/JSE Top 40 Index were statistically significant variables when the ZAR was the dependent variable
- Spot after crisis: aluminium, copper, palladium and the FTSE/JSE Top 40 Index were statistically significant variables when the ZAR was the dependent variable
- Future after crisis: aluminium, palladium, and the FTSE/JSE Top 40 Index were statistically significant variables when the ZAR was the dependent variable.

Copper becomes significant for spot after the crisis, whereas gold is no longer significant for both spot and future after the crisis.

The short run dynamics of the first relationship of the FTSE/JSE Top 40 Index and the five commodities indicated that the FTSE/JSE Top 40 Index and copper entered the cointegrating equation significantly with a small negative error correction coefficient at a 90% confidence level for future after crisis. For the second relationship between all seven variables, palladium, and platinum were statistically significant with a small negative error correction coefficient for spot and future after crisis as compared to aluminium and copper before the crisis for both spot and future.

The block exogeneity for the first relationship shows that palladium and platinum were exogenous for spot after crisis, and the FTSE/JSE Top 40 Index and copper were exogenous for future after crisis. The second relationship showed that the FTSE/JSE Top 40 Index, copper, palladium and platinum were not rejected for both spot and future after crisis. In addition, aluminium was not rejected for future after crisis. The results were similar, which indicates that the model is robust.

The empirical results indicate that there is opportunity for further study in metal commodities. Further research can be done related to the forecasting ability of metal commodities. Further research can also be done to identify the presence of speculative bubbles, which can create the prospect for short term profit opportunities.

The previous literature discussed in this chapter showed studies comparing commodities to exchange rates, equity prices and monetary policy instruments. The results of the studies are mixed as different aspects of the relationships were investigated. Groenewold and Paterson (2013) compared equity prices and exchange rates in Australia with commodity prices. The results obtained showed that the exchange rate had a short run effect, but not a long effect on commodity prices. The results also showed that commodity prices influenced equity prices in the short run. The directional relationship found in the study was that the exchange rate had a strong effect on commodity prices, but commodity prices did not have a strong effect on the exchange rate.

The exchange rate, equity price and commodity price relationship was investigated by Kurihara and Fukushima (2014) related to Japan and the Euro area. The results showed mostly weak relationships, with only the commodity prices and the exchange rate in Japan showing significant results. The results indicated that there was a significant effect of the commodity results from the exchange rate in Japan. The results obtained by Groenewold and Paterson (2013) and Kurihara and Fukushima (2014) indicate that further research should be done using commodities, as the results are currently mixed. The results of this

study indicated that within the metal commodities group, certain metal commodities were affected by equity prices and the exchange rate, and certain metal commodities were affecting the equity prices and the exchange rate.

Exploratory research should be undertaken to identify the initial relationships of commodities on other financial variables. Once the initial relationships are identified, focused research can be done to look for more meaningful results between commodities and other financial variables.

In addition, further studies can be undertaken in soft commodities and in energy commodities, which will be done in the next two chapters. At this point, relationships between the variables have been identified, but the cross hedging relationships as well as optimal hedge ratios will be explored further in Chapter 7.



CHAPTER 5

ESSAY 2: SOFT COMMODITIES

5.1. INTRODUCTION

Relationships in financial data, both positive and negative, have an impact on the investment decisions individuals and institutions make. These relationships provide an indication of diversification opportunities available in both traditional and alternative investments. A second aspect of these relationships is that they could provide possible cross hedging opportunities. The determination of significant relationships between variables is one of the first steps to determine whether cross hedging opportunities are available between selected variables.

The variables chosen for the study are five soft agricultural commodities, namely corn, cotton, soyabean, sugar and wheat, the FTSE/JSE Top 40 Index and the South African Rand (versus the United States Dollar), denoted as ZAR. These commodities were chosen as they are part of the international benchmarks for soft agricultural commodities. The five agricultural commodities were selected as they are produced in South Africa; however, not to the same extent as metal commodities are produced (United States Department of Agriculture, 2015). The FTSE/JSE Top 40 Index and the ZAR were chosen as the variables to represent the South African Equity Index and currency respectively.

The objective of the study was to determine the possible long and short run significant relationships between the five agricultural commodities against the FTSE/JSE Top 40 Index. A second relationship that was investigated was the possible long and short run significant relationships between the five agricultural commodities and the FTSE/JSE Top 40 Index against the ZAR. The sample includes daily data points from before as well as after the 2007-2009 financial crisis, which will be split in the analysis section in order to compare the two periods. In addition, the variables are represented by spot as well as future prices of all seven variables, which will also be compared against each other. The initial analysis included visual representations and correlation. Causality analysis immediately followed the initial analysis as it applies to all fourteen variables included in the study. The Pairwise Granger causality test and Toda Yamamoto test apply to all fourteen variables included in

the study. The Toda Yamamoto test tests for causality without testing for cointegration first (Toda & Yamamoto, 1995), which is why both tests are included to identify the differences. The remainder of the empirical results were divided into two sections as per the two relationships under investigation related to the objective of the study.

The first section after the Granger causality results tested the relationships between the commodities and the FTSE/JSE Top 40 Index both spot and future as well as before and after the crisis. The second section of the analysis tested the relationships present between the commodities and the FTSE/JSE Top 40 Index against the ZAR again both spot and future as well as before and after the crisis. Within each section, the VAR results, the long relationship represented by the Johansen cointegration test, and the short run dynamics were included. The short run dynamics were evaluated using the VECM and innovation accounting methods of impulse responses and variance decomposition.

The remainder of the chapter is structured as follows; part 2 provides a brief review of current literature. Parts 3 and 4 discuss the methodology and explanation of the data. Part 5 illustrates the results and interprets the findings. The final part, part 6, discusses the conclusion and implication of the study.

5.2. REVIEW OF THE LITERATURE

Commodity prices are used in the analysis of a wide array of datasets. Investigations are done between the effects of prices of different commodities, both in the spot price and future price; however, limited studies are done in the South African market comparing the commodities to an equity market index and the ZAR.

An initial study to identify the relationship between metal commodities, specifically copper, palladium, platinum and silver showed a cointegrating relationship with the FTSE/JSE Top 40 Index. A cointegration relationship was also present between the ZAR and the FTSE/JSE Top 40 Index and four commodities. The cointegration was tested using the Johansen cointegration test (Le Roux, 2014).

Schaling *et al.* (2014) investigated whether the ZAR is a commodity currency using nominal data, namely the monthly USD ZAR nominal exchange rate and the non-fuel commodity price index, from 1996 to 2010. The methodology used in the study included the Johansen cointegration test, the VECM and the Granger causality test. The results of the study indicate that the ZAR is a commodity currency, but the strength of the relationship identified is weaker than other countries that export commodities, for instance Australia.

Other studies that included commodities as part of the study have had varying objectives and comparative datasets. A number of studies have been done between commodities datasets. Harri, Nalley and Hudson (2009) explored the relationship between oil, exchange rates and commodity prices. Analysis of the data included the Johansen Trace cointegration test, error correction model and Granger causality test. The data analysed in the study was monthly observations from January 2000 to September 2008. The empirical evidence suggests that there is an interrelating link between exchange rates, corn and oil prices.

Co-movements of several variables, namely the world gold price, world oil price, United States equity price (Dow-Jones Industrial Index), and the real exchange rate for the United States Dollar were investigated by Samanta and Zadeh (2012). Daily closing prices from January 1989 through to September 2009 were included in the study. The method used in the study included Johansen cointegration test, vector autoregression, Stock-Watson's common trend test, Granger causality test and the Diebold and Yilmaz methodology. The analysis of the data shows that initially the existence of co-movements were present between the datasets, but further analysis indicates that the equity price and the gold price tend to move on their own; however, the oil price and exchange rates are affected by other variables.

Bhunja (2013) explored the relationships between two commodity market indices, the world crude index and the Indian gold price, as well as the equity market index of the Bombay stock exchange, Sensex. Daily closing prices from 2 January 1991 to 31 December 2012 were used in the study. The Johansen multivariate cointegration test and the Granger causality test were utilised in the study. The results of the analysis show that there is a cointegration relationship in the long run between the included variables.

The long-term relationship between the price of crude oil and four vegetable oils, being palm, sunflower, soyabean and rapeseed oils prices, was investigated by Hameed and Arshad (2009). The sample period included in the study was from January 1983 to March 2008, using monthly data. The Johansen cointegration test and Granger causality test were used to analyse the data in the study. The results of the study indicated that there is a long run relationship between the price of crude oil and the prices of the vegetable oils.

Booth and Ciner (2001) explored alternative explanations of long-term co-movements between the prices of agricultural commodity futures on the Tokyo Grain Exchange. The time period included in the analysis was the daily closing prices on the Tokyo Grain Exchange from the beginning of July 1993 to the end of March 1998. The commodities which

formed part of the study were corn, redbean, soyabean and sugar. The Johansen cointegration test, including the vector autoregression model, was utilised in the study. The empirical findings show that only the prices of corn and soyabean contracts are cointegrated.

Bhar and Hamori (2006) relooked at the study done by Booth and Ciner (2001) for a more recent period, from 1 August 1994 to 29 December 2003. The data was analysed over the full period as well as over two sub-sample periods, 1 August 1994 to 28 December 1999 and 4 January 2000 to 26 December 2003. The sub-sample period of 2000 to 2003 showed a cointegrating relationship, whereas the earlier sub-sample period and the entire period from 1994 to 2003 did not show a cointegrating relationship.

The cointegration relationship of grain market prices of wheat and teff commodities in Northern Ethiopia was examined by Jaleta and Gebermedhin (2009). Bi-monthly retail price data from May 2006 to October 2008 was included in the study. Johansen cointegration test, vector autoregression model, vector error correction model and Granger causality test were used to analyse the data. The results showed that a cointegration relationship was more evident for wheat retail prices.

The main objective of this chapter was on commodities and the significant relationships that exist between the variables included in the study. The analysis will lead to a further study in Chapter 7 that evaluated the optimal hedging ratios between all the variables included in this thesis. The results of this chapter can be used for understanding the relationships between the included variables for investment decisions involving commodities.

5.3. METHODOLOGY

The study included historical time-series data to investigate the relationships between the seven variables. Financial econometric tests were applied to the data to determine the relationships that are present between the variables. Initial movements between the variables were investigated by the use of correlation and causality testing of the Pairwise Granger causality test and the Toda Yamamoto test. The relationships to be investigated were:

1. Movements in the commodity price against movements in the FTSE/JSE Top 40 Index and vice-versa;
2. Movements in the commodity price against movements in the ZAR and vice-versa;

3. Movements in the FTSE/JSE Top 40 Index against movements in the ZAR and vice-versa.

Once the initial analysis had been completed, the relationships were further investigated by the use of VAR, followed by the Johansen cointegration test to determine whether any long run relationships exist. The VECM and impulse responses and variance decomposition tested the short run dynamics. The VAR, long run relationship test and short run dynamics tests were done in two separate sections in order to test the three main relationships listed above (Asteriou & Hall, 2011; Johansen, 1991; Luetkepohl, 2011; Watson, 1994).

5.4. DATA

Five soft agricultural commodities were included in the study, namely corn, cotton, soyabean, sugar and wheat. These commodities were compared to the FTSE/JSE Top 40 Index initially, followed by the comparison of the five commodities and the FTSE/JSE Top 40 Index against the ZAR. All prices were the daily spot and future prices available from the commodity benchmarks from the Thomson Reuters DataStream database. The sample period ran from 1 January 2000 to 30 June 2007 as well as from 1 October 2009 to 31 December 2016. These dates were chosen as each dataset was active at this time and to ignore the effects of the 2007 financial crisis. A total of 1954 data points for the time period before the 2007-2009 financial crisis and 1892 data points for the time period after the 2007-2009 financial crisis were included in the study. The data points were cleaned by removing any data that had no value in any of the datasets from all datasets. The data was analysed using financial econometric techniques in EViews.

The empirical results are referenced as follows (the code represents the daily spot price followed by the daily future price):

- South African Rand against the United States Dollar: ZAR and ZAR_F
- FTSE/JSE Top 40 Index: FTSE/JSE40 and FTSE/JSE40_F
- Corn: CORN and CORN_F
- Cotton: COTTON and COTTON_F
- Soyabean: SOYABEAN and SOYABEAN_F
- Sugar: SUGAR and SUGAR_F
- Wheat: WHEAT and WHEAT_F.

In the analysis, the above codes appear with either the letters “L” or “DL” at the start of each code. When only the letter “L” is included in front of the code, the logged data was utilised

as part of the test. If the letters “DL” precede the code, then the first differenced logged data was used. The different data transformation methods were used to ensure that the results obtained as part of the empirical analysis were reliable.

5.5. EMPIRICAL RESULTS

The results included in the empirical results section were separated into the initial analysis, Pairwise Granger causality test results, Toda Yamamoto test results, VAR results, long run relationship analysis and the short run dynamics results in order to determine the relationships present between the seven variables included in this study. The variables include spot and future prices analysed before and after the 2007-2009 financial crisis.

5.5.1. Initial analysis

The initial analysis of the data which is represented by the graphical representations, descriptive statistics and correlation requires the data to be transformed accordingly. As part of the data transformation process, the stationarity of the variables needs to be tested by means of unit root tests. The unit root tests used in the analysis are the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The null hypotheses of the two unit root tests are:

- ADF test: variable has a unit root.
- PP test: variable has a unit root.

The two tests mentioned above were used to test for unit roots and the results are shown in Table 5.1. The order of the tests started by testing for stationarity at level with intercept only as well as trend and intercept, followed by first difference of the intercept only, and trend and intercept for the ADF and PP test respectively.

Table 5.1: Unit root test using the Augmented Dickey-Fuller and Phillips-Perron method

| ADF before crisis | Level | | 1st Difference | |
|-------------------|-----------|---------------------|----------------|---------------------|
| | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| CORN | -1.369 | -1.915 | -44.240* | -44.236* |
| CORN_F | -1.435 | -2.017 | -42.002* | -41.996* |
| COTTON | -2.132 | -2.138 | -48.550* | -48.539* |
| COTTON_F | -2.258 | -2.266 | -44.076* | -44.066* |
| SOYABEAN | -1.333 | -1.771 | -47.569* | -47.560* |
| SOYABEAN_F | -1.360 | -1.907 | -43.616* | -43.610* |
| SUGAR | -1.601 | -1.552 | -49.797* | -49.791* |
| SUGAR_F | -1.671 | -1.663 | -43.558* | -43.554* |

| | | | | |
|-------------------------|------------------|----------------------------|-----------------------|----------------------------|
| WHEAT | -1.310 | -2.774 | -47.597* | -47.594* |
| WHEAT_F | -0.540 | -2.077 | -44.291* | -44.304* |
| FTSE_JSE40 | 1.790 | -0.508 | -44.278* | -44.403* |
| FTSE_JSE40_F | 1.716 | -0.561 | -43.871* | -43.986* |
| ZAR | -1.439 | -1.970 | -43.834* | -43.841* |
| ZAR_F | -1.534 | -2.038 | -43.495* | -43.499* |
| PP before crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| CORN | -1.385 | -1.932 | -44.247* | -44.246* |
| CORN_F | -1.497 | -2.087 | -41.951* | -41.944* |
| COTTON | -2.087 | -2.093 | -48.856* | -48.846* |
| COTTON_F | -2.245 | -2.253 | -44.084* | -44.073* |
| SOYABEAN | -1.623 | -2.075 | -47.546* | -47.538* |
| SOYABEAN_F | -1.484 | -2.040 | -43.629* | -43.623* |
| SUGAR | -1.654 | -1.678 | -49.549* | -49.545* |
| SUGAR_F | -1.704 | -1.712 | -43.561* | -43.557* |
| WHEAT | -1.392 | -2.881 | -47.587* | -47.584* |
| WHEAT_F | -0.538 | -2.128 | -44.292* | -44.304* |
| FTSE_JSE40 | 2.475 | -0.119 | -44.664* | -45.364* |
| FTSE_JSE40_F | 2.572 | -0.082 | -44.551* | -45.530* |
| ZAR | -1.399 | -1.942 | -43.856* | -43.864* |
| ZAR_F | -1.524 | -2.029 | -43.489* | -43.499* |
| ADF after crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| CORN | -1.333 | -2.061 | -42.672* | -42.700* |
| CORN_F | -1.497 | -2.281 | -42.816* | -42.837* |
| COTTON | -1.696 | -2.317 | -39.540* | -39.540* |
| COTTON_F | -1.767 | -2.460 | -40.363* | -40.363* |
| SOYABEAN | -1.765 | -2.126 | -44.586* | -44.601* |
| SOYABEAN_F | -1.804 | -2.192 | -43.727* | -43.741* |
| SUGAR | -2.084 | -2.248 | -46.506* | -46.500* |
| SUGAR_F | -2.077 | -2.310 | -24.480* | -24.478* |
| WHEAT | -2.486 | -3.158 | -45.904* | -45.949* |
| WHEAT_F | -1.967 | -2.834 | -43.133* | -43.150* |
| FTSE_JSE40 | -1.509 | -2.904 | -33.594* | -33.598* |
| FTSE_JSE40_F | -1.489 | -3.010 | -33.467* | -33.469* |
| ZAR | -0.601 | -2.950 | -42.591* | -42.584* |
| ZAR_F | -0.563 | -2.901 | -41.684* | -41.677* |
| PP after crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| CORN | -1.382 | -2.085 | -42.685* | -42.708* |
| CORN_F | -1.489 | -2.282 | -42.816* | -42.837* |
| COTTON | -1.704 | -2.326 | -39.526* | -39.523* |
| COTTON_F | -1.765 | -2.459 | -40.368* | -40.367* |
| SOYABEAN | -1.756 | -2.115 | -44.576* | -44.599* |
| SOYABEAN_F | -1.726 | -2.123 | -43.779* | -43.799* |

| | | | | |
|---------------------|--------|--------|----------|----------|
| SUGAR | -2.116 | -2.275 | -46.478* | -46.473* |
| SUGAR_F | -2.056 | -2.287 | -44.295* | -44.288* |
| WHEAT | -2.332 | -3.042 | -46.152* | -46.257* |
| WHEAT_F | -1.937 | -2.808 | -43.133* | -43.150* |
| FTSE_JSE40 | -1.443 | -2.494 | -45.224* | -45.245* |
| FTSE_JSE40_F | -1.410 | -2.588 | -45.611* | -45.630* |
| ZAR | -0.415 | -2.725 | -43.282* | -43.284* |
| ZAR_F | -0.438 | -2.765 | -41.991* | -41.991* |

Notes: The critical values for the Augmented Dickey-Fuller (Trend and Intercept) tests are -3.959, -3.410, and -3.127 at the 1%, 5% and 10% significance levels.

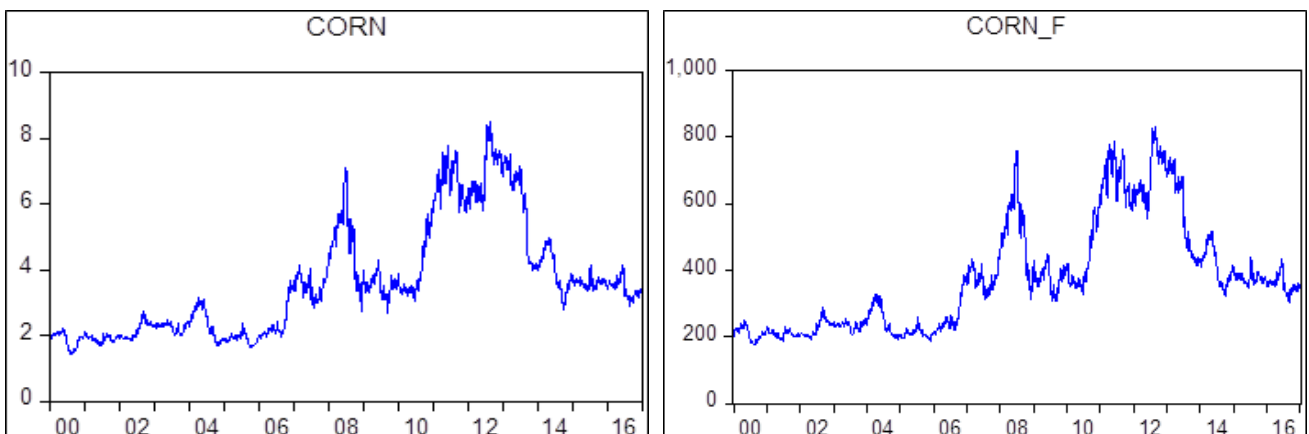
The critical values for the Augmented Dickey-Fuller (Intercept only) tests are -3.431, -2.861, and -2.567 at the 1%, 5% and 10% significance levels.

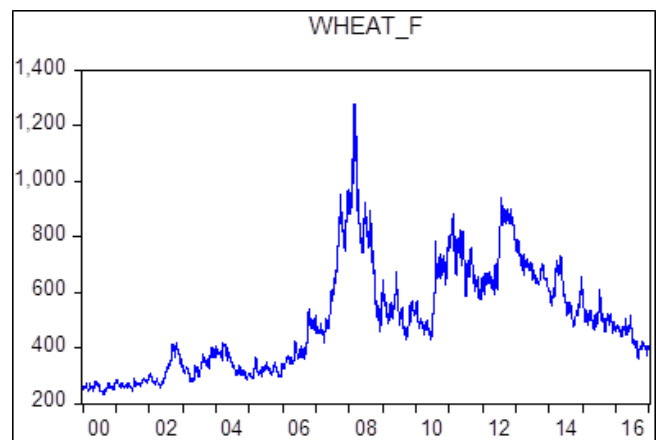
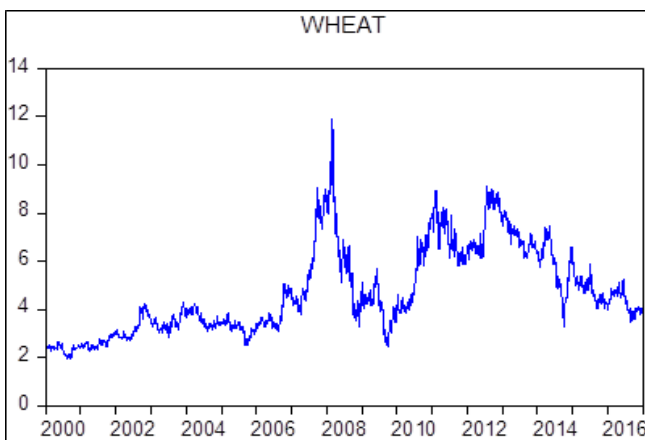
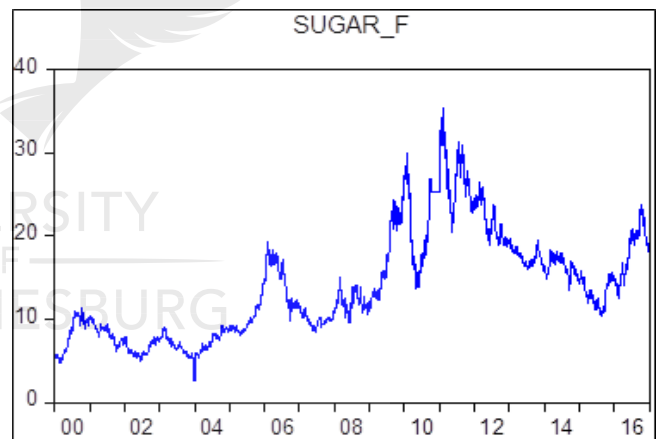
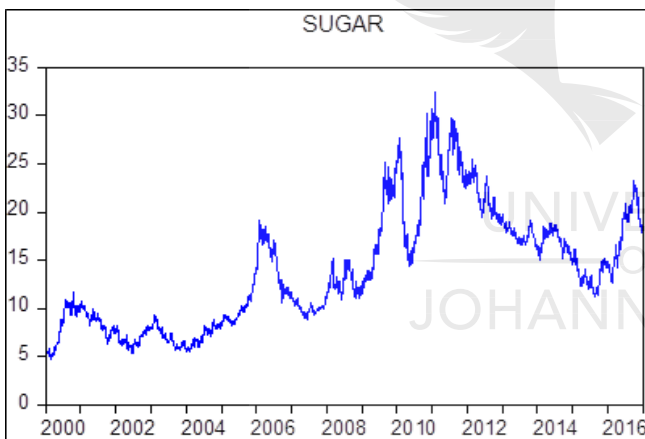
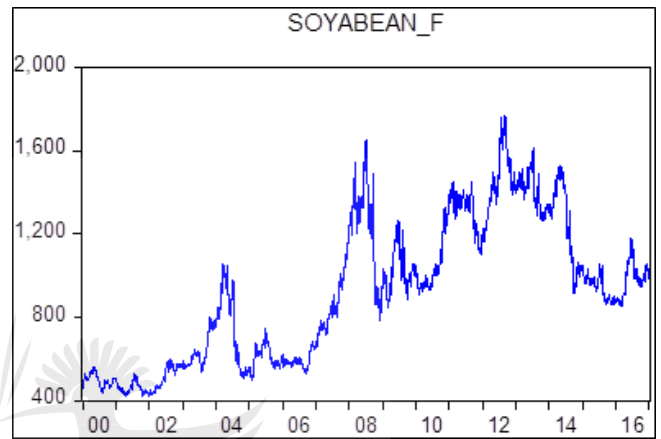
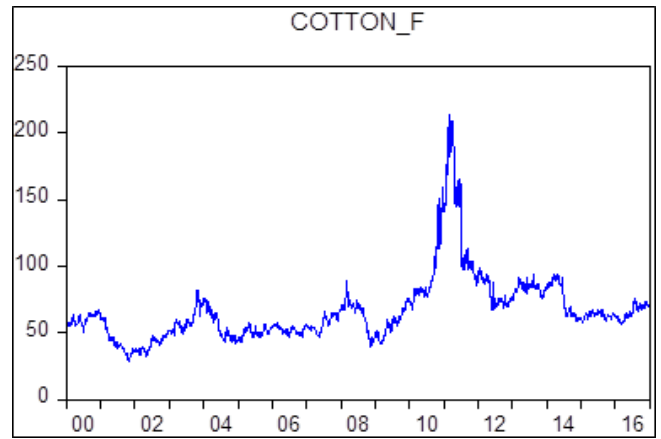
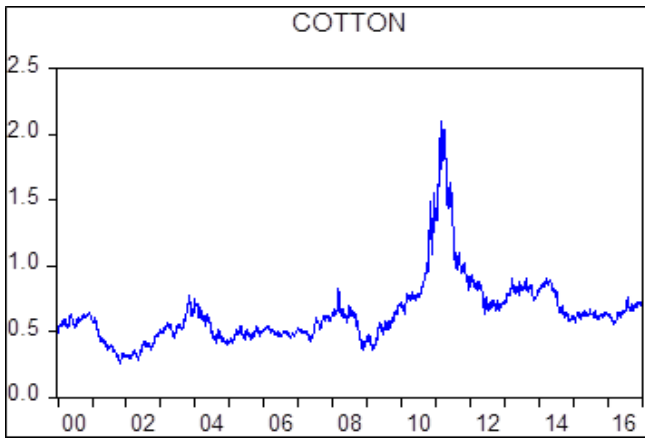
An asterisk (*) indicates that the null hypothesis of a unit root is rejected (at a 1% significance level).

Source: Thomson Reuters DataStream and EViews.

The unit root tests indicate that all the variables are stationary at first difference at a 1% significance level, therefore we conclude that the variables are integrated of order one. The Johansen cointegration test is appropriate to use since all variables have the same order of integration. It is also appropriate to use the logged data within the VAR model as well as for further analysis that is required after the VAR model.

The graphical illustrations of the variables start off the initial evaluation of the data in Figures 5.1 and 5.2, which shows the movements between the spot and future variables, from the daily price on the line graph as well as on the log differenced graphs illustrating the volatility present. The period of the data is from 2000 to 2016, which includes the global financial crisis that occurred. In the graphs below, the line graphs which display the variables included in the study show that the data seems to be trended. The log differenced graphs show signs of volatility clustering throughout the data period.





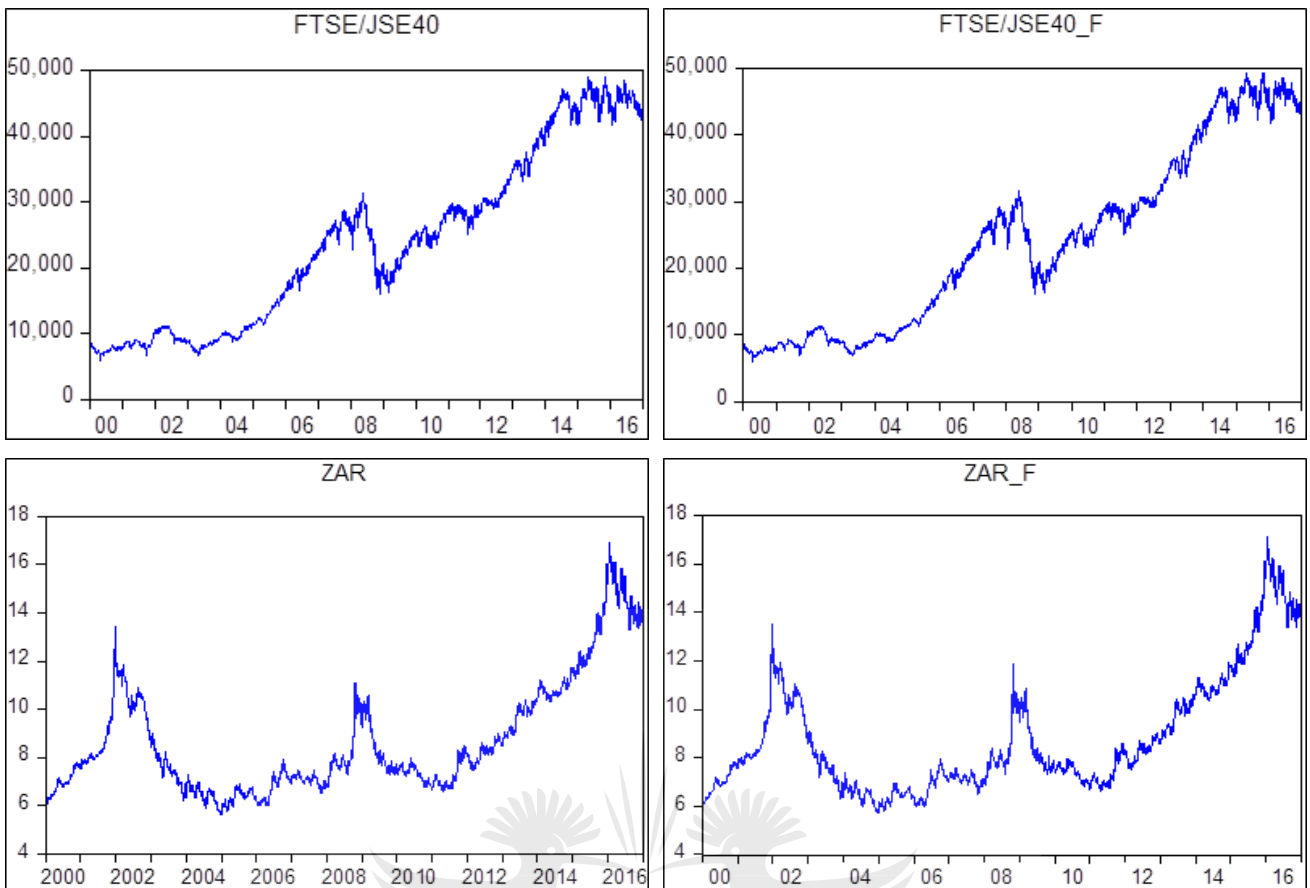
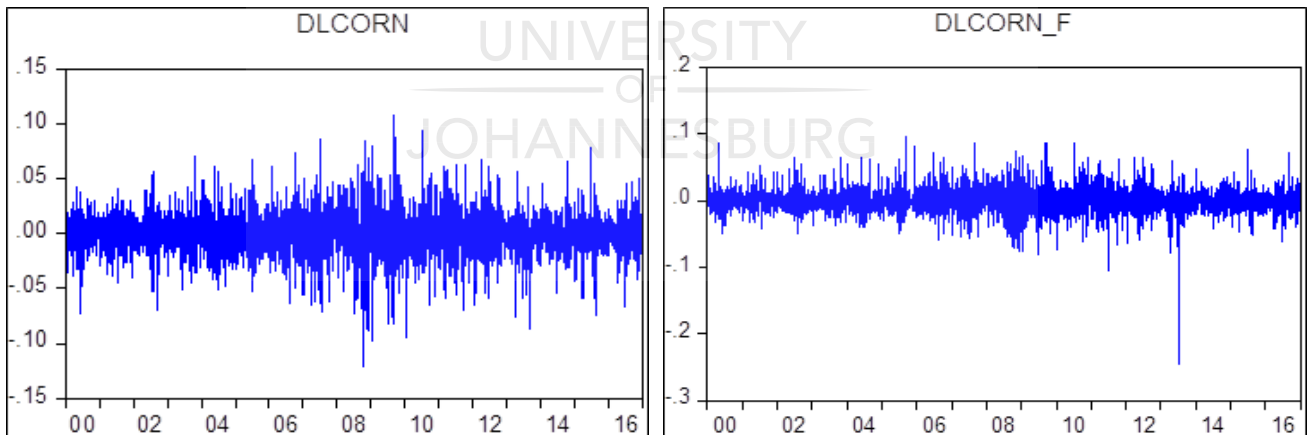
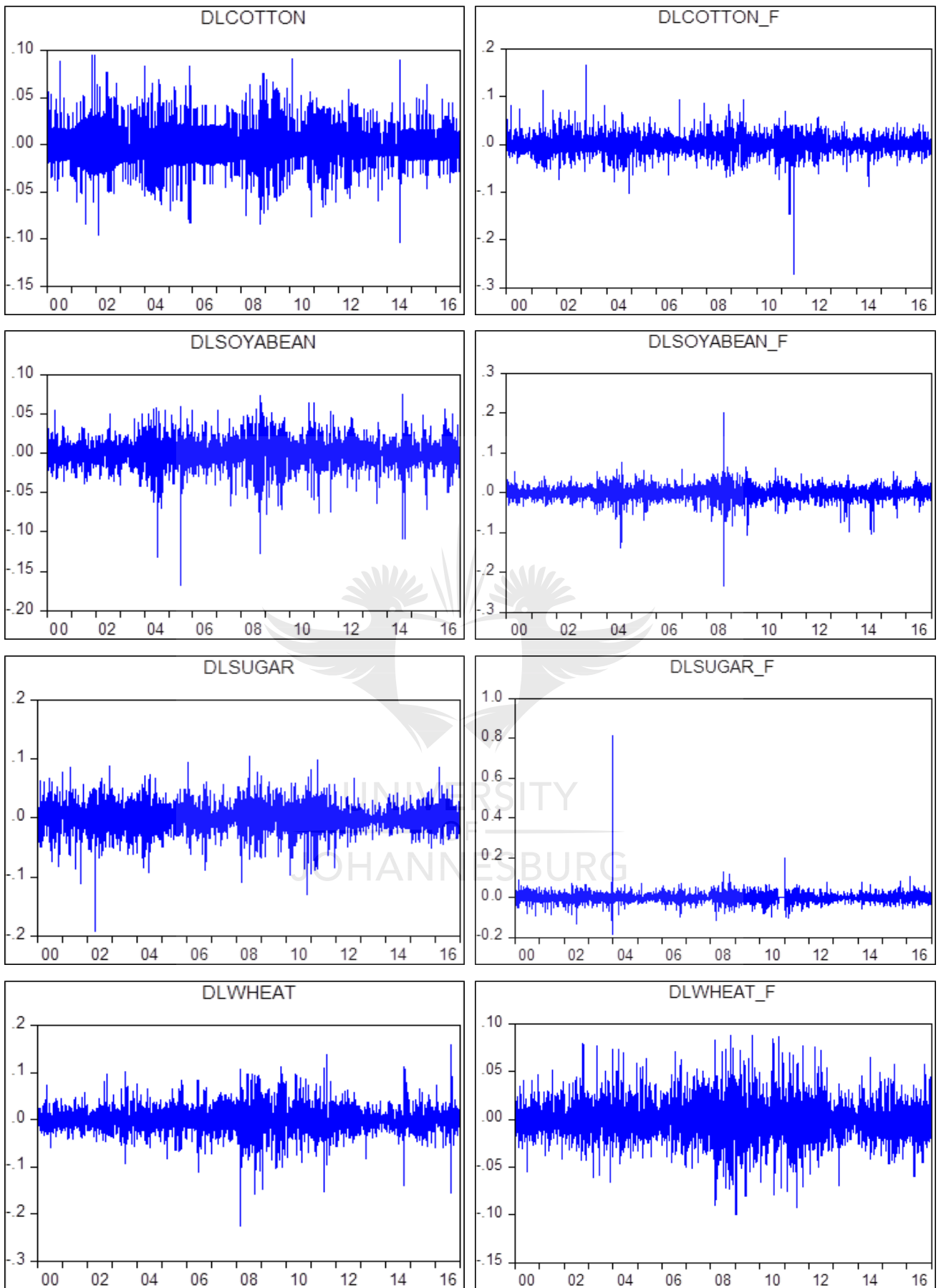


Figure 5.1: Price movement in the seven datasets

Source: Thomson Reuters DataStream and EViews.





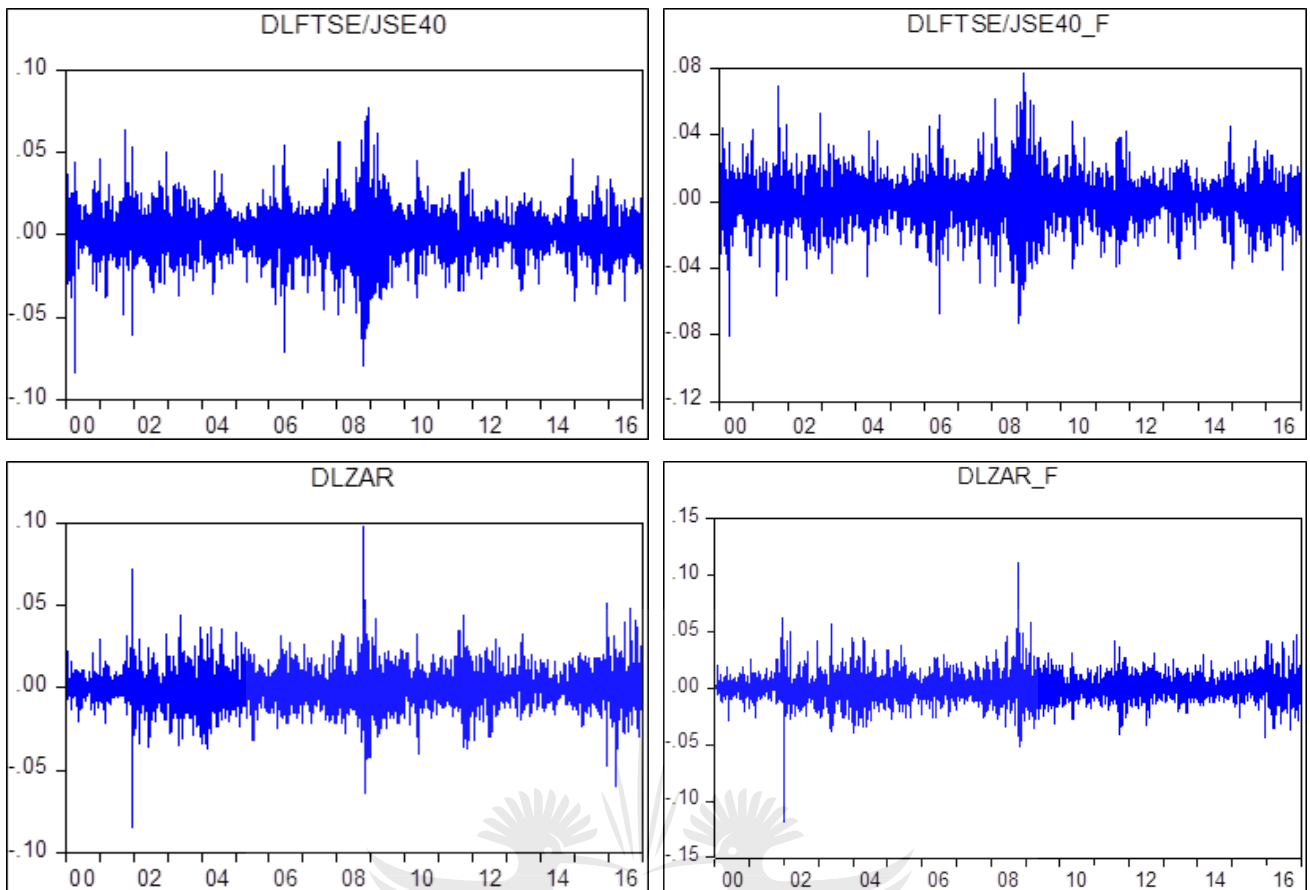
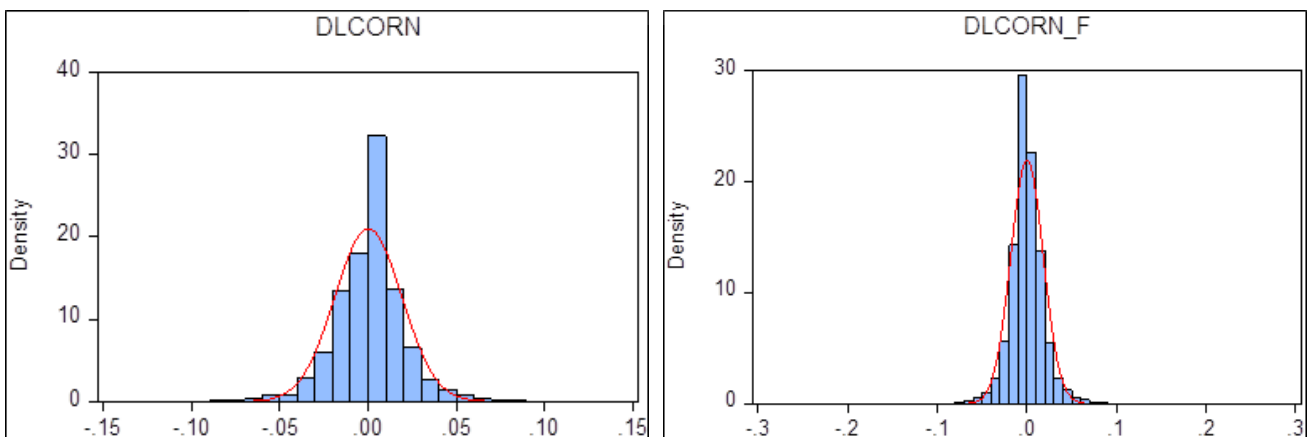
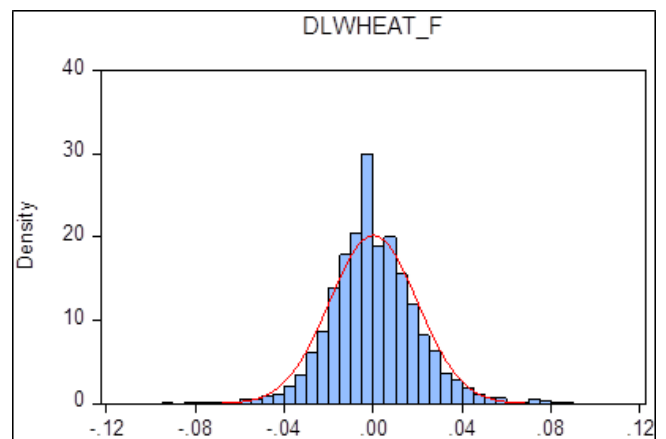
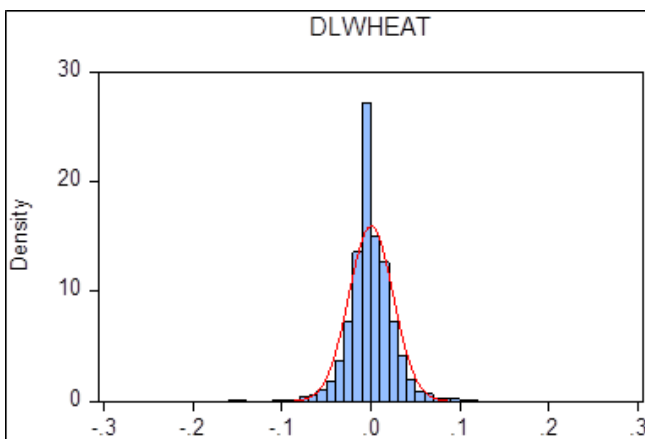
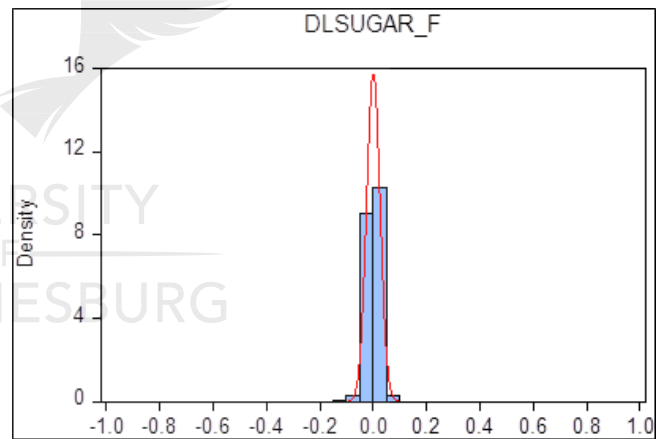
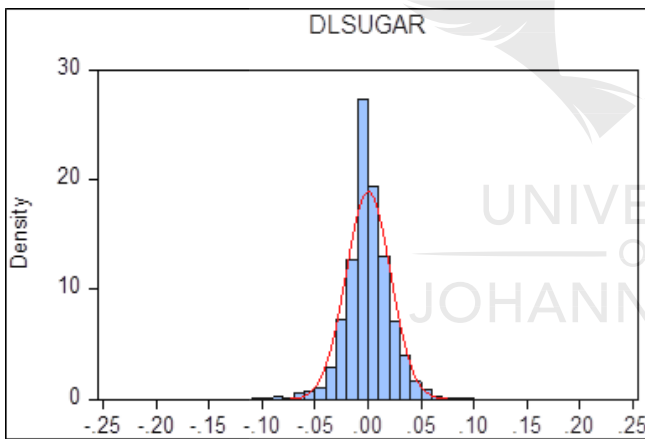
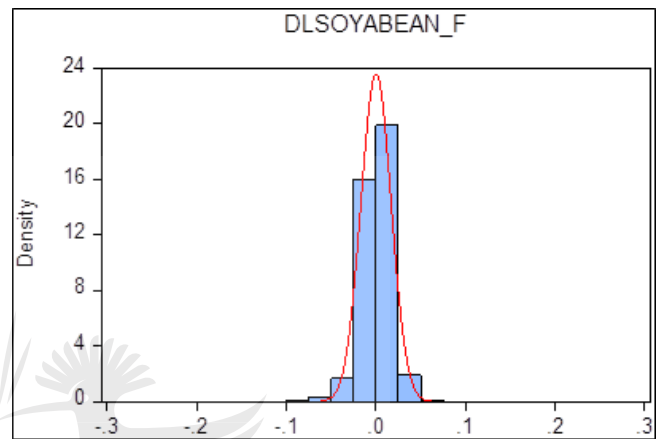
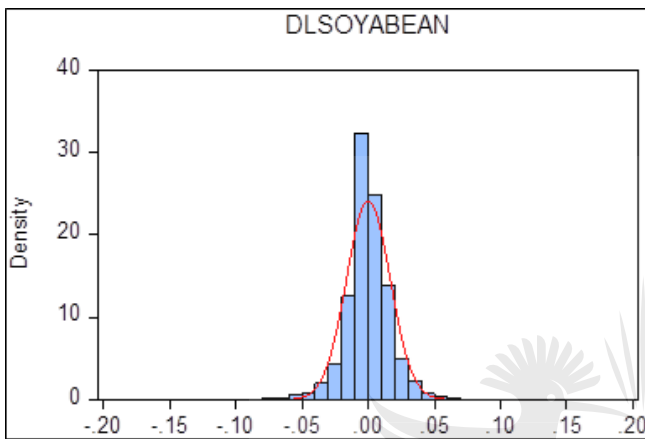
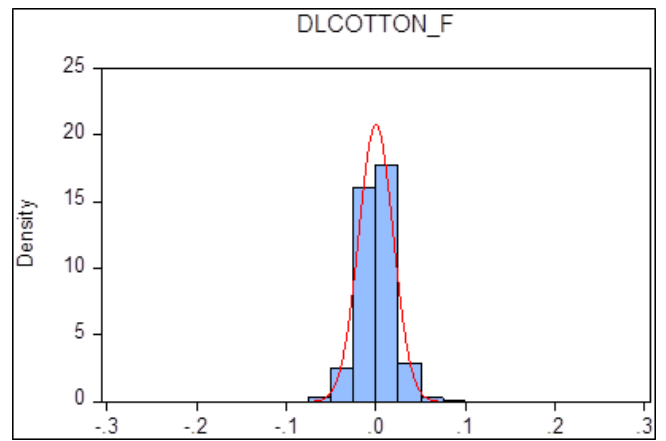
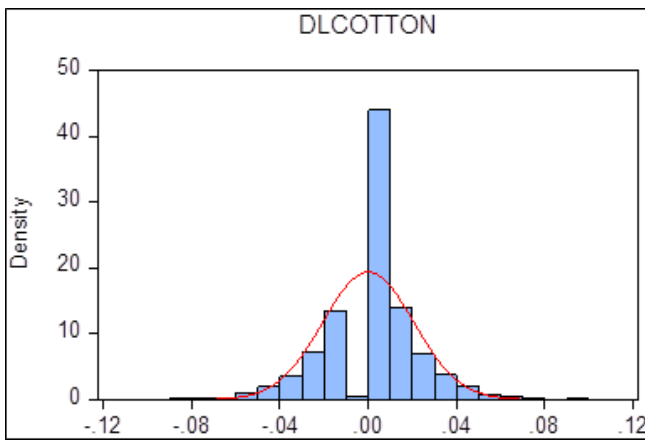


Figure 5.2: Volatility movement in the seven datasets

Source: Thomson Reuters DataStream and EViews.

The histograms graphically illustrate the distribution of the data as well as the skewness and kurtosis of the data as shown in Figure 5.3. When comparing the histograms against the normal distribution, the log returns (i.e. first differencing) of the data are not normally distributed. The data also shows signs of leptokurtosis, which is excess kurtosis.





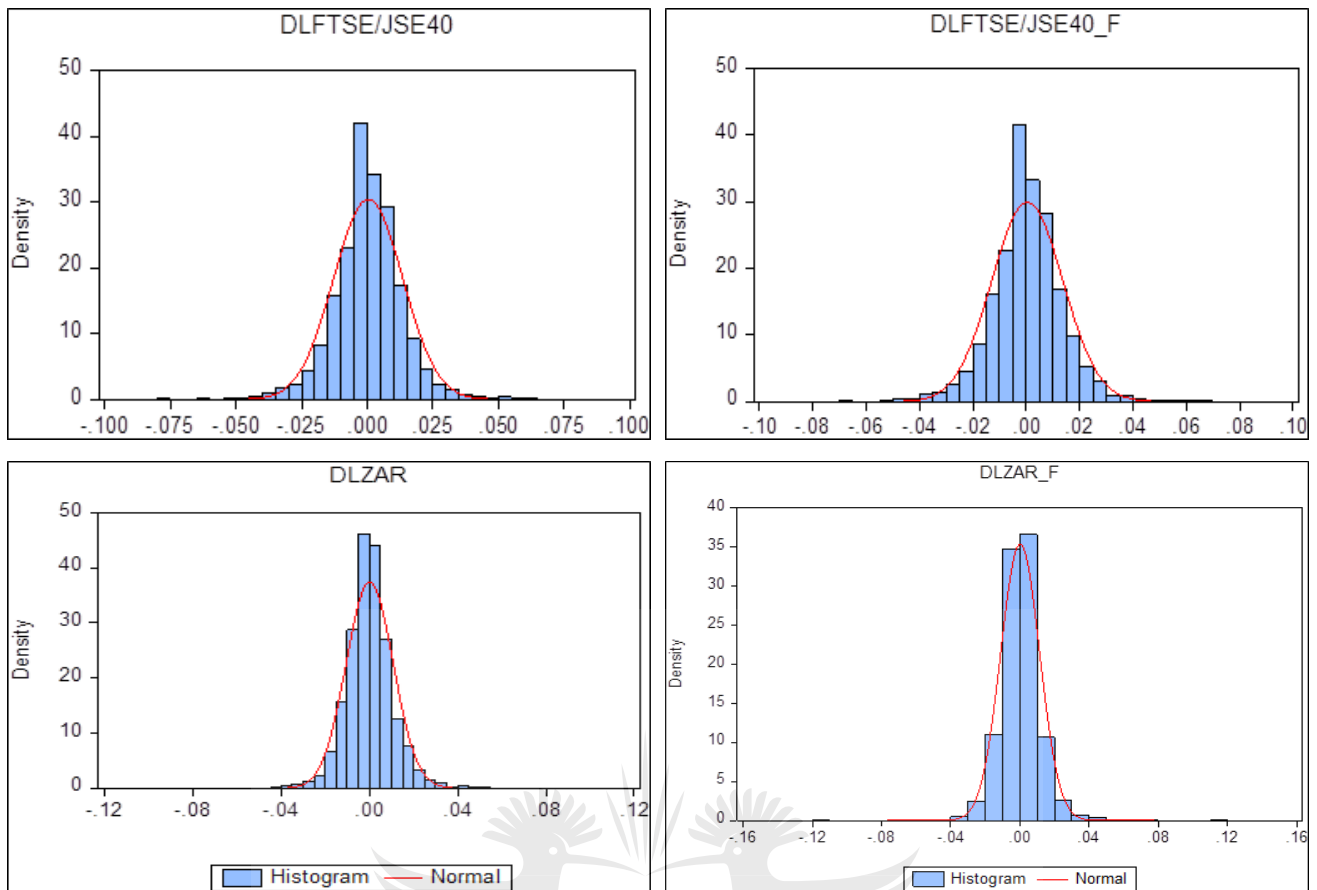


Figure 5.3: Histograms of the log returns of the seven datasets

Source: Thomson Reuters DataStream and EViews.

Table 5.2 shows the descriptive statistics of the seven variables. A total of 3846 observations are included for all seven variables, spot and future, before and after the crisis. The descriptive statistics confirm that the log returns of the variables included are not normally distributed and are leptokurtic as seen on the histograms. In addition, the skewness indicates that most of the variables are slightly negatively skewed. The table also includes the synchronicity or co-movement of the variables with the ZAR and the FTSE/JSE Top 40 Index on a spot and future basis. Synchronicity in Table 5.2 is based on the R^2 of two variables adjusted as per the methodology $(= \log(R^2/(1- R^2)))$ from Morck *et al.* (2000). The higher the value of the synchronicity results, the more synchronised or co-movement exists between the variables. The spot variables indicate that corn has the highest synchronicity with ZAR, whereas sugar has the highest synchronicity with the FTSE/JSE Top 40 Index. Wheat future shows the highest synchronicity with ZAR future and sugar remains the highest for the future combination with the FTSE/JSE Top 40 Index.

Table 5.2: Descriptive statistics

| Before crisis spot | DLCORN | DLCOTTON | DLFTSE_JSE 40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
|---|--------------|----------------|--------------------|------------------|---------------|---------------|-------------|
| Mean | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.074 | 0.095 | 0.064 | 0.060 | 0.095 | 0.101 | 0.072 |
| Minimum | -0.074 | -0.095 | -0.084 | -0.167 | -0.193 | -0.113 | -0.085 |
| Std. Dev. | 0.017 | 0.021 | 0.012 | 0.016 | 0.023 | 0.021 | 0.010 |
| Skewness | 0.023 | 0.119 | -0.214 | -0.959 | -0.390 | 0.109 | 0.097 |
| Kurtosis | 4.509 | 4.781 | 6.303 | 13.194 | 7.045 | 5.484 | 8.201 |
| Jarque-Bera | 185.465 | 262.905 | 902.985 | 8759.439 | 1381.539 | 506.388 | 2205.554 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.538 | 0.134 | 1.186 | 0.591 | 0.436 | 0.854 | 0.142 |
| Sum Sq. Dev. | 0.558 | 0.871 | 0.303 | 0.484 | 0.990 | 0.833 | 0.204 |
| Observations | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 |
| After crisis spot | DLCORN | DLCOTTON | DLFTSE_JSE 40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.095 | 0.091 | 0.047 | 0.076 | 0.098 | 0.158 | 0.052 |
| Minimum | -0.095 | -0.104 | -0.040 | -0.109 | -0.130 | -0.156 | -0.060 |
| Std. Dev. | 0.018 | 0.018 | 0.011 | 0.015 | 0.019 | 0.024 | 0.010 |
| Skewness | -0.048 | -0.065 | -0.142 | -0.566 | -0.405 | 0.224 | 0.191 |
| Kurtosis | 5.774 | 4.837 | 4.409 | 8.737 | 7.279 | 8.791 | 5.891 |
| Jarque-Bera | 607.226 | 267.245 | 162.920 | 2696.232 | 1494.829 | 2659.615 | 670.581 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.030 | 0.185 | 0.678 | 0.066 | -0.254 | 0.422 | 0.590 |
| Sum Sq. Dev. | 0.610 | 0.634 | 0.210 | 0.411 | 0.693 | 1.106 | 0.184 |
| Observations | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 |
| Synchronicity with ZAR - full period | -9.026 | -8.760 | -3.533 | -7.624 | -5.503 | -5.852 | N/A |
| Synchronicity with FTSE/JSE40 - full period | -5.413 | -8.574 | N/A | -5.301 | -14.205 | -6.306 | -3.533 |
| Before crisis future | DLCORN_ F | DLCOTTON_ F | DLFTSE_JSE 40_F | DLSOYABEAN_ F | DLSUGAR_ F | DLWHEAT_ F | DLZAR_ F |
| Mean | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.098 | 0.167 | 0.070 | 0.076 | 0.816 | 0.079 | 0.063 |
| Minimum | -0.060 | -0.103 | -0.081 | -0.138 | -0.186 | -0.066 | -0.119 |
| Std. Dev. | 0.016 | 0.019 | 0.013 | 0.015 | 0.029 | 0.017 | 0.011 |
| Skewness | 0.644 | 0.600 | -0.139 | -0.822 | 11.334 | 0.426 | -0.117 |
| Kurtosis | 6.070 | 8.865 | 5.604 | 10.433 | 337.449 | 4.419 | 12.415 |
| Jarque-Bera | 902.354 | 2918.338 | 558.316 | 4718.036 | 9148777.000 | 223.008 | 7221.459 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.496 | 0.136 | 1.167 | 0.622 | 0.397 | 0.855 | 0.152 |
| Sum Sq. Dev. | 0.500 | 0.696 | 0.322 | 0.461 | 1.610 | 0.571 | 0.238 |
| Observations | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 |
| After crisis future | DLCORN_ F | DLCOTTON_ F | DLFTSE_JSE 40_F | DLSOYABEAN_ F | DLSUGAR_ F | DLWHEAT_ F | DLZAR_ F |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.086 | 0.070 | 0.049 | 0.064 | 0.203 | 0.087 | 0.048 |
| Minimum | -0.245 | -0.271 | -0.041 | -0.105 | -0.105 | -0.092 | -0.044 |
| Std. Dev. | 0.018 | 0.018 | 0.011 | 0.014 | 0.021 | 0.019 | 0.010 |
| Skewness | -1.252 | -2.068 | -0.102 | -0.905 | 0.441 | 0.180 | 0.236 |
| Kurtosis | 21.983 | 30.473 | 4.422 | 9.067 | 9.946 | 4.818 | 4.807 |
| Jarque-Bera | 28901.940 | 60847.140 | 162.658 | 3159.449 | 3864.978 | 270.678 | 275.121 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 0.023 | 0.141 | 0.676 | 0.072 | -0.212 | -0.115 | 0.604 |
| Sum Sq. Dev. | 0.629 | 0.640 | 0.221 | 0.396 | 0.807 | 0.714 | 0.183 |
| Observations | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 |
| Synchronicity with ZAR_F - full period | -10.392 | -6.711 | -4.101 | -10.233 | -6.083 | -14.046 | N/A |
| Synchronicity with FTSE/JSE40_F - full period | -4.852 | -6.165 | N/A | -5.519 | -9.209 | -5.782 | -4.101 |

Source: Thomson Reuters DataStream and EViews.

The correlation results based on the log returns (first differencing) of the data displayed in Table 5.3 are used to determine the initial relationships present between the variables.

Table 5.3: Correlation matrix

| Spot before crisis | DLCORN | DLCOTTON | DLFTSE_JSE40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
|----------------------|--------------|----------|--------------|------------|---------|--------------|--------|
| DLCORN | 1.000 | 0.107 | 0.067 | 0.489 | 0.008 | 0.452 | -0.011 |
| DLCOTTON | 0.107 | 1.000 | 0.014 | 0.138 | 0.056 | 0.084 | -0.013 |
| DLFTSE_JSE40 | 0.067 | 0.014 | 1.000 | 0.070 | 0.001 | 0.043 | 0.169 |
| DLSOYABEAN | 0.489 | 0.138 | 0.070 | 1.000 | 0.045 | 0.305 | -0.022 |
| DLSUGAR | 0.008 | 0.056 | 0.001 | 0.045 | 1.000 | 0.066 | -0.064 |
| DLWHEAT | 0.452 | 0.084 | 0.043 | 0.305 | 0.066 | 1.000 | -0.054 |
| DLZAR | -0.011 | -0.013 | 0.169 | -0.022 | -0.064 | -0.054 | 1.000 |
| Spot after crisis | DLCORN | DLCOTTON | DLFTSE_JSE40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
| DLCORN | 1.000 | 0.190 | 0.092 | 0.518 | 0.148 | 0.539 | -0.127 |
| DLCOTTON | 0.190 | 1.000 | 0.156 | 0.180 | 0.127 | 0.159 | -0.188 |
| DLFTSE_JSE40 | 0.092 | 0.156 | 1.000 | 0.150 | 0.115 | 0.096 | -0.283 |
| DLSOYABEAN | 0.518 | 0.180 | 0.150 | 1.000 | 0.141 | 0.340 | -0.174 |
| DLSUGAR | 0.148 | 0.127 | 0.115 | 0.141 | 1.000 | 0.099 | -0.122 |
| DLWHEAT | 0.539 | 0.159 | 0.096 | 0.340 | 0.099 | 1.000 | -0.132 |
| DLZAR | -0.127 | -0.188 | -0.283 | -0.174 | -0.122 | -0.132 | 1.000 |
| Future before crisis | DLCORN | DLCOTTON | DLFTSE_JSE40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
| DLCORN_F | 1.000 | 0.166 | 0.088 | 0.497 | 0.058 | 0.530 | 0.006 |
| DLCOTTON_F | 0.166 | 1.000 | 0.046 | 0.157 | 0.065 | 0.123 | -0.035 |
| DLFTSE_JSE40_F | 0.088 | 0.046 | 1.000 | 0.063 | 0.010 | 0.055 | 0.128 |
| DLSOYABEAN_F | 0.497 | 0.157 | 0.063 | 1.000 | 0.065 | 0.347 | -0.006 |
| DLSUGAR_F | 0.058 | 0.065 | 0.010 | 0.065 | 1.000 | 0.054 | -0.048 |
| DLWHEAT_F | 0.530 | 0.123 | 0.055 | 0.347 | 0.054 | 1.000 | 0.001 |
| DLZAR_F | 0.006 | -0.035 | 0.128 | -0.006 | -0.048 | 0.001 | 1.000 |
| Future after crisis | DLCORN | DLCOTTON | DLFTSE_JSE40 | DLSOYABEAN | DLSUGAR | DLWHEAT | DLZAR |
| DLCORN_F | 1.000 | 0.166 | 0.084 | 0.490 | 0.129 | 0.643 | -0.130 |
| DLCOTTON_F | 0.166 | 1.000 | 0.149 | 0.166 | 0.175 | 0.163 | -0.175 |
| DLFTSE_JSE40_F | 0.084 | 0.149 | 1.000 | 0.157 | 0.120 | 0.082 | -0.196 |
| DLSOYABEAN_F | 0.490 | 0.166 | 0.157 | 1.000 | 0.114 | 0.409 | -0.183 |
| DLSUGAR_F | 0.129 | 0.175 | 0.120 | 0.114 | 1.000 | 0.143 | -0.155 |
| DLWHEAT_F | 0.643 | 0.163 | 0.082 | 0.409 | 0.143 | 1.000 | -0.148 |
| DLZAR_F | -0.130 | -0.175 | -0.196 | -0.183 | -0.155 | -0.148 | 1.000 |

Source: Thomson Reuters DataStream and EViews.

The correlation matrix in Table 5.3 shows that there is a strong positive correlation (0.55 and above) between the following dataset combinations:

- Corn and wheat (after the crisis for future only).

No agricultural commodity shows a strong positive or negative correlation with the FTSE/JSE Top 40 Index or the ZAR. The conclusion from Baur and Lucey (2010) applies in this context as most of the relationships showed a low or negative correlation. Baur and Lucey (2010) state that an asset can be utilised as a hedging asset if the correlation between the hedging asset and asset to be hedged is low or negative.

5.5.2. Granger causality

The Pairwise Granger causality tests and the Toda Yamamoto test indicate which variables cause another variable. If one variable is found to Granger cause another variable, then the past value of the variable that is Granger causing another variable should be able to assist in predicting the future values of the variable being Granger caused. The causality tests are only run once the VAR results are obtained; however, it will be displayed before the VAR results as the causality test is applied to all fourteen variables included in this study.

The full Pairwise Granger causality test results and Toda Yamamoto test results for all seven variables before and after the crisis as well as both spot and future are included in Appendix B.1. These apply to the next section of analysis, which includes only six variables, as well as the last section of analysis that includes all seven variables. The Pairwise Granger causality test is applied to the log differenced data as all variables were found to be of order 1, $I(1)$. The Toda Yamamoto test is applied to the logged data.

Appendix B.1 indicates that the following datasets have a feedback or bilateral causal relationship at a 10% level of significance:

- Cotton and corn: spot before crisis for Toda Yamamoto test only
- Soyabean and corn: spot after crisis for both tests
- Sugar and soyabean: spot after crisis for both tests
- Wheat and soyabean: spot after crisis for Toda Yamamoto test only, future before crisis for both tests
- ZAR and cotton: future before crisis for Toda Yamamoto test only
- ZAR and sugar: future before crisis for Toda Yamamoto test only

The following datasets have a unidirectional causal relationship at a 10% level of significance:

- From corn to cotton: spot after crisis for Toda Yamamoto test only, future after crisis for both tests
- From corn to sugar: spot after crisis for both tests, future before crisis for both tests
- From corn to wheat: spot after crisis for both tests
- From corn to FTSE/JSE Top 40 Index: spot after crisis for both tests, future after crisis for both tests
- From corn to ZAR: spot before crisis for Toda Yamamoto test only,
- From cotton to soyabean: spot before crisis for both tests, spot after crisis for both tests, future before crisis for both tests
- From cotton to sugar: spot after crisis for both tests
- From cotton to wheat: spot after crisis for both tests
- From cotton to ZAR: spot before crisis for both tests
- From soyabean to corn: spot before crisis for both tests, future before crisis for both tests
- From soyabean to FTSE/JSE Top 40 Index: spot after crisis for both tests
- From sugar to corn: spot before crisis for both tests, future after crisis for Toda Yamamoto test only
- From sugar to cotton: future before crisis for Pairwise Granger causality test only, future after crisis for both tests
- From sugar to soyabean: future after crisis for Toda Yamamoto test only
- From sugar to wheat: future after crisis for Toda Yamamoto test only
- From wheat to corn: future before crisis for Pairwise Granger causality test only
- From wheat to cotton: future after crisis for both tests
- From wheat to soyabean: spot before crisis for Pairwise Granger causality test only
- From wheat to sugar: future before crisis for both tests
- From wheat to FTSE/JSE Top 40 Index: future after crisis for both tests
- From ZAR to sugar: spot before crisis for both tests, future before crisis for Pairwise Granger causality test only

- From ZAR to FTSE/JSE Top 40 Index: spot after crisis for both tests, future after crisis for both tests.

The unidirectional relationships between the commodities are expected as the commodities fall within the same commodity category and spill-over between the commodities is in line with expectations. The unidirectional relationship from the ZAR to the FTSE/JSE Top 40 Index was also observed in the previous chapter.

A summary of the number of variables that each variable causes as well as the number that a variable is caused by the other variables respectively is listed below:

- Corn:
 - Spot before crisis: 2 (Toda Yamamoto test) and 3 (2 Toda Yamamoto test and 1 both tests)
 - Spot after crisis: 5 (1 Toda Yamamoto test and 4 both tests) and 1 (both tests)
 - Future before crisis: 1 (both tests) and 2 (1 Pairwise Granger causality test and 1 both tests)
 - Future after crisis: 2 (both tests) and 1 (Toda Yamamoto test)
- Cotton:
 - Spot before crisis: 3 (2 Toda Yamamoto test and 1 both tests) and 1 (Toda Yamamoto test)
 - Spot after crisis: 3 (both tests) and 1 (Toda Yamamoto test)
 - Future before crisis: 2 (1 Toda Yamamoto test and 1 both tests) and 2 (1 Pairwise Granger causality test and 1 Toda Yamamoto test)
 - Future after crisis: 0 and 3 (both tests)
- Soyabean:
 - Spot before crisis: 1 (both tests) and 1 (both tests)
 - Spot after crisis: 4 (1 Toda Yamamoto test and 3 both tests) and 4 (both tests)
 - Future before crisis: 2 (both tests) and 2 (both tests)
 - Future after crisis: 0 and 1 (Toda Yamamoto test)
- Sugar:
 - Spot before crisis: 1 (both tests) and 1 (both tests)
 - Spot after crisis: 1 (both tests) and 3 (both tests)
 - Future before crisis: 2 (1 Pairwise Granger causality test and 1 Toda Yamamoto test) and 3 (both tests)
 - Future after crisis: 4 (3 Toda Yamamoto test and 1 both tests) and 0

- Wheat:
 - Spot before crisis: 0 and 0
 - Spot after crisis: 1 (both tests) and 3 (1 Toda Yamamoto test and 2 both tests)
 - Future before crisis: 3 (1 Pairwise Granger causality test and 2 both tests) and 1 (both tests)
 - Future after crisis: 2 (both tests) and 1 (Toda Yamamoto test)
- FTSE/JSE Top 40 Index:
 - Spot before crisis: 0 and 0
 - Spot after crisis: 0 and 3 (both tests)
 - Future before crisis: 0 and 0
 - Future after crisis: 0 and 3 (both tests)
- ZAR:
 - Spot before crisis: 1 (both tests) and 2 (1 Toda Yamamoto test and 1 both tests)
 - Spot after crisis: 1 (both tests) and 0
 - Future before crisis: 2 (1 Toda Yamamoto test and 1 both tests) and 2 (Toda Yamamoto test)
 - Future after crisis: 1 (both tests) and 0

Therefore, corn causes the most variables to change and soyabean, sugar, cotton and corn are caused to move the most by the other variables. A possible reason why corn (also known as maize) causes the most variables to change is that it is produced on a larger scale than any of the other agricultural commodities included in this study (United States Department of Agriculture, 2015).

The remaining datasets do not have statistically significant causal relationships, which implies independence.

The results for the relationship between the FTSE/JSE Top 40 Index and the five commodities before and after the crisis as well as both spot and future will be shown and discussed in the next section, followed by the results for the relationship between the FTSE/JSE Top 40 Index and the five commodities against the ZAR in the last section of results before and after the crisis as well as both spot and future.

5.5.3. VAR results between commodities and the FTSE/JSE Top 40 Index

The long run relationship and the short run dynamics analysis start with the VAR model, which requires the optimal lag length to be determined and the output is shown in Table 5.4. The VAR analyses for all four data sets are included in Appendix B.2.

Table 5.4 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model is estimated using two lags and results in 14 significant relationships in the VAR results. Spot after crisis is two lags, and 15 significant relationships exist. Future before crisis is two lags and 17 significant relationships exist. Future after crisis is one lag and 10 significant relationships exist.

Table 5.4: VAR lag order selection criteria of the FTSE/JSE Top 40 Index and the five commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|-----------------------------|-----|-----------|-----------|--------|----------|----------|----------|
| Spot before crisis | 2 | 31073.440 | 105.000* | 0.000* | -31.839* | -31.616 | -31.757 |
| Spot after crisis | 2 | 31022.310 | 71.585 | 0.000* | -32.711* | -32.482 | -32.627 |
| Future before crisis | 2 | 31394.610 | 82.730 | 0.000* | -32.169* | -31.946 | -32.087 |
| Future after crisis | 1 | 31358.290 | 52974.090 | 0.000* | -33.104* | -32.981* | -33.059* |

* 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: Thomson Reuters DataStream and EViews.

The estimated VAR that is obtained in the analysis will be stable, otherwise known as stationary, if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 5.4, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

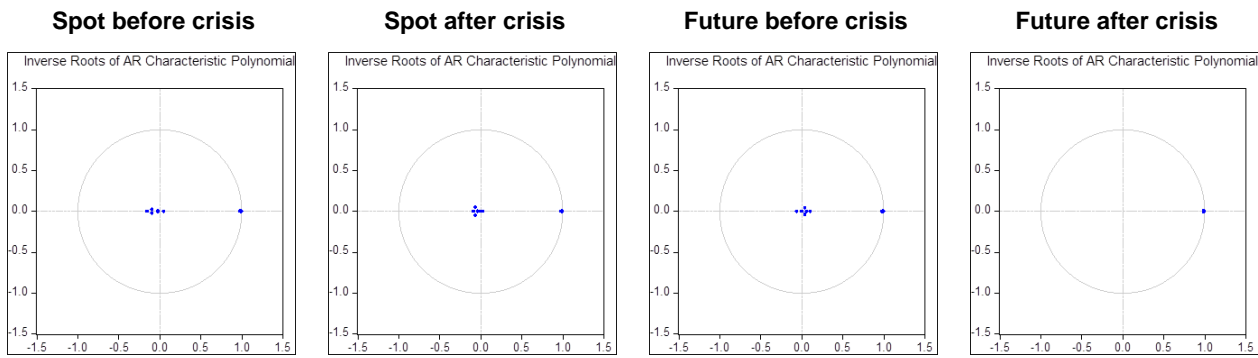


Figure 5.4: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

5.5.4. Long run relationship between commodities against the FTSE/JSE Top 40 Index

The investigation of the relationships between the datasets leads to the determination of whether the six variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done in order to identify which relationships are present between the variables by means of the Johansen cointegration test. The long run relationship analysis was followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required to determine whether an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables both showing a common stochastic drift. A stochastic drift is the change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once (Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

The cointegration test in Table 5.5 shows there is a cointegrating relationship when the data is not linear, testing no intercept and no trend as well as when the data is linear, testing intercept and trend and lastly, when the data is quadratic, testing intercept and trend.

Table 5.5: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Spot before crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Spot after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Spot after crisis: Max-Eig | 1 | 0 | 0 | 0 | 0 |
| Future before crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future before crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Max-Eig | 0 | 0 | 0 | 1 | 1 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred as all the variables have trends that are stochastic. The Johansen cointegration test indicates that there are no cointegrating relationships. The results indicate the variables are not cointegrated and therefore no VECM results were included.

5.5.5. Short run dynamics between commodities against the FTSE/JSE Top 40 Index

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities and the FTSE/JSE Top 40 Index are displayed in Table 5.6.

Table 5.6: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|--------------------|--------------------|----------|--------|----|-------|
| Spot before crisis | DLFTSE_JSE40 | All | 3.006 | 10 | 0.981 |
| Spot before crisis | DLCORN | All | 13.697 | 10 | 0.187 |
| Spot before crisis | DLCOTTON | All | 6.029 | 10 | 0.813 |
| Spot before crisis | DLSOYABEAN | All | 11.712 | 10 | 0.305 |
| Spot before crisis | DLSUGAR | All | 7.388 | 10 | 0.688 |
| Spot before crisis | DLWHEAT | All | 11.716 | 10 | 0.305 |

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|--------|----|--------|
| Spot after crisis | DLFTSE_JSE40 | All | 13.261 | 10 | 0.210 |
| Spot after crisis | DLCORN | All | 9.690 | 10 | 0.468 |
| Spot after crisis | DLCOTTON | All | 7.474 | 10 | 0.680 |
| Spot after crisis | DLSOYABEAN | All | 20.569 | 10 | 0.024* |
| Spot after crisis | DLSUGAR | All | 21.138 | 10 | 0.020* |
| Spot after crisis | DLWHEAT | All | 15.826 | 10 | 0.105 |
| Future before crisis | DLFTSE_JSE40_F | All | 4.646 | 10 | 0.914 |
| Future before crisis | DLCORN_F | All | 14.910 | 10 | 0.135 |
| Future before crisis | DLCOTTON_F | All | 13.299 | 10 | 0.207 |
| Future before crisis | DLSOYABEAN_F | All | 21.509 | 10 | 0.018* |
| Future before crisis | DLSUGAR_F | All | 21.442 | 10 | 0.018* |
| Future before crisis | DLWHEAT_F | All | 14.059 | 10 | 0.170 |
| Future after crisis | DLFTSE_JSE40_F | All | 11.509 | 5 | 0.042* |
| Future after crisis | DLCORN_F | All | 6.885 | 5 | 0.229 |
| Future after crisis | DLCOTTON_F | All | 16.712 | 5 | 0.005* |
| Future after crisis | DLSOYABEAN_F | All | 6.972 | 5 | 0.223 |
| Future after crisis | DLSUGAR_F | All | 9.346 | 5 | 0.096 |
| Future after crisis | DLWHEAT_F | All | 3.784 | 5 | 0.581 |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: None
- Spot after crisis: Soyabean and sugar
- Future before crisis: Soyabean and sugar
- Future after crisis: FTSE/JSE Top 40 Index and cotton

The null hypothesis can be rejected for the remainder of the variables. The variables ranked from the most exogenous to the most endogenous are indicated by Chi-square value. A higher Chi-square value indicates that the variable is more exogenous.

Appendix B.3 shows the response of the FTSE/JSE Top 40 Index when one of the other variables experiences a shock. The impulse response when five periods on a daily basis are included indicates whether the FTSE/JSE Top 40 Index increases or decreases and whether this effect is likely to be permanent. As shown by the impulse response, a rapid increase in a commodity price will cause an initial increase in the FTSE/JSE Top 40 Index. Thereafter it seems to decrease slowly to equilibrium. On average, the move back to the equilibrium is between two and three days for the FTSE/JSE Top 40 Index.

The variance decomposition of the six variables is displayed in Appendix B.3 to indicate that the percentage value of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the dependent variable being the FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals. The variance decomposition of the FTSE/JSE Top 40 Index illustrates that at period 1, most of the movement is explained by its own variance. Cotton explains the second highest amount of the movement for spot after the crisis at above 2%.

The results for the relationship between the ZAR and the FTSE/JSE Top 40 Index and five commodities before and after the crisis as well as both spot and future are shown below in the remainder of the section.

5.5.6. VAR results between commodities, FTSE/JSE Top 40 Index and ZAR

The long run relationship and short run dynamics analysis for the relationship between the commodities and the FTSE/JSE Top 40 Index against the ZAR begins with the VAR model, which requires the optimal lag length to be determined, and the output is shown in Table 5.7. The VAR analyses for all four datasets are included in Appendix B.4.

Table 5.7: VAR lag order selection criteria of the ZAR, FTSE/JSE Top 40 Index and the five commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|-----------------------------|-----|-----------|-----------|--------|----------|----------|----------|
| Spot before crisis | 2 | 37294.440 | 128.205 | 0.000* | -38.202* | -37.901 | -38.091 |
| Spot after crisis | 1 | 37175.020 | 61013.660 | 0.000* | -39.238* | -39.074* | -39.177* |
| Future before crisis | 2 | 37447.360 | 106.222 | 0.000* | -38.359* | -38.058 | -38.248 |
| Future after crisis | 1 | 37379.450 | 60422.810 | 0.000* | -39.621* | -39.457* | -39.561* |

* 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: Thomson Reuters DataStream and EViews.

Table 5.7 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model is estimated using two lags and results in 17 significant relationships in the VAR results. Spot after crisis is three lags, and 17 significant

relationships exist. Future before crisis is two lags and 21 significant relationships exist. Future after crisis is two lags and 16 significant relationships exist.

The estimated VAR that is obtained in the analysis will be stable or stationary if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 5.5, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

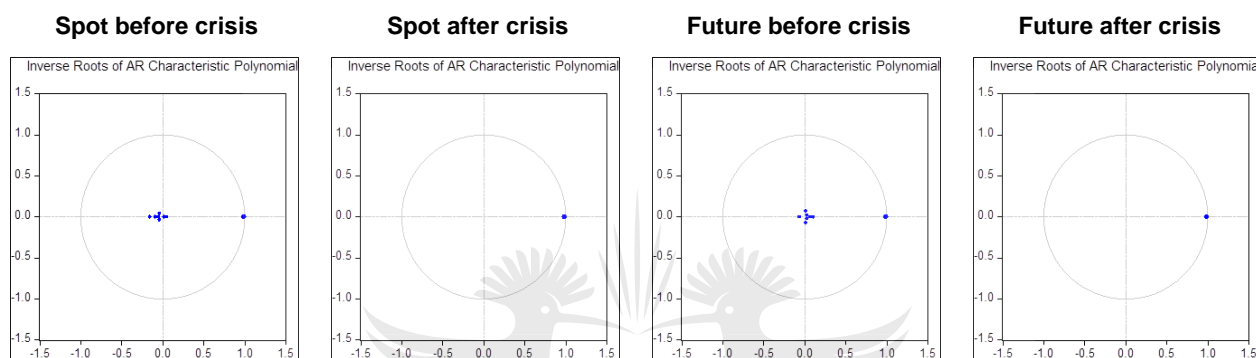


Figure 5.5: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

5.5.7. Long run relationship between commodities and the FTSE/JSE Top 40 Index against the ZAR

The examination of the relationships between the variables leads to the objective of whether the seven variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done to determine which relationships are present between the variables. In order to identify whether the variables are cointegrated, the Johansen cointegration test will be done. The long run relationship analysis will be followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required in order to determine whether an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables both showing a common stochastic drift. A stochastic drift is the change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once

(Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

Table 5.8: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Spot before crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Spot after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Spot after crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Future before crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future before crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Max-Eig | 1 | 0 | 0 | 0 | 0 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The Johansen cointegration test in Table 5.8 shows there is a cointegrating relationship when there is no trend in the data, not testing intercept and trend.

The remainder of the empirical analysis will focus on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred as all the variables have trends that are stochastic. The Johansen cointegration test indicates that no cointegrating relationships exist. The results indicate the variables are not cointegrated and therefore no VECM results were included.

5.5.8. Short run dynamics between commodities and the FTSE/JSE Top 40 Index against the ZAR

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities, FTSE/JSE Top 40 Index, and the ZAR are displayed in Table 5.9.

Table 5.9: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|--------|----|--------|
| Spot before crisis | DLZAR | All | 14.849 | 12 | 0.250 |
| Spot before crisis | DLFTSE_JSE40 | All | 3.542 | 12 | 0.990 |
| Spot before crisis | DLCORN | All | 15.592 | 12 | 0.211 |
| Spot before crisis | DLCOTTON | All | 7.766 | 12 | 0.803 |
| Spot before crisis | DLSOYABEAN | All | 12.383 | 12 | 0.416 |
| Spot before crisis | DLSUGAR | All | 14.622 | 12 | 0.263 |
| Spot before crisis | DLWHEAT | All | 12.628 | 12 | 0.397 |
| Spot after crisis | DLZAR | All | 4.495 | 6 | 0.610 |
| Spot after crisis | DLFTSE_JSE40 | All | 20.568 | 6 | 0.002* |
| Spot after crisis | DLCORN | All | 3.497 | 6 | 0.744 |
| Spot after crisis | DLCOTTON | All | 5.401 | 6 | 0.494 |
| Spot after crisis | DLSOYABEAN | All | 15.623 | 6 | 0.016* |
| Spot after crisis | DLSUGAR | All | 16.416 | 6 | 0.012* |
| Spot after crisis | DLWHEAT | All | 14.619 | 6 | 0.023* |
| Future before crisis | DLZAR_F | All | 10.279 | 12 | 0.592 |
| Future before crisis | DLFTSE_JSE40_F | All | 5.540 | 12 | 0.938 |
| Future before crisis | DLCORN_F | All | 15.389 | 12 | 0.221 |
| Future before crisis | DLCOTTON_F | All | 16.733 | 12 | 0.160 |
| Future before crisis | DLSOYABEAN_F | All | 25.332 | 12 | 0.013* |
| Future before crisis | DLSUGAR_F | All | 38.037 | 12 | 0.000* |
| Future before crisis | DLWHEAT_F | All | 14.991 | 12 | 0.242 |
| Future after crisis | DLZAR_F | All | 2.738 | 6 | 0.841 |
| Future after crisis | DLFTSE_JSE40_F | All | 34.441 | 6 | 0.000* |
| Future after crisis | DLCORN_F | All | 7.025 | 6 | 0.319 |
| Future after crisis | DLCOTTON_F | All | 16.741 | 6 | 0.010* |
| Future after crisis | DLSOYABEAN_F | All | 7.217 | 6 | 0.301 |
| Future after crisis | DLSUGAR_F | All | 10.277 | 6 | 0.114 |
| Future after crisis | DLWHEAT_F | All | 3.867 | 6 | 0.695 |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: None
- Spot after crisis: FTSE/JSE Top 40 Index, soyabean, sugar and wheat
- Future before crisis: Soyabean and sugar
- Future after crisis: FTSE/JSE Top 40 Index and cotton

This shows robustness of the results since adding the ZAR to the combination of variables has only slightly changed the dynamics from the previous analysis. The null hypothesis can

be rejected for the remainder of the variables. The variables ranked from the most exogenous to the most endogenous are indicated by Chi-square value. A higher Chi-square value indicates that the variable is more exogenous.

In Appendix B.5, the response of the ZAR when one of the other variables experiences a shock is displayed. The impulse response when five periods are included indicates whether the ZAR increases or decreases and whether this effect is likely to be permanent. The response of the FTSE/JSE Top 40 Index is opposite to the response obtained for the ZAR as the response of the ZAR is upward sloping, starting from a negative base, except before the crisis.

On average, the move back to the equilibrium is between two and three days. The ZAR shows an opposite reaction to the FTSE/JSE Top 40 Index as the flow of funds related to international trade is different between the currency and the equity Index. With the ZAR against the USD, two currencies are being affected, the ZAR and the USD. With the FTSE/JSE Top 40 Index, only the index is involved and not two currencies (Rossi, 2012; Chaban, 2009).

The variance decomposition of the seven variables is displayed in Appendix B.5 to indicate how much of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the ZAR and FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals. The variance decomposition of the ZAR shows that most of the movement is explained by itself.

The FTSE/JSE Top 40 Index illustrates that the majority of the movement is explained by its own variance. The ZAR explains between 4% and 8% of the FTSE/JSE Top 40 Index movement after the crisis for both spot and future.

5.6. CONCLUSION

Overall, the empirical results show that there are significant relationships in the long run and short run of the included variables, but none based on Johansen Cointegration. The objectives addressing the movement relationships between the variables were the main focus of this chapter. The correlation analysis showed that one set of variables moved

together in a positive manner. The variables that moved together were: corn and wheat for future after crisis.

The spot variables indicate that corn spot and wheat future had the highest synchronicity with ZAR spot and ZAR future respectively, whereas sugar spot and future had the highest synchronicity with the FTSE/JSE Top 40 Index spot and future respectively.

The causality results showed that soyabean and corn as well as sugar and soyabean had a bilateral causal relationship for spot after crisis only by both tests. Wheat and soyabean were shown to have a bilateral causal relationship for spot after crisis by the Toda Yamamoto test only. The unilateral causal relationships after the crisis for ZAR and the FTSE/JSE Top 40 Index existed only for the following:

- From corn to FTSE/JSE Top 40 Index: spot and future (both tests)
- From soyabean to FTSE/JSE Top 40 Index (both tests)
- From wheat to FTSE/JSE Top 40 Index: future (both tests)
- From ZAR to FTSE/JSE Top 40 Index: spot and future (both tests)

The remainder of the analysis focused on VAR, Johansen cointegration, VECM and innovation accounting methods. The analysis indicates that there are no significant relationships between the seven variables based on the Johansen cointegration and VECM results.

The block exogeneity for the first relationship shows that soyabean and sugar were not rejected, therefore they were exogenous for spot after crisis. FTSE/JSE Top 40 Index and cotton were not rejected for future after crisis. The second relationship showed that the FTSE/JSE Top 40 Index, soyabean, sugar and wheat were not rejected for spot after crisis, while the FTSE/JSE Top 40 Index and cotton were not rejected for future after crisis, which shows robustness of the results.

The empirical results indicate that there is opportunity for further study in soft commodities. Further research can be done related to the forecasting ability of soft commodities. Further research can also be done to identify the presence of speculative bubbles that can create the opportunity for short term profit opportunities.

Metal commodities are an important commodity category for the South African market, but soft commodities can be evaluated in other financial markets as well. The literature discussed in this chapter, similar to the literature on metal commodities, also showed mixed

results when comparing soft commodities to other commodities and to financial variables (Hameed & Arshad, 2009; Harri *et al.*, 2009; Bhar & Hamori, 2006; Booth & Ciner, 2001). The selection of commodities and related financial variables is vital to consider when investigating the relationship of commodities to other variables.

In addition, further studies can be undertaken in other types of soft commodities, as well as in energy commodities, which will be done in the following chapter. At this point, relationships between the variables have been identified, but the cross hedging relationships and optimal hedge ratios will be explored further in Chapter 7.



CHAPTER 6

ESSAY 3: ENERGY COMMODITIES

6.1. INTRODUCTION

In the financial market context, relationships between variables are vital to understand as the relationships guide investment related decisions. These relationships cause investors to buy, sell or hold investments. The relationships can be linked to economic variables, financial statement variables or between other financial or real assets, to name a few. By understanding relationships, investments are better understood in how they react to outside factors. Understanding which factors affect the investment is very important in the investment process.

This chapter explores the relationships between energy commodities, the FTSE/JSE Top 40 Index and the South African Rand (versus the United States Dollar), denoted as ZAR, which will be used for a further study related to hedging relationships. The commodities were selected as they are produced in South Africa. South Africa does not rank as high as the metal commodities production in the energy commodities production. The historical time-series datasets examined in the study are four energy commodities, crude oil, jet kerosene, naphtha and natural gas, the FTSE/JSE Top 40 Index and the ZAR. These commodities formed part of the study, as they are part of the international benchmarks for energy commodities. The FTSE/JSE Top 40 Index and the ZAR were chosen as they represent the South African equity market as well as the South African currency in this study.

The objective of the study was to determine the possible long and short run significant relationships between the four energy commodities against the FTSE/JSE Top 40 Index. A second relationship that was investigated is the possible long and short run significant relationships between the four energy commodities and the FTSE/JSE Top 40 Index against the ZAR. The sample includes data points on a daily basis from before as well as after the 2007-2009 financial crisis, which will be split in the analysis section in order to compare the two periods. In addition, the variables are represented by spot as well as future prices for all available variables, which will also be compared against each other.

The initial analysis included visual representations and correlation. The Pairwise Granger causality test and Toda Yamamoto test immediately followed the initial analysis as it applies to all six variables included in the study. The remainder of the empirical results were divided into two sections as per the two relationships that are under investigation related to the objective of the study.

The first section after the causality results tested the relationships between the commodities and the FTSE/JSE Top 40 Index both spot and future as well as before and after the crisis. The second section of the analysis tested the relationships present between the commodities and the FTSE/JSE Top 40 Index against the ZAR, again both spot and future as well as before and after the crisis. Within each section, the VAR results, the long relationship represented by the Johansen cointegration test, and the short run dynamics were included. The short run dynamics were evaluated using the VECM and innovation accounting methods of impulse responses and variance decomposition. Should cointegration relationships not be found in the Johansen cointegration test, then VECM will not be included, but innovation accounting methods will be included.

The remainder of the chapter is structured as follows; part 2 provides a brief review of current literature. Parts 3 and 4 discuss the methodology and explanation of the data. Part 5 illustrates the results and interprets the findings. The final part, part 6, discusses the conclusion and implication of the study.

6.2. REVIEW OF THE LITERATURE

The long run relationships between similar variables in South Africa are not often studied. Prior studies that investigated the relationships that metal, agricultural and chemical commodities have with the FTSE/JSE Top 40 Index and ZAR have been explored by Le Roux (2015a, 2015b, 2014). The relationships between metal commodities and agricultural commodities against the FTSE/JSE Top 40 Index as well as the commodities and the FTSE/JSE Top 40 Index against the ZAR have been investigated by Le Roux (2015a, 2014). The results indicated that there was a cointegrating relationship in all the datasets tested.

The agricultural commodities explored to test for a long run relationship between the FTSE/JSE Top 40 Index and the ZAR were cocoa, coffee, corn, cotton, soyabean, sugar and wheat. These commodities were compared firstly against the FTSE/JSE Top 40 Index and then the seven commodities and the FTSE/JSE Top 40 Index were compared against the ZAR, similar to methodology in this chapter. Both datasets tested showed that a

cointegrating relationship exists between the variables. Breaking the data down to investigate relationships between the variables showed that strong relationships exist between soyabean and cocoa, soyabean and corn, wheat and corn, and wheat and soyabean (Le Roux, 2015a).

The metal commodities, copper, palladium, platinum and silver, were compared to the FTSE/JSE Top 40 Index and the ZAR in the same manner as the agricultural commodities. Both relationships investigated showed that a long run relationship existed between the four commodities against FTSE/JSE Top 40 Index as well as between the four commodities and the FTSE/JSE Top 40 Index against the ZAR. The strongest relationships between the variables were between platinum and copper, silver and copper, FTSE/JSE Top 40 Index and copper, silver and platinum, FTSE/JSE Top 40 Index and platinum, and FTSE/JSE Top 40 Index and silver (Le Roux, 2014).

The chemical commodities were compared to the FTSE/JSE Top 40 Index and the ZAR following the same methodology. The chemical commodities included in the analysis were naphtha, paraffinic-xylene, poly vinyl chloride, polyethylene, styrene, terephthalic acid and vinyl chloride monomer. The empirical results showed that a cointegrating relationship exists between the seven commodities against FTSE/JSE Top 40 Index as well as between the seven commodities and the FTSE/JSE Top 40 Index and the ZAR. Naphtha and paraffinic-xylene, naphtha and polyethylene, naphtha and styrene, paraffinic-xylene and terephthalic acid, and polyethylene and styrene showed the strongest interrelationships (Le Roux, 2015b).

In the previous chapter, studies including oil as a commodity were discussed. Harri *et al.* (2009) explored the relationship between oil, exchange rates and commodity prices. The authors found empirical evidence suggests that there is an interrelating link between exchange rates, corn and oil prices. Samanta and Zadeh (2012) investigated the co-movements of several variables, namely the world gold price, world oil price, United States equity price (Dow-Jones Industrial Index), and the real exchange rate for the United States Dollar. The analysis of the data showed that initially the existence of co-movements was present between the datasets, but further analysis indicated that the equity price and the gold price tend to move on their own; however, the oil price and exchange rates were affected by other variables. Bhunia (2013) explored the relationships between two commodity market indices, the world crude index and the Indian gold price as well as the

equity market index of the Bombay stock exchange, Sensex. The results of the analysis show that there is a cointegration relationship in the long run between the included variables.

Ciner (2001) investigated the long run relationship between the gold and silver future contract prices that traded on the Tokyo Commodity Exchange. The study included 1720 data points from 1992 to 1998. The Johansen's full information maximum likelihood cointegration analysis was used to analyse the data. The results of the analysis indicated that there is no long run relationship between the gold and silver future contract prices.

The long run relationship between petroleum and cereal prices, namely maize, rice and wheat, was examined by Arshad and Hameed (2009). Monthly data from January 1980 to March 2008 was included in the study and analysed using Johansen cointegration and Granger causality tests. The results indicate that a long run relationship exists between the petroleum price and the three cereal prices included in the study. The results further indicate that there is unidirectional causality from the petroleum price to the cereal prices.

Ziegelbäck and Kastner (2011) explored the long run relationship between rapeseed and diesel prices. The period of study was from January 2005 to December 2010, with daily data utilised in the analysis and threshold cointegration analysis applied to the data. The results indicated that only in extreme situations a long run relationship was identified.

Nazlioglu and Soytas (2012) applied panel cointegration and Granger causality to investigate the dynamic relationship presented between variables. The variables were the world oil price and twenty-four world agricultural commodity prices, some being maize, coffee, sugar, and rice. The prices of oil and the agricultural commodities took into account the changes in the relative strength of the United States Dollar. The study showed that oil prices have a strong effect on the agricultural commodity prices.

The relationship between the United Kingdom wholesale gas price and the Brent oil price was explored by Panagiotidis and Rutledge (2004). Empirical analysis included Johansen integration, Breitung nonparametric procedure, vector error correction models (VECM), McLeod-Li, Engle test for (G)ARCH effects and the Brock, Dechert and Scheinkman (BDS) test statistic; with data from 1996 to 2003. The results indicated that a long run relationship exists through the period included.

Relationships between the energy commodities, the FTSE/JSE Top 40 Index and the ZAR have not yet been investigated and will be explored in the remainder of this chapter. These relationships between commodities are important when considering alternative investment

opportunities, either between the alternative investments or between the alternative investments and traditional investments. The objective of searching for alpha as well as ensuring minimum loss situations is vital in the investment management environment, keeping in mind the objective of the investment.

6.3. METHODOLOGY

The data methodology applied in this study is based on historical time-series data which was used to explore the relationships that exist between the six variables included. The presence of relationships between the variables were examined using financial econometric tests applied to the data, namely correlation, Granger causality test and the Toda Yamamoto test, VAR, Johansen cointegration, VECM and innovation accounting methods. Initial movements between the variables were investigated by the use of correlation and the causality tests. The relationships to be investigated were:

1. Movements in the commodity price against movements in the FTSE/JSE Top 40 Index and vice-versa;
2. Movements in the commodity price against movements in the ZAR and vice-versa;
3. Movements in the FTSE/JSE Top 40 Index against movements in ZAR and vice-versa.

Once the initial analysis had been completed, the relationships were further investigated by the use of VAR, followed by the Johansen cointegration test to determine if any long run relationships exist. The VECM and impulse responses and variance decomposition tested the short run dynamics. The VAR, long run relationship test and short run dynamics tests were done in two separate sections in order to test the three main relationships listed above (Asteriou & Hall, 2011; Luetkepohl, 2011; Watson, 1994; Johansen, 1991).

6.4. DATA

Four energy commodities were included in the study, namely crude oil, jet kerosene, naphtha, and natural gas. These commodities were examined against the FTSE/JSE Top 40 Index initially, followed by the comparison of the four commodities and the FTSE/JSE Top 40 Index against the ZAR. The prices of the datasets were daily spot and future prices available from the commodity benchmarks from the Thomson Reuters DataStream database. The sample period was from 1 January 2000 to 30 June 2007 as well as from 1 October 2009 to 31 December 2016. These dates were chosen as each dataset was active at this time and to ignore the effects of the 2007 financial crisis. A total of 1954 data points

for the period before the 2007-2009 financial crisis and 1892 data points for the period after the 2007-2009 financial crisis were included in the study. The data points were cleaned by removing any data that had no value in any of the datasets from all datasets. The data was analysed using financial econometric techniques in EViews.

The empirical results are referenced as follows (the code represents the daily spot price followed by the daily future price):

- South African Rand against the United States Dollar: ZAR and ZAR_F
- FTSE/JSE Top 40 Index: FTSE/JSE40 and FTSE/JSE40_F
- Crude Oil-Brent: BRENT OIL and BRENT OIL_F
- Jet Kerosene: JET KEROSENE and JET KEROSENE_F
- Naphtha: NAPHTHA and NAPHTHA_F
- Natural Gas: NATURAL GAS and NATURAL GAS_F

In the analysis, there are instances where the above codes are preceded by the letters “L” and “DL”. When the analysis includes the codes with the letter “L” in front of the code, the logged data was utilised within the test. If the letters “DL” precede the code, then the first differenced logged data was used. The different data transformations are used in order to ensure that the results of the analysis were reliable.

6.5. EMPIRICAL RESULTS

The empirical results included the initial analysis, Pairwise Granger causality test results, Toda Yamamoto test results, VAR results, long run relationship analysis and the short run dynamics results in order to determine the relationships present between the seven variables included in this study. The variables include spot and future prices analysed before and after the 2007-2009 financial crisis.

6.5.1. Initial analysis

In order to view the data graphically, the data needs to be transformed accordingly. When exploring the relationship between time series data, there is a risk that the data is not stationary. The unit root tests, namely the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, are run to determine whether the time series is stationary or not. The null hypotheses of the two unit root tests are:

- ADF test: variable has a unit root
- PP test: variable has a unit root.

The two tests mentioned above were used to test for unit roots and the results are shown in Table 6.1. The order of the tests started by testing for stationarity at level with intercept only as well as trend and intercept, followed by first difference of the intercept only, and trend and intercept for the ADF and PP test respectively. No futures price based on the spot variable was available for jet kerosene and naphtha, so therefore the futures price for jet kerosene and naphtha are not included in this chapter.

Table 6.1: Unit root test using the Augmented Dickey-Fuller and Phillips-Perron method

| ADF before crisis | Level | | 1st Difference | |
|--------------------------|------------------|----------------------------|-----------------------|----------------------------|
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| BRENTOIL | -0.501 | -2.505 | -45.188* | -45.191* |
| BRENTOIL_F | -0.451 | -2.347 | -46.493* | -46.496* |
| JETKEROSENE | -0.546 | -2.523 | -46.281* | -46.284* |
| NAPHTHA | -0.340 | -2.410 | -43.985* | -43.994* |
| NATURALGAS | -3.166 | -3.787 | -17.821* | -17.820* |
| NATURALGAS_F | -2.534 | -3.010 | -44.094* | -44.086* |
| FTSE_JSE40 | 1.790 | -0.508 | -44.278* | -44.403* |
| FTSE_JSE40_F | 1.716 | -0.561 | -43.871* | -43.986* |
| ZAR | -1.439 | -1.970 | -43.834* | -43.841* |
| ZAR_F | -1.534 | -2.038 | -43.495* | -43.499* |
| PP before crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| BRENTOIL | -0.523 | -2.571 | -45.177* | -45.180* |
| BRENTOIL_F | -0.394 | -2.286 | -46.476* | -46.478* |
| JETKEROSENE | -0.439 | -2.432 | -46.334* | -46.353* |
| NAPHTHA | -0.342 | -2.419 | -43.985* | -43.994* |
| NATURALGAS | -2.881 | -3.500 | -42.447* | -42.420* |
| NATURALGAS_F | -2.500 | -2.998 | -44.115* | -44.108* |
| FTSE_JSE40 | 2.475 | -0.119 | -44.664* | -45.364* |
| FTSE_JSE40_F | 2.572 | -0.082 | -44.551* | -45.530* |
| ZAR | -1.399 | -1.942 | -43.856* | -43.864* |
| ZAR_F | -1.524 | -2.029 | -43.489* | -43.499* |

| ADF after crisis | Level | | 1st Difference | |
|-------------------------|------------------|----------------------------|-----------------------|----------------------------|
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| BRENTOIL | -0.918 | -2.091 | -42.013* | -42.050* |
| BRENTOIL_F | -0.980 | -2.051 | -45.321* | -45.353* |
| JETKEROSENE | -0.851 | -2.071 | -42.382* | -42.436* |
| NAPHTHA | -1.057 | -2.322 | -42.388* | -42.420* |
| NATURALGAS | -2.401 | -2.938 | -12.669* | -12.666* |
| NATURALGAS_F | -2.740 | -3.012 | -46.136* | -46.132* |
| FTSE_JSE40 | -1.509 | -2.904 | -33.594* | -33.598* |
| FTSE_JSE40_F | -1.489 | -3.010 | -33.467* | -33.469* |
| ZAR | -0.601 | -2.950 | -42.591* | -42.584* |
| ZAR_F | -0.563 | -2.901 | -41.684* | -41.677* |
| PP after crisis | Level | | 1st Difference | |
| Variable | Intercept | Trend and Intercept | Intercept | Trend and Intercept |
| BRENTOIL | -0.985 | -2.117 | -42.041* | -42.069* |
| BRENTOIL_F | -0.930 | -2.023 | -45.325* | -45.372* |
| JETKEROSENE | -0.923 | -2.088 | -42.445* | -42.483* |
| NAPHTHA | -1.137 | -2.358 | -42.436* | -42.459* |
| NATURALGAS | -3.080 | -3.855 | -41.652* | -41.634* |
| NATURALGAS_F | -2.461 | -2.650 | -46.809* | -46.817* |
| FTSE_JSE40 | -1.443 | -2.494 | -45.224* | -45.245* |
| FTSE_JSE40_F | -1.410 | -2.588 | -45.611* | -45.630* |
| ZAR | -0.415 | -2.725 | -43.282* | -43.284* |
| ZAR_F | -0.438 | -2.765 | -41.991* | -41.991* |

Notes: The critical values for the Augmented Dickey-Fuller (Trend and Intercept) tests are -3.959, -3.410, and -3.127 at the 1%, 5% and 10% significance levels.

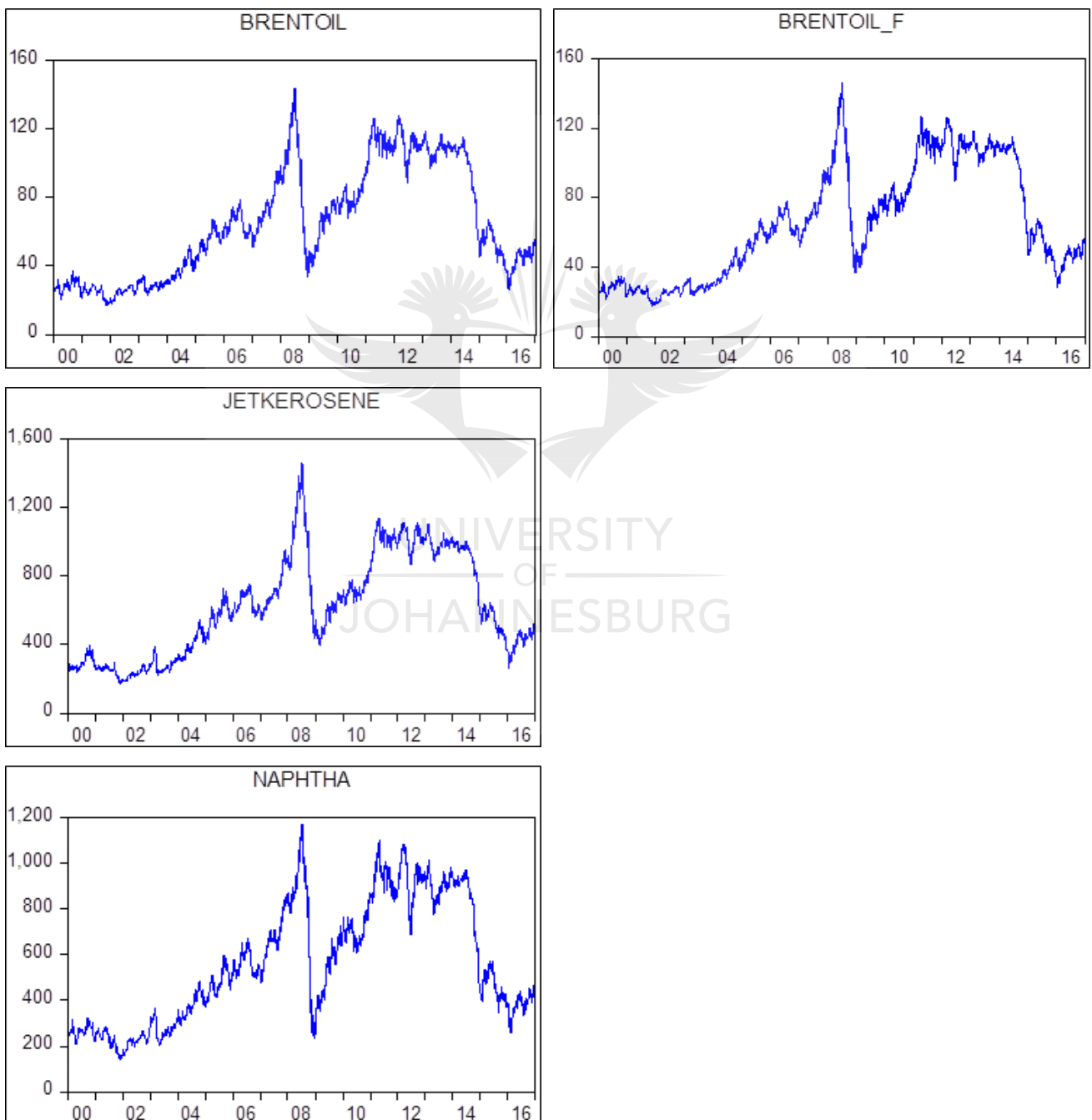
The critical values for the Augmented Dickey-Fuller (Intercept only) tests are -3.431, -2.861, and -2.567 at the 1%, 5% and 10% significance levels.

An asterisk (*) indicates that the null hypothesis of a unit root is rejected (at a 1% significance level).

Source: Thomson Reuters DataStream and EViews.

The unit root tests indicate that all the variables are stationary at first difference at a 1% significance level, therefore we conclude that the variables are integrated of order one. Therefore, the Johansen cointegration test is appropriate since all variables have the same order of integration. It is also appropriate to use the logged data within the VAR model as well as for further analysis that is required after the VAR model.

An initial evaluation of the data by means of a graphical representation illustrated in Figures 6.1 and 6.2 shows movements between the spot and future datasets, from the daily price on the line graph as well as on the log differenced graphs illustrating the volatility present. The global financial crisis of 2007-2009 was not included in the dataset in order to remove the effects of the crisis on the commodities, index and currency. The graphs below however include the entire data period from 2000 to 2016. In the graphs below, the line graphs which display the variables included in the study shows that the data seem to be trended. The log differenced graphs show signs of volatility clustering throughout the data period.



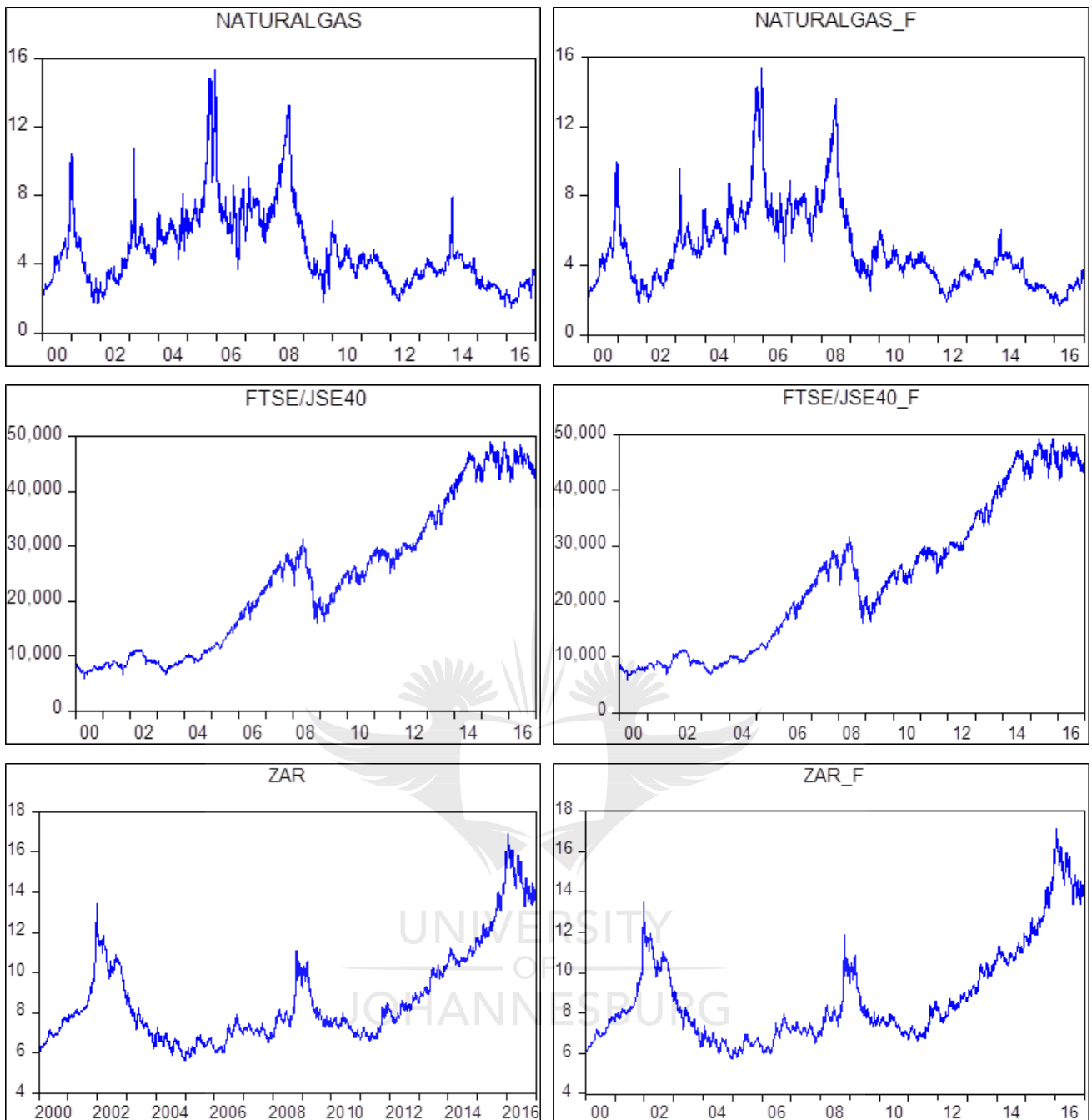
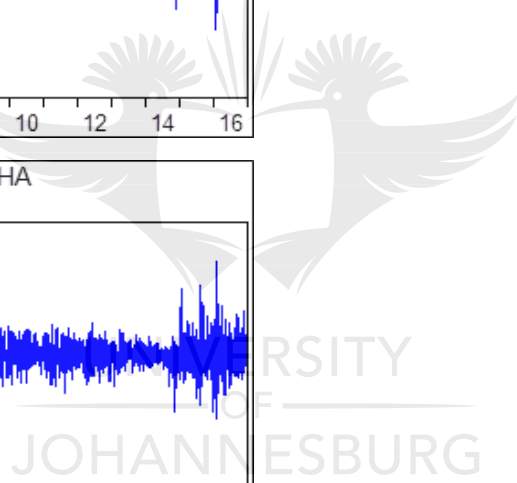
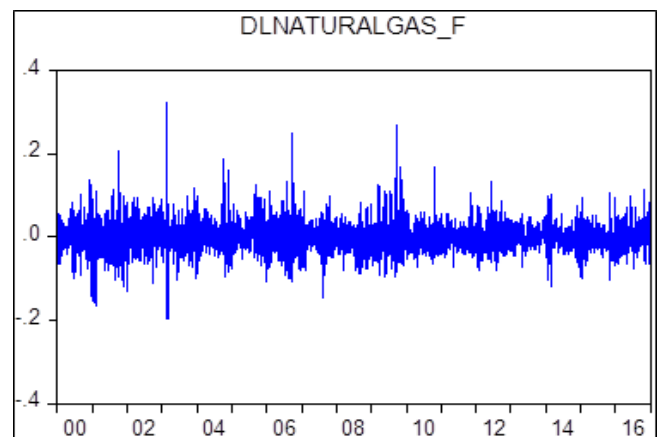
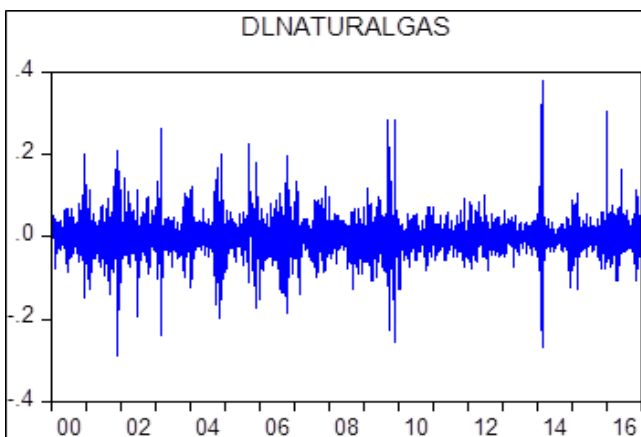
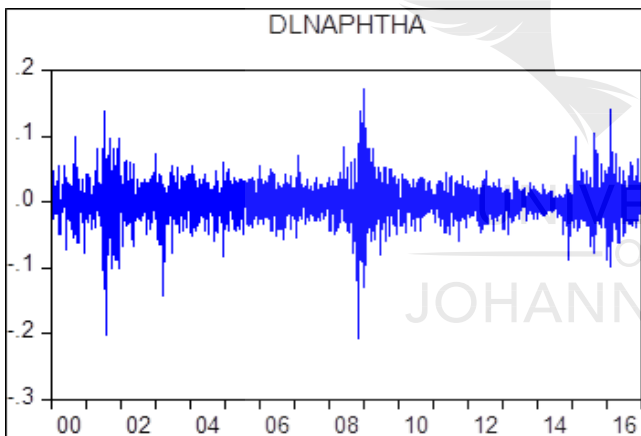
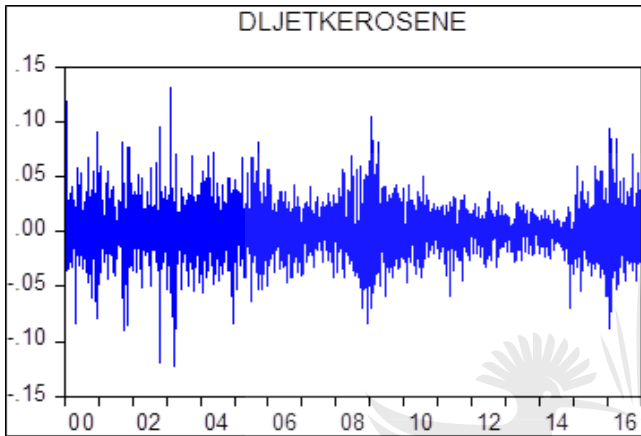
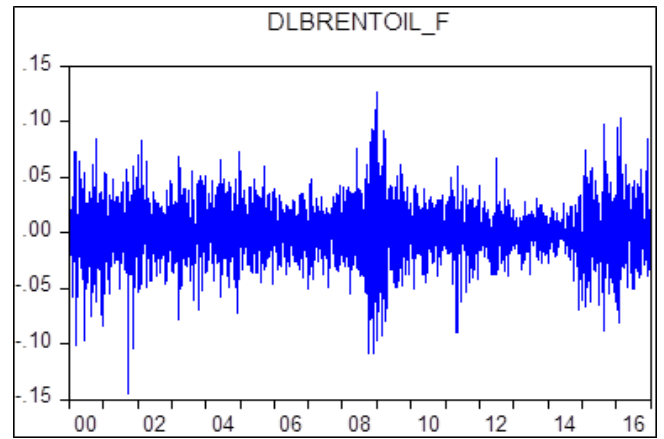
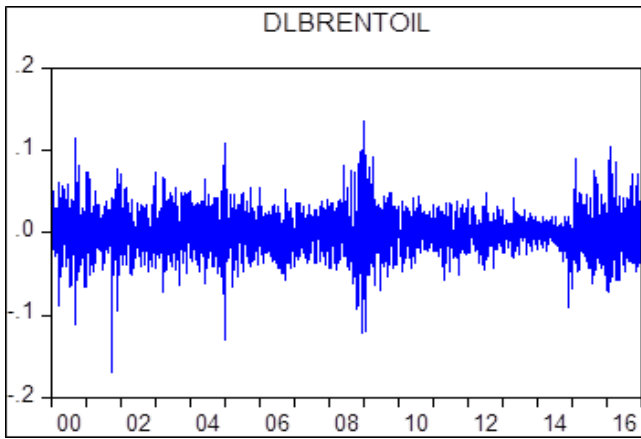


Figure 6.1: Price movement in the six datasets

Source: Thomson Reuters DataStream and EViews.



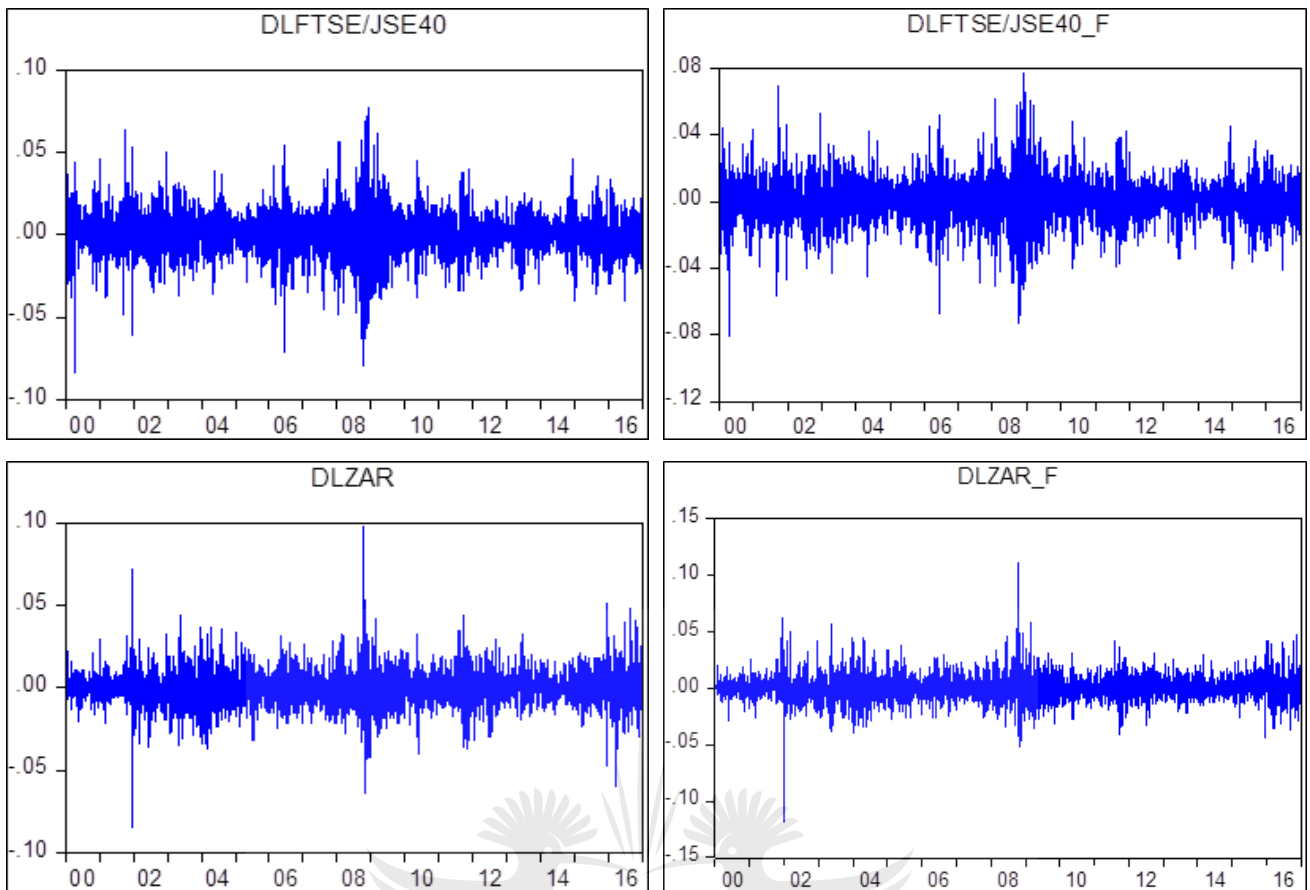
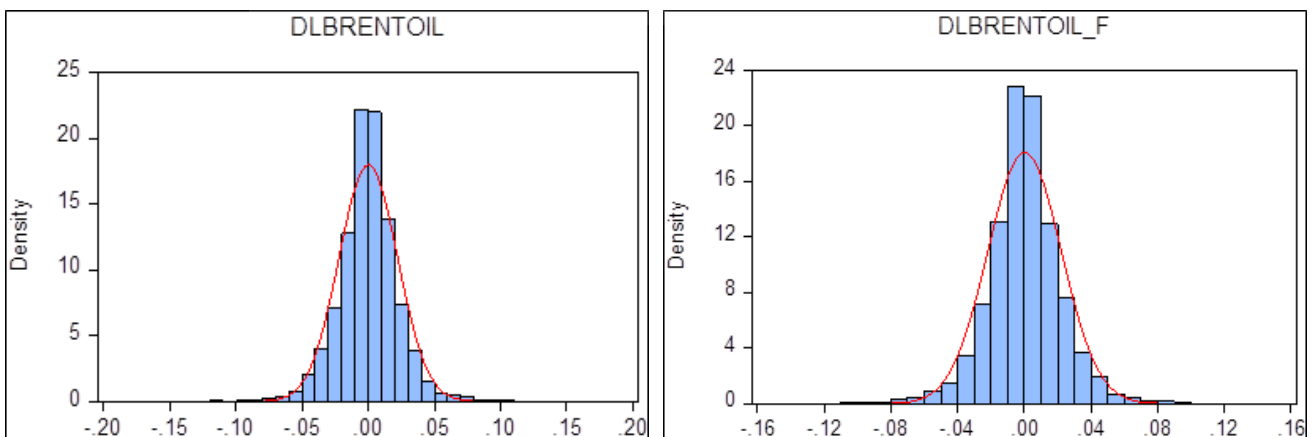
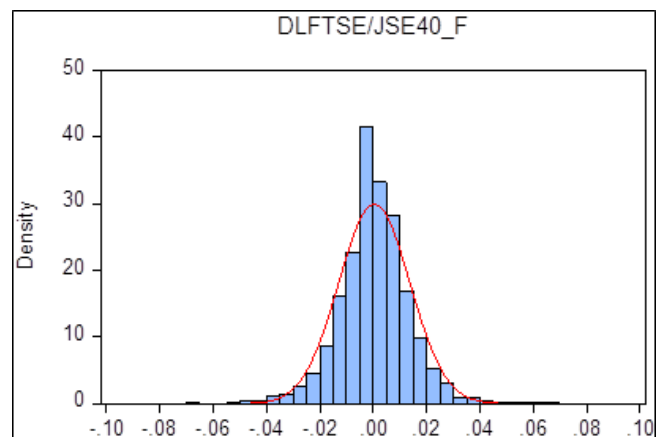
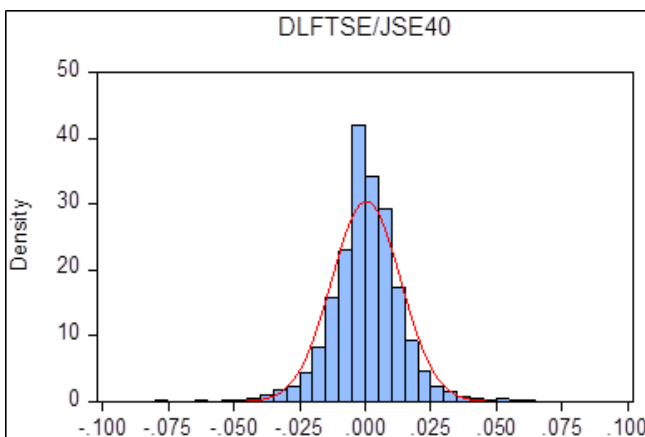
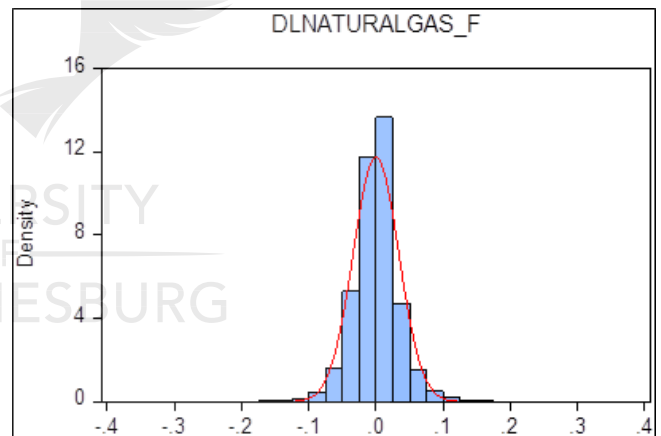
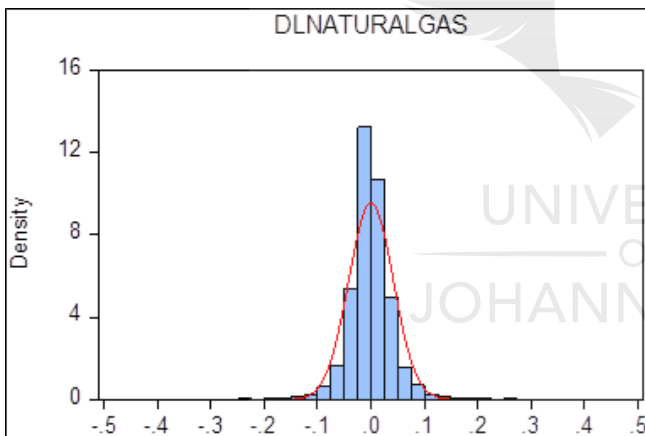
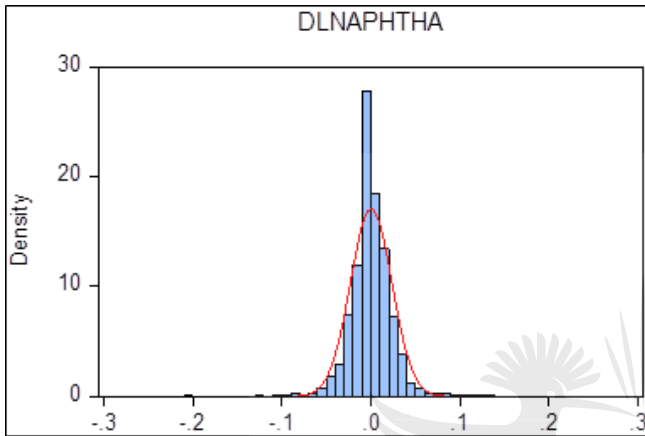
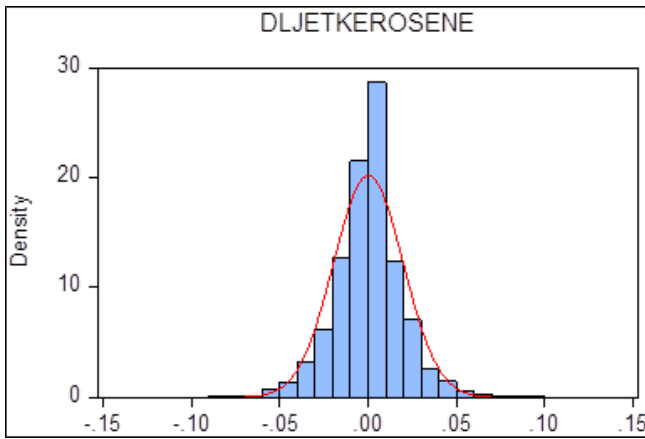


Figure 6.2: Volatility movement in the six datasets

Source: Thomson Reuters DataStream and EViews

Histograms graphically illustrating the distribution of the data as well as the skewness and kurtosis of the data are shown in Figure 6.2. When comparing the histograms against the normal distribution, the log returns (i.e. first differencing) of the data are not normally distributed. The data also shows signs of leptokurtosis, which is excess kurtosis.





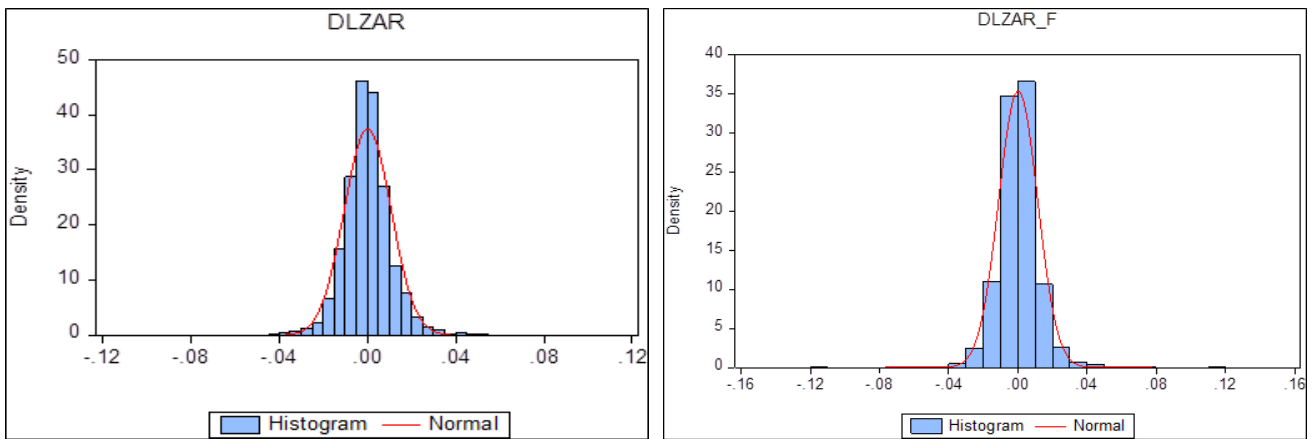


Figure 6.3: Histograms of the log returns of the six datasets

Source: Thomson Reuters DataStream and EViews.

Table 6.2 shows the descriptive statistics of the six datasets. A total of 3846 observations are included for all seven variables, spot and future, before and after the crisis. The descriptive statistics confirm that the log returns of the variables included are not normally distributed and are leptokurtic as seen on the histograms. In addition, the skewness indicates that the majority of the variables are slightly negatively skewed. The table also includes the synchronicity or co-movement of the variables with the ZAR and the FTSE/JSE Top 40 Index on a spot and future basis. Synchronicity in Table 4.2 is based on the R^2 of two variables adjusted as per the methodology ($= \log(R^2/(1- R^2))$) from Morck *et al.* (2000). The higher the value of the synchronicity results, the more synchronised or co-movement exists between the variables. Naphtha spot and brent future provided the highest synchronicity for ZAR spot and future respectively. For the FTSE/JSE Top 40 Index, natural gas showed the highest synchronicity for the spot and future combinations.

Table 6.2: Descriptive statistics

| Before crisis spot | DLBRENTOIL | DLFTSE_JSE40 | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLZAR |
|--------------------|------------|--------------|---------------|-----------|--------------|----------|
| Mean | 0.001 | 0.001 | 0.000 | 0.001 | 0.001 | 0.000 |
| Median | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.115 | 0.064 | 0.132 | 0.139 | 0.263 | 0.072 |
| Minimum | -0.170 | -0.084 | -0.123 | -0.202 | -0.289 | -0.085 |
| Std. Dev. | 0.023 | 0.012 | 0.022 | 0.023 | 0.045 | 0.010 |
| Skewness | -0.298 | -0.214 | -0.013 | -0.526 | 0.193 | 0.097 |
| Kurtosis | 6.204 | 6.303 | 6.414 | 9.891 | 8.084 | 8.201 |
| Jarque-Bera | 864.699 | 902.985 | 949.062 | 3955.921 | 2116.759 | 2205.554 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | 1.055 | 1.186 | 0.906 | 1.135 | 1.023 | 0.142 |
| Sum Sq. Dev. | 1.045 | 0.303 | 0.921 | 1.077 | 4.025 | 0.204 |
| Observations | 1954 | 1954 | 1954 | 1954 | 1954 | 1954 |

| | | | | | | |
|---|------------|----------------|----------------|-----------|--------------|---------|
| Before crisis spot | DLBRENTA | DLFTSE_JSE40 | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLZAR |
| After crisis spot | DLBRENTA | DLFTSE_JSE40 | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLZAR |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Maximum | 0.058 | 0.067 | 0.047 | 0.054 | 0.089 | 0.051 |
| Minimum | -0.075 | -0.078 | -0.040 | -0.102 | -0.117 | -0.062 |
| Std. Dev. | 0.013 | 0.014 | 0.011 | 0.011 | 0.019 | 0.012 |
| Skewness | -0.101 | -0.079 | -0.142 | -0.769 | -0.263 | -0.114 |
| Kurtosis | 4.813 | 5.524 | 4.409 | 9.769 | 5.695 | 4.392 |
| Jarque-Bera | 262.303 | 504.366 | 162.920 | 3798.876 | 594.273 | 156.742 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Sum | -0.085 | -0.107 | 0.678 | 0.144 | 0.824 | -0.360 |
| Sum Sq. Dev. | 0.314 | 0.390 | 0.210 | 0.217 | 0.657 | 0.286 |
| Observations | 1892 | 1892 | 1892 | 1892 | 1892 | 1892 |
| Synchronicity with ZAR - full period | -5.518 | -3.533 | -6.096 | -8.050 | -6.401 | N/A |
| Synchronicity with FTSE/JSE40 - full period | -5.425 | N/A | -6.818 | -6.894 | -7.671 | -3.533 |
| Before crisis future | DLBRENTA_F | DLFTSE_JSE40_F | DLNATURALGAS_F | DLZAR_F | | |
| Mean | 0.001 | 0.001 | 0.001 | 0.000 | | |
| Median | 0.001 | 0.000 | 0.000 | 0.000 | | |
| Maximum | 0.084 | 0.070 | 0.324 | 0.063 | | |
| Minimum | -0.144 | -0.081 | -0.199 | -0.119 | | |
| Std. Dev. | 0.022 | 0.013 | 0.038 | 0.011 | | |
| Skewness | -0.347 | -0.139 | 0.494 | -0.117 | | |
| Kurtosis | 5.282 | 5.604 | 8.746 | 12.415 | | |
| Jarque-Bera | 463.276 | 558.316 | 2767.578 | 7221.459 | | |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | | |
| Sum | 1.046 | 1.167 | 1.068 | 0.152 | | |
| Sum Sq. Dev. | 0.915 | 0.322 | 2.812 | 0.238 | | |
| Observations | 1954 | 1954 | 1954 | 1954 | | |
| After crisis future | DLBRENTA_F | DLFTSE_JSE40_F | DLNATURALGAS_F | DLZAR_F | | |
| Mean | 0.000 | 0.000 | 0.000 | 0.000 | | |
| Median | 0.000 | 0.000 | 0.000 | 0.000 | | |
| Maximum | 0.104 | 0.049 | 0.167 | 0.048 | | |
| Minimum | -0.090 | -0.041 | -0.119 | -0.044 | | |
| Std. Dev. | 0.019 | 0.011 | 0.028 | 0.010 | | |
| Skewness | 0.179 | -0.102 | 0.449 | 0.236 | | |
| Kurtosis | 5.928 | 4.422 | 5.600 | 4.807 | | |
| Jarque-Bera | 686.042 | 162.658 | 596.647 | 275.121 | | |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | | |
| Sum | -0.195 | 0.676 | -0.262 | 0.604 | | |
| Sum Sq. Dev. | 0.705 | 0.221 | 1.509 | 0.183 | | |
| Observations | 1892 | 1892 | 1892 | 1892 | | |
| Synchronicity with ZAR_F - full period | -7.472 | -4.101 | -6.122 | N/A | | |
| Synchronicity with FTSE/JSE40_F - full period | -5.419 | -2.691 | -7.605 | -4.101 | | |

Source: Thomson Reuters DataStream and EViews.

The correlation results based on the log returns (first differencing) of the data are shown in Table 6.3 to determine the initial relationships present between the variables.

Table 6.3: Correlation matrix

| Spot before crisis | DLBRENTTOIL | DLFTSE_JSE40 | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLZAR |
|----------------------|---------------|----------------|----------------|--------------|--------------|--------|
| DLBRENTTOIL | 1.000 | 0.066 | 0.464 | 0.379 | 0.159 | -0.063 |
| DLFTSE_JSE40 | 0.066 | 1.000 | 0.033 | 0.032 | 0.022 | 0.169 |
| DLJETKEROSENE | 0.464 | 0.033 | 1.000 | 0.470 | 0.200 | -0.047 |
| DLNAPHTHA | 0.379 | 0.032 | 0.470 | 1.000 | 0.143 | -0.018 |
| DLNATURALGAS | 0.159 | 0.022 | 0.200 | 0.143 | 1.000 | -0.041 |
| DLZAR | -0.063 | 0.169 | -0.047 | -0.018 | -0.041 | 1.000 |
| Spot after crisis | DLBRENTTOIL | DLFTSE_JSE40 | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLZAR |
| DLBRENTTOIL | 1.000 | 0.390 | 0.892 | 0.829 | 0.070 | -0.340 |
| DLFTSE_JSE40 | 0.390 | 1.000 | 0.377 | 0.353 | 0.033 | -0.283 |
| DLJETKEROSENE | 0.892 | 0.377 | 1.000 | 0.789 | 0.082 | -0.307 |
| DLNAPHTHA | 0.829 | 0.353 | 0.789 | 1.000 | 0.041 | -0.298 |
| DLNATURALGAS | 0.070 | 0.033 | 0.082 | 0.041 | 1.000 | -0.051 |
| DLZAR | -0.340 | -0.283 | -0.307 | -0.298 | -0.051 | 1.000 |
| Future before crisis | DLBRENTTOIL_F | DLFTSE_JSE40_F | DLNATURALGAS_F | DLZAR_F | | |
| DLBRENTTOIL_F | 1.000 | 0.066 | 0.303 | -0.024 | | |
| DLFTSE_JSE40_F | 0.066 | 1.000 | 0.022 | 0.128 | | |
| DLNATURALGAS_F | 0.303 | 0.022 | 1.000 | -0.047 | | |
| DLZAR_F | -0.024 | 0.128 | -0.047 | 1.000 | | |
| Future after crisis | DLBRENTTOIL_F | DLFTSE_JSE40_F | DLNATURALGAS_F | DLZAR_F | | |
| DLBRENTTOIL_F | 1.000 | 0.314 | 0.121 | -0.345 | | |
| DLFTSE_JSE40_F | 0.314 | 1.000 | 0.030 | -0.196 | | |
| DLNATURALGAS_F | 0.121 | 0.030 | 1.000 | -0.043 | | |
| DLZAR_F | -0.345 | -0.196 | -0.043 | 1.000 | | |

Source: Thomson Reuters DataStream and EViews.

The correlation matrix in Table 6.3 shows that there is a strong positive correlation (0.55 and above) between the following dataset combinations:

- Brent oil and jet kerosene (after the crisis for spot only)
- Brent oil and naphtha (after the crisis for spot only)
- Jet kerosene and naphtha (after the crisis for spot only).

The strong positive relationships among the energy commodities are expected, considering they are part of the same commodity class. No energy commodity shows a strong positive or negative correlation with the FTSE/JSE Top 40 Index or the ZAR. The statement by Baur and Lucey (2010) applies in this analysis as well, as most of the correlations obtained are low as well as negative in certain cases.

6.5.2. Granger causality

The Pairwise Granger causality tests and the Toda Yamamoto test show which variables cause another variable. If one variable causes another variable, then the past values of the first variable should be able to assist in predicting the future values of the variable being caused. The causality tests are only run once the VAR tests are completed, but it will be shown before the VAR results as the causality results apply to all ten variables in the study.

The full Pairwise Granger causality test results and Toda Yamamoto test results are for all seven variables before and after the crisis as well as both spot and future are included in Appendix C.1. The Pairwise Granger causality test is applied to the log differenced data as all variables were found to be of order 1, $I(1)$. The Toda Yamamoto test is applied to the logged data.

Appendix C.1 indicates that the following datasets have a feedback or bilateral causal relationship at a 10% level of significance:

- Naphtha and Brent oil: spot before crisis for Pairwise Granger causality test only
- Naphtha and natural gas: spot before crisis for both tests
- Naphtha and FTSE/JSE Top 40 Index: spot before crisis for Toda Yamamoto test only
- Brent oil and FTSE/JSE Top 40 Index: future before crisis for Toda Yamamoto test only.

Naphtha is produced by constituent parts of the FTSE/JSE Top 40 Index, which is the most likely reason that there is a bilateral relationship between the two variables; however, evidence is only identified before the crisis in the spot price.

The following datasets have a unidirectional causal relationship at a 10% level of significance:

- From Brent oil to jet kerosene: spot before crisis for both tests, spot after crisis for both tests
- From Brent oil to Naphtha: spot before crisis for Toda Yamamoto test only, spot after crisis for Toda Yamamoto test only
- From Brent oil to natural gas: future before crisis for both tests
- From Brent oil to FTSE/JSE Top 40 Index: spot before crisis for both tests, spot after crisis for both tests, future after crisis for both tests

- From brent oil to ZAR: future after crisis for both tests
- From jet kerosene to naphtha: spot before crisis for both tests
- From jet kerosene to natural gas: spot before crisis for Toda Yamamoto test only
- From jet kerosene to FTSE/JSE Top 40 Index: spot after crisis for both tests
- From naphtha to jet kerosene: spot after crisis for Pairwise Granger causality test only
- From naphtha to FTSE/JSE Top 40 Index: spot after crisis for both tests
- From natural gas to jet kerosene: spot after crisis for both tests
- From natural gas to naphtha: spot after crisis for both tests
- From FTSE/JSE Top 40 Index to brent oil: future before crisis for Pairwise Granger causality test only
- From FTSE/JSE Top 40 Index to naphtha: spot before crisis for Pairwise Granger causality test only
- From FTSE/JSE Top 40 Index to natural gas: spot after crisis for Toda Yamamoto test only
- From ZAR to jet kerosene: spot after crisis for Toda Yamamoto test only
- From ZAR to FTSE/JSE Top 40 Index: spot after crisis for both tests, future after crisis for both tests.

The unidirectional relationships between the commodities are expected, as the commodities fall within the same commodity category and spill-over between the commodities is in line with expectations. The unidirectional relationship from the ZAR to the FTSE/JSE Top 40 Index was also observed in the previous two chapters. The most likely source of the relationships linked to the ZAR and FTSE/JSE Top 40 Index are from companies that produce and trade these commodities in South Africa.

A summary of the number of variables that each variable causes as well as the number that a variable is caused by the other variables respectively is listed below:

- Brent oil:
 - Spot before crisis: 4 (both tests) and 1 (Pairwise Granger causality test)
 - Spot after crisis: 3 (2 both tests and 1 Toda Yamamoto test) and 0
 - Future before crisis: 2 (1 both tests and 1 Toda Yamamoto test) and 1 (both tests)
 - Future after crisis: 2 (both tests) and 0

- Jet kerosene:
 - Spot before crisis: 2 (1 both tests and 1 Toda Yamamoto test) and 1 (both tests)
 - Spot after crisis: 1 (both tests) and 4 (2 both tests, 1 Toda Yamamoto test and 1 Pairwise Granger causality test)
 - Future before crisis: 0 and 0
 - Future after crisis: 0 and 0
- Naphtha:
 - Spot before crisis: 3 (1 both tests, 1 Toda Yamamoto test and 1 Pairwise Granger causality test) and 4 (both tests)
 - Spot after crisis: 2 (1 both tests and 1 Pairwise Granger causality test) and 2 (1 both tests and 1 Toda Yamamoto test)
 - Future before crisis: 0 and 0
 - Future after crisis: 0 and 0
- Natural gas:
 - Spot before crisis: 1 (both tests) and 3 (2 both tests and 1 Toda Yamamoto test)
 - Spot after crisis: 2 (both tests) and 1 (Toda Yamamoto test)
 - Future before crisis: 0 and 1 (both tests)
 - Future after crisis: 0 and 0
- FTSE/JSE Top 40 Index:
 - Spot before crisis: 1 (both tests) and 2 (1 both tests and 1 Toda Yamamoto test)
 - Spot after crisis: 1 (Toda Yamamoto test) and 4 (both tests)
 - Future before crisis: 1 (both tests) and 1 (Toda Yamamoto test)
 - Future after crisis: 0 and 2 (both tests)
- ZAR:
 - Spot before crisis: 0 and 0
 - Spot after crisis: 2 (1 both tests and 1 Toda Yamamoto test) and 0
 - Future before crisis: 0 and 0
 - Future after crisis: 1 (both tests) and 1 (both tests).

Therefore, Brent oil and naphtha cause the most variables to change and the FTSE/JSE Top 40 Index is caused to move the most by the other variables. A possible reason that Brent oil causes the largest change is that it outranks the production quantity as compared to the other commodities in the South African context. The effect of energy commodities on the South African market is much lower than metal commodities and soft commodities. The

FTSE/JSE Top 40 Index is the most caused variable as companies that produce and export energy commodities are constituents part of the FTSE/JSE Top 40 Index.

The remaining datasets do not have statistically significant causal relationships, which implies independence.

The results for the relationship between the FTSE/JSE Top 40 Index and the four commodities before and after the crisis as well as both spot and future will be shown and discussed first, followed by the results for the relationship between the ZAR and the FTSE/JSE Top 40 Index and four commodities before and after the crisis as well as both spot and future.

6.5.3. VAR results between commodities and the FTSE/JSE Top 40 Index

The long run relationship and the short run dynamics analysis starts with the VAR model, which requires the optimal lag length to be determined and the output is shown in Table 6.4. The VAR analyses for all four data sets are included in Appendix C.2.

Table 6.4: VAR lag order selection criteria of the FTSE/JSE Top 40 Index and the four commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|-----------------------------|-----|-----------|---------|--------|----------|---------|----------|
| Spot before crisis | 3 | 23684.550 | 87.419 | 0.000* | -24.247* | -24.018 | -24.163 |
| Spot after crisis | 3 | 27158.550 | 126.710 | 0.000* | -28.624* | -28.390 | -28.537* |
| Future before crisis | 2 | 14151.400 | 25.267* | 0.000* | -14.515* | -14.454 | -14.493 |
| Future after crisis | 2 | 14881.830 | 65.651* | 0.000* | -15.709* | -15.648 | -15.686* |

* 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: Thomson Reuters DataStream and EViews.

Table 6.4 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model is estimated using two lags and results in 22 significant relationships in the VAR results. Spot after crisis is three lags, and 20 significant relationships exist. Future before crisis is two lags and 7 significant relationships exist. Future after crisis is two lags and 8 significant relationships exist.

The estimated VAR that is obtained in the analysis will be stable, otherwise known as stationary, if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 6.4, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

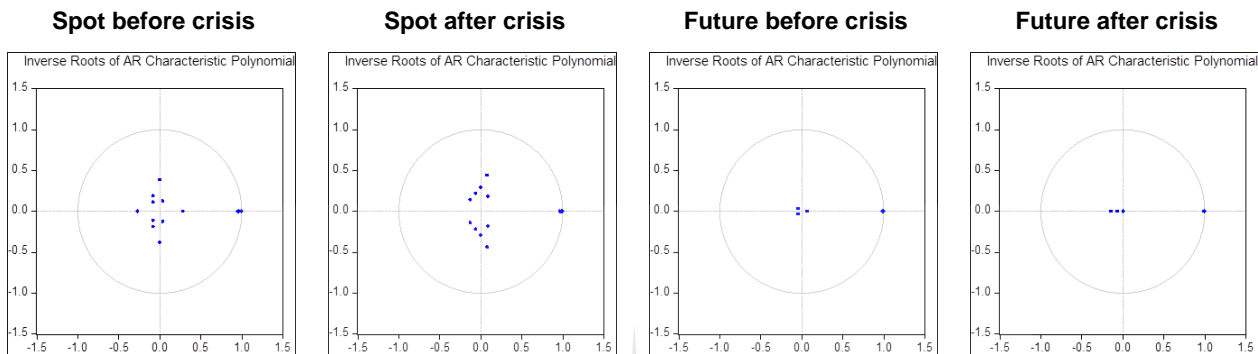


Figure 6.4: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

6.5.4. Long run relationship between commodities against the FTSE/JSE Top 40 Index

The investigation of the relationships between the datasets leads to the determination of whether the five variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done in order to determine which relationships are present between the variables. In order to identify whether the variables are cointegrated, the Johansen cointegration test was done. The long run relationship analysis was followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required in order to determine whether an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables, both showing a common stochastic drift. A stochastic drift is the change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once (Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

The Johansen cointegration test in Table 6.5 shows there is a cointegrating relationship when the data is not linear, testing intercept no trend, as well as when the data is linear, testing intercept no trend, and intercept and trend and lastly, when the data is quadratic, testing intercept and trend.

Table 6.5: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 2 | 2 | 2 | 2 | 2 |
| Spot before crisis: Max-Eig | 2 | 2 | 2 | 2 | 2 |
| Spot after crisis: Trace | 0 | 1 | 1 | 0 | 1 |
| Spot after crisis: Max-Eig | 0 | 0 | 1 | 1 | 1 |
| Future before crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future before crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred as all the variables have trends that are stochastic. The Johansen cointegration test indicates that only spot before and after crisis have cointegrating relationships. The remainder of the results indicate the variables are not cointegrated and therefore no VECM results were included. When cointegration exists, it implies that Granger causality exists in at least one direction between the included variables, which was discussed in an earlier section. The Pairwise Granger causality test and Toda Yamamoto test indicated that causality was found between a number of variables. The vector error correction model (VECM) identified the short and long run dynamics of the included variables based on one cointegration relationship for spot before and after the crisis.

Table 6.6: Maximum eigenvalue statistics and trace statistics

| Hypothesized number of Cointegrating Equations | Eigen-value | Trace Statistic | 5% Critical Value | Prob** |
|--|-------------|-----------------|-------------------|--------|
| Spot before crisis: At most 1* | 0.019 | 60.853 | 47.856 | 0.002 |
| Spot after crisis: None* | 0.018 | 74.159 | 69.819 | 0.022 |

| Hypothesized number of Cointegrating Equations | Eigen-value | Max-Eig Statistic | 5% Critical Value | Prob** |
|--|-------------|-------------------|-------------------|--------|
| Spot before crisis: At most 1* | 0.019 | 37.018 | 27.584 | 0.002 |
| Spot after crisis: None* | 0.018 | 34.331 | 33.877 | 0.044 |

Spot before crisis:

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level

Spot after crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

** denotes rejection of the hypothesis at the 0.05 level*

***MacKinnon-Haug-Michelis (1999) p-values*

Source: Thomson Reuters DataStream and EViews.

Table 6.6 reports the maximum eigenvalue statistics and trace statistics as allowance for an intercept and no trend in the data was made. The table illustrates that the null hypothesis based on the trace statistic and maximum eigenvalue of no cointegrating equations can be rejected. Therefore, according to the trace test, cointegration is present within the combination of variables, which indicates a long run relationship.

6.5.5. Short run dynamics between commodities against the FTSE/JSE Top 40 Index

The VECM further investigates the long run and short run dynamics of the variables. It is a restricted VAR designed for use with nonstationary series that are known to be cointegrated. Table 6.7 is linked to the results from the Johansen cointegration test based on one cointegrating relationship.

Table 6.7: Cointegration equation – normalised for the FTSE/JSE Top 40 Index

| Cointegrating Eq: | LFTSE_JSE40(-1) | LBRENTOIL(-1) | LJETKEROSENE(-1) | LNAPHTHA(-1) | LNATURALGAS(-1) |
|-------------------------------------|-----------------|---------------|------------------|--------------|-----------------|
| Spot before crisis: CointEq1 | 1.000 | 0.000 | 8.877 | -10.868 | 0.882 |
| | | | (1.587) | (1.687) | (0.469) |
| | | | [5.595] | [-6.441] | [1.881] |
| Spot after crisis: CointEq1 | LFTSE_JSE40(-1) | LBRENTOIL(-1) | LJETKEROSENE(-1) | LNAPHTHA(-1) | LNATURALGAS(-1) |
| | 1.000 | -118.528 | 80.068 | 48.072 | 2.023 |
| | | (20.439) | (16.457) | (11.780) | (2.284) |
| | | [-5.799] | [4.865] | [4.081] | [0.886] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

In Table 6.7, when the cointegrating equation (normalised for the FTSE/JSE Top 40 Index) is considered, it is evident that jet kerosene, brent oil and naphtha are statistically significant variables when the FTSE/JSE Top 40 Index is the dependent variable in the long run. In spot after the crisis, brent oil is the most significant variable with the highest t-statistic of absolute value of 5.799. Brent oil has a positive relationship with the FTSE/JSE Top 40 Index of 118.528 units. The coefficient obtained in the results is inverted, therefore a positive value results in a negative relationship. Jet kerosene has a negative relationship with the FTSE/JSE Top 40 Index.

Table 6.8: Vector Error Correction Model (VECM) short run

| Error Correction: | D(LFTSE_JSE40) | D(LBRENTOIL) | D(LJETKEROSENE) | D(LNAPHTHA) | D(LNATURALGAS) |
|---------------------------------|----------------|--------------|-----------------|-------------|----------------|
| Spot before crisis: CointEq1 | 0.000 | 0.001 | -0.005 | 0.000 | 0.001 |
| | 0.000 | -0.001 | -0.001 | -0.001 | -0.002 |
| | [-0.084] | [1.337] | [-5.730] | [-0.569] | [0.734] |
| | D(LFTSE_JSE40) | D(LBRENTOIL) | D(LJETKEROSENE) | D(LNAPHTHA) | D(LNATURALGAS) |
| Spot after crisis: CointEq1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | [-0.771] | [-0.404] | [-2.754] | [-2.135] | [-0.475] |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

When the short run dynamics are considered, as shown in Table 6.8, jet kerosene is the only statistically significant variable as the *t-statistic* is above 1.96 both before and after the crisis. The error correction coefficients of jet kerosene before the crisis are negative. This implies that if a shock occurs, the variables will move back to the equilibrium. The coefficients for crude oil are also close to zero, which implies that the move back to the equilibrium will be very slow.

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities and the FTSE/JSE Top 40 Index are displayed in Table 6.9.

Table 6.9: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|--------------------|--------------------|----------|--------|----|-------|
| Spot before crisis | DLFTSE_JSE40 | All | 20.867 | 12 | 0.052 |
| Spot before crisis | DLBRENTOIL | All | 19.759 | 12 | 0.072 |

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|---------|----|--------|
| Spot before crisis | DLJETKEROSENE | All | 134.878 | 12 | 0.000* |
| Spot before crisis | DLNAPHTHA | All | 187.422 | 12 | 0.000* |
| Spot before crisis | DLNATURALGAS | All | 35.447 | 12 | 0.000* |
| Spot after crisis | DLFTSE_JSE40 | All | 19.017 | 12 | 0.088 |
| Spot after crisis | DLBRENTAOL | All | 15.854 | 12 | 0.198 |
| Spot after crisis | DLJETKEROSENE | All | 40.529 | 12 | 0.000* |
| Spot after crisis | DLNAPHTHA | All | 27.472 | 12 | 0.007* |
| Spot after crisis | DLNATURALGAS | All | 18.033 | 12 | 0.115 |
| Future before crisis | DLFTSE_JSE40_F | All | 4.904 | 4 | 0.297 |
| Future before crisis | DLBRENTAOL_F | All | 7.190 | 4 | 0.126 |
| Future before crisis | DLNATURALGAS_F | All | 8.099 | 4 | 0.088 |
| Future after crisis | DLFTSE_JSE40_F | All | 35.446 | 4 | 0.000* |
| Future after crisis | DLBRENTAOL_F | All | 2.995 | 4 | 0.559 |
| Future after crisis | DLNATURALGAS_F | All | 2.328 | 4 | 0.676 |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: Jet kerosene, naphtha and natural gas
- Spot after crisis: Jet kerosene and naphtha
- Future before crisis: None
- Future after crisis: FTSE/JSE Top 40 Index.

The null hypothesis can be rejected for the remainder of the variables. The variables ranked from the most exogenous to the most endogenous are indicated by Chi-square value. A higher Chi-square value indicates that the variable is more exogenous.

Appendix C.3 shows the response of the FTSE/JSE Top 40 Index when one of the other variables experiences a shock. The impulse response when five periods on a daily basis are included indicates whether the FTSE/JSE Top 40 Index increases or decreases and whether this effect is likely to be permanent. As shown by the impulse response, a rapid increase in a commodity price will cause an initial increase in the FTSE/JSE Top 40 Index. Thereafter it seems to decrease slowly to equilibrium. On average it takes two to three days for the FTSE/JSE Top 40 Index to move back to equilibrium.

The most noticeable difference as compared to other impulse responses is the effect of the natural gas on the FTSE/JSE Top 40 Index, as the movement of the FTSE/JSE Top 40 Index remains very close to zero.

The variance decomposition of the five variables is displayed in Appendix C.3 to indicate that the percentage value of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals. The variance decomposition of the FTSE/JSE Top 40 Index illustrates that at period 1, most of the movement is explained by its own variance. Brent oil explains the second highest amount of the movement after the crisis at above 10%.

The results for the relationship between the ZAR and the FTSE/JSE Top 40 Index and four commodities before and after the crisis as well as both spot and future are shown below in the remainder of the section.

6.5.6. VAR results between commodities, FTSE/JSE Top 40 Index and ZAR

The long run relationship and short run dynamics analysis for the relationship between the commodities and the FTSE/JSE Top 40 Index against the ZAR begins with the VAR model, which requires the optimal lag length to be determined, and the output is shown in Table 6.10. The VAR analyses for all four datasets are included in Appendix C.4.

Table 6.10: VAR lag order selection criteria of the ZAR, FTSE/JSE Top 40 Index and the four commodities

| | Lag | LogL | LR | FPE | AIC | SC | HQ |
|-----------------------------|-----|-----------|-----------|--------|----------|----------|----------|
| Spot before crisis | 3 | 29914.970 | 106.325 | 0.000* | -30.612* | -30.286 | -30.492 |
| Spot after crisis | 3 | 33391.460 | 139.454 | 0.000* | -35.177* | -34.843 | -35.054 |
| Future before crisis | 1 | 20180.500 | 38319.290 | 0.000* | -20.709* | -20.652* | -20.688* |
| Future after crisis | 2 | 21013.080 | 87.648* | 0.000* | -22.269* | -22.163 | -22.230* |

* 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: Thomson Reuters DataStream and EViews.

Table 6.10 illustrates the optimal lag length for the different datasets. Spot before crisis is two lags and therefore the VAR model is estimated using two lags and results in 26 significant relationships in the VAR results. Spot after crisis is three lags, and 21 significant relationships exist. Future before crisis is one lag and 7 significant relationships exist. Future after crisis is two lags and 14 significant relationships exist.

The estimated VAR that is obtained in the analysis will be stable or stationary if all roots have modulus less than one and lie inside the unit circle. If the VAR is not stable, meaning that a root lies outside the circle, then certain results such as impulse responses will not be valid (Luetkepohl, 2005).

As shown in Figure 6.5, no root lies outside the unit circle, which shows that VAR satisfies the stability condition.

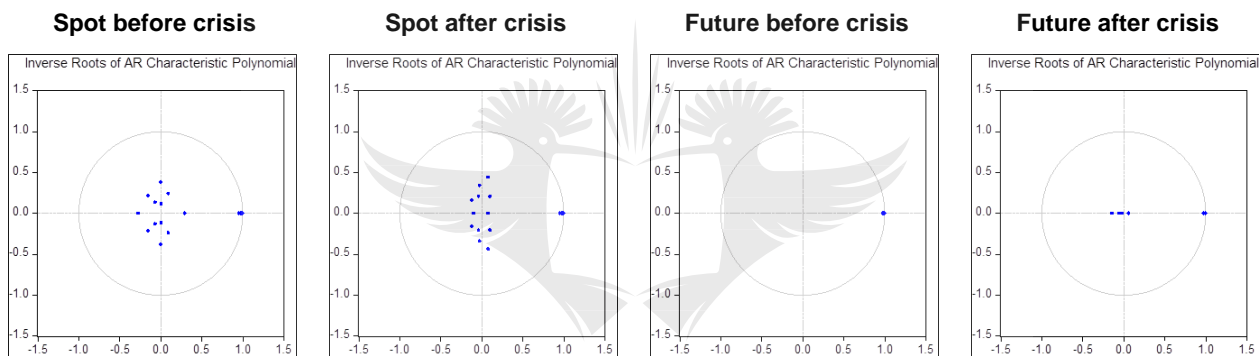


Figure 6.5: Roots of characteristic polynomial

Source: Thomson Reuters DataStream and EViews.

6.5.7. Long run relationship between commodities and the FTSE/JSE Top 40 Index against the ZAR

The examination of the relationships between the variables leads to the objective of whether the six variables are cointegrated and to capture the long and short run dynamics of the time series data. The analysis is done to determine which relationships are present between the variables. To identify whether the variables are cointegrated, the Johansen cointegration test will be done. The long run relationship analysis will be followed by the short run dynamics analysis, which includes the VECM and innovation accounting methods.

The Johansen cointegration test is required to determine whether an economically significant stable long run relationship exists between the variables. The Johansen cointegration test tests all variables as endogenous variables. Cointegration is the property of two time series variables, both showing a common stochastic drift. A stochastic drift is the

change in average value of the random or stochastic process. The Johansen cointegration test has the advantage of being able to handle several time series variables at once (Johansen, 1991). The number of cointegrating relationships obtained in the Johansen cointegration results will be required for VECM analysis.

Table 6.11: Summary of all assumptions of the Johansen cointegration test

| Data Trend: | None | None | Linear | Linear | Quadratic |
|-------------------------------|--------------|-----------|-----------|-----------|-----------|
| Test Type | No Intercept | Intercept | Intercept | Intercept | Intercept |
| | No Trend | No Trend | No Trend | Trend | Trend |
| Spot before crisis: Trace | 3 | 3 | 3 | 2 | 2 |
| Spot before crisis: Max-Eig | 2 | 2 | 3 | 2 | 2 |
| Spot after crisis: Trace | 1 | 1 | 1 | 0 | 1 |
| Spot after crisis: Max-Eig | 1 | 1 | 1 | 0 | 1 |
| Future before crisis: Trace | 1 | 1 | 1 | 0 | 0 |
| Future before crisis: Max-Eig | 1 | 0 | 0 | 0 | 0 |
| Future after crisis: Trace | 0 | 0 | 0 | 0 | 0 |
| Future after crisis: Max-Eig | 0 | 0 | 0 | 0 | 0 |

Selected (0.05 level) Number of Cointegrating Relations by Model*

**Critical values based on MacKinnon-Haug-Michelis (1999)*

Source: Thomson Reuters DataStream and EViews.

The cointegration test in Table 6.11 shows there are cointegrating relationships at the following sets:

- No trend in the data, not testing intercept and trend
- No trend in the data, testing intercept and not trend
- Data is linear, testing intercept and not trend
- Data is linear, testing intercept and trend
- Data is quadratic, testing intercept and trend.

The remainder of the empirical analysis focused on the linear relationship with an intercept and no trend that is based on the output in the third column of results (linear, intercept, no trend). That option is preferred as all the variables have trends that are stochastic. The Johansen cointegration test indicates that three data sets – spot before crisis, spot after crisis, and future before crisis have at least one cointegrating relationship. When cointegration exists, it implies that Granger causality exists in at least one direction between the included variables, which was discussed in an earlier section. The Pairwise Granger causality test and Toda Yamamoto test indicated that causality was found between a number of variables. The vector error correction model (VECM) identified the short and long

run dynamics of the included variables based on one cointegration relationship in three data sets – spot before crisis, spot after crisis, and future before crisis.

Table 6.12: Maximum eigenvalue statistics and trace statistics

| Hypothesized number of Cointegrating Equations | Eigen-value | Trace Statistic | 5% Critical Value | Prob** |
|--|-------------|-------------------|-------------------|--------|
| Spot before crisis: At most 2* | 0.014 | 51.495 | 47.856 | 0.022 |
| Spot after crisis: None* | 0.023 | 103.760 | 95.754 | 0.013 |
| Future before crisis: None* | 0.013 | 49.710 | 47.856 | 0.033 |
| Hypothesized number of Cointegrating Equations | Eigen-value | Max-Eig Statistic | 5% Critical Value | Prob** |
| Spot before crisis: At most 2* | 0.014 | 28.057 | 27.584 | 0.044 |
| Spot after crisis: None* | 0.023 | 44.047 | 40.078 | 0.017 |
| Future before crisis: At most 1 * | 0.012 | 22.669 | 21.132 | 0.030 |

Spot before crisis:

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level

Spot after crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

Future before crisis:

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Max-eigenvalue test indicates no cointegration at the 0.05 level

** denotes rejection of the hypothesis at the 0.05 level*

***MacKinnon-Haug-Michelis (1999) p-values*

Source: Thomson Reuters DataStream and EViews.

Table 6.12 reports the maximum eigenvalue statistics and trace statistics as allowance for an intercept and no trend in the data was made. The table illustrates that the null hypothesis based on the trace test and maximum eigenvalue of no cointegrating equations can be rejected. Therefore, cointegration is present within the combination of variables, which indicates a long run relationship.

The remainder of the empirical analysis will focus on the linear relationship with an intercept and no trend.

6.5.8. Short run dynamics between commodities and the FTSE/JSE Top 40 Index against the ZAR

The VECM will identify the short and long run dynamics of the included time series variables. The VECM is a restricted VAR that is intended to use with nonstationary series that are

known to be cointegrated. Table 6.13 is based on the results from the Johansen cointegration test, based on one cointegrating relationship.

Table 6.13: Cointegration equation – normalised for the ZAR

| Cointegrating Eq | LZAR(-1) | LBRENTOIL(-1) | LJETKEROSENE(-1) | LNAPHTHA(-1) | LNATURALGAS(-1) | LFTSE_JSE40(-1) |
|-----------------------------------|-------------------|------------------------|--------------------------|--------------------------|-----------------|------------------|
| Spot before crisis: CointEq1 | 1.000 | 0.000 | 0.000 | 1.482 | -0.499 | -0.964 |
| | | | | (0.194) | (0.123) | (0.154) |
| | | | | [7.639] | [-4.046] | [-6.279] |
| Spot after crisis: CointEq1 | 1.000 | -3.605 | 2.832 | 1.341 | 0.113 | -0.811 |
| | | (0.569) | (0.470) | (0.331) | (0.064) | (0.075) |
| | | [-6.339] | [6.025] | [4.050] | [1.772] | [-10.744] |
| | LZAR_F(-1) | LBRENTOIL_F(-1) | LNATURALGAS_F(-1) | LFTSE_JSE40_F(-1) | | |
| Future before crisis: CointEq1 | 1.000 | -0.165 | 0.818 | -0.096 | | |
| | | (0.300) | (0.178) | (0.254) | | |
| | | [-0.549] | [4.597] | [-0.380] | | |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

As illustrated in Table 6.13, spot before crisis, naphtha, natural gas and the FTSE/JSE Top 40 Index are statistically significant variables when the ZAR is the dependent variable in the cointegrating relationship (normalised for the ZAR) in the long run. Spot after the crisis, natural gas is no longer statistically significant. Future after the crisis, only natural gas is statistically significant. The FTSE/JSE Top 40 Index is the most significant variable, with the highest t-statistic of absolute value of 10.744 for spot after the crisis. The coefficient obtained in the results is inverted; therefore, a negative value results in a positive relationship.

Table 6.14: Vector Error Correction Model (VECM) short run

| Error Correction: | D(LZAR) | D(LBRENTOIL) | D(LJETKEROSENE) | D(LNAPHTHA) | D(LNATURALGAS) | D(LFTSE_JSE40) |
|-----------------------------------|------------------|-----------------------|-------------------------|-------------------------|-----------------|-----------------|
| Spot before crisis: CointEq1 | -0.003 | -0.007 | -0.004 | -0.018 | 0.009 | -0.004 |
| | (0.001) | (0.003) | (0.003) | (0.003) | (0.007) | (0.002) |
| | [-1.863] | [-2.232] | [-1.469] | [-5.534] | [1.417] | [-2.282] |
| Spot after crisis: CointEq1 | -0.004 | 0.000 | -0.009 | -0.008 | -0.003 | 0.003 |
| | (0.002) | (0.005) | (0.004) | (0.005) | (0.009) | (0.003) |
| | [-1.613] | [0.101] | [-2.454] | [-1.722] | [-0.339] | [1.380] |
| | D(LZAR_F) | D(LBRENTOIL_F) | D(LNATURALGAS_F) | D(LFTSE_JSE40_F) | | |
| Future before crisis: CointEq1 | -0.004 | -0.002 | -0.011 | 0.002 | | |
| | (0.001) | (0.002) | (0.004) | (0.001) | | |
| | [-3.265] | [-0.794] | [-3.054] | [1.372] | | |

Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

When the short run dynamics are considered as shown in Table 6.14, Brent oil, naphtha and the FTSE/JSE Top 40 Index are statistically significant for spot before the crisis as the *t*-statistics are significant on a 95% confidence level (critical value = 1.96). Future before the crisis only ZAR and natural gas are statistically significant, whereas jet kerosene is the only statistically significant variable for spot after the crisis.

All statistically significant variables have a negative error correction coefficient and therefore will move back to the long run equilibrium if there are short-term shocks. The coefficients are close to zero, which implies that the move back to the equilibrium will be slow.

The Block exogeneity Wald test examines the causal relationship among the variables based on the VAR model. The test treats all variables as exogenous in order to determine which variables should be treated as exogenous and endogenous going forward. The Block exogeneity tested by the Block exogeneity Wald test for the commodities, FTSE/JSE Top 40 Index, and the ZAR is displayed in Table 6.15.

Table 6.15: Block exogeneity Wald test

| | Dependent Variable | Excluded | Chi-sq | df | Prob. |
|----------------------|--------------------|----------|---------|----|--------|
| Spot before crisis | DLZAR | All | 15.251 | 15 | 0.434 |
| Spot before crisis | DLFTSE_JSE40 | All | 22.111 | 15 | 0.105 |
| Spot before crisis | DLBRENTAOL | All | 20.377 | 15 | 0.158 |
| Spot before crisis | DLJETKERSENE | All | 141.553 | 15 | 0.000* |
| Spot before crisis | DLNAPHTHA | All | 190.044 | 15 | 0.000* |
| Spot before crisis | DLNATURALGAS | All | 36.458 | 15 | 0.002* |
| Spot after crisis | DLZAR | All | 13.110 | 15 | 0.594 |
| Spot after crisis | DLFTSE_JSE40 | All | 28.183 | 15 | 0.021 |
| Spot after crisis | DLBRENTAOL | All | 16.965 | 15 | 0.321 |
| Spot after crisis | DLJETKERSENE | All | 42.749 | 15 | 0.000* |
| Spot after crisis | DLNAPHTHA | All | 28.230 | 15 | 0.020 |
| Spot after crisis | DLNATURALGAS | All | 18.755 | 15 | 0.225 |
| Future before crisis | DLZAR_F | All | 2.128 | 3 | 0.546 |
| Future before crisis | DLFTSE_JSE40_F | All | 5.912 | 3 | 0.116 |
| Future before crisis | DLBRENTAOL_F | All | 8.084 | 3 | 0.044 |
| Future before crisis | DLNATURALGAS_F | All | 5.587 | 3 | 0.134 |
| Future after crisis | DLZAR_F | All | 11.507 | 6 | 0.074 |
| Future after crisis | DLFTSE_JSE40_F | All | 51.826 | 6 | 0.000* |
| Future after crisis | DLBRENTAOL_F | All | 6.197 | 6 | 0.402 |
| Future after crisis | DLNATURALGAS_F | All | 3.279 | 6 | 0.773 |

* indicates significance at a 1% level of significance

Source: Thomson Reuters DataStream and EViews.

The following variables are exogenous and therefore the null hypothesis that the dependent variable is exogenous is accepted:

- Spot before crisis: Jet kerosene, naphtha and natural gas
- Spot after crisis: Jet kerosene
- Future before crisis: None
- Future after crisis: FTSE/JSE Top 40 Index.

This shows robustness of the results since adding the ZAR to the combination of variables has only slightly changed the dynamics from the previous analysis. The null hypothesis can be rejected for the remainder of the variables. The variables are ranked from the most exogenous to the most endogenous, with a higher Chi-square value indicating that the variable is more exogenous.

In Appendix C.5, the response of the ZAR when one of the other variables experiences a shock is illustrated. The impulse response when five periods are included indicates whether the ZAR increases or decreases and whether this effect is likely to be permanent. The response of the FTSE/JSE Top 40 Index is opposite to the response obtained for the ZAR as the response of the ZAR is in upward sloping starting from a negative base, except before the crisis. On average, the move back to the equilibrium is between two and three days. Similar to the results in Appendix C.3, the most noticeable difference as compared to other impulse responses is the effect of the natural gas on the ZAR, as the movement of the ZAR remains very close to zero. The ZAR shows an opposite reaction to the FTSE/JSE Top 40 Index as the flow of funds related to international trade is different between the currency and the equity Index. With the ZAR against the USD, two currencies are being affected, the ZAR and the USD. With the FTSE/JSE Top 40 Index, only the index is involved and not two currencies.

The variance decomposition of the seven variables is displayed in Appendix C.5 to indicate how much of the forecast variance in a variable is attributed to variation in the other variables at a 1, 5, 10 and 20 period horizon.

The variance decomposition results indicate the percentage amount that each variable contributes to the variance of the ZAR and FTSE/JSE Top 40 Index at 1, 5, 10 and 20-day intervals. The variance decomposition of the ZAR shows that most of the movement is explained by itself.

The FTSE/JSE Top 40 Index illustrates that most of the movement is explained by its own variance. Brent oil explains between 9% and 12% of the FTSE/JSE Top 40 Index movement after the crisis for both spot and future.

The VECM results, where only the FTSE/JSE Top 40 Index and the four commodities were included, showed that in the long run, jet kerosene, brent oil and naphtha were statistically significant for spot after the crisis when the FTSE/JSE Top 40 Index was the dependent variable. In the short run, no variable was statistically significant, with a small negative coefficient. The VECM results where all six variables were included showed that the FTSE/JSE Top 40 Index, jet kerosene, brent oil and naphtha were statistically significant variables for spot after crisis when the ZAR was the dependent variable. Considering the short run dynamics, the VECM results showed that only jet kerosene was statistically significant, with a small negative error correction coefficient. The Cholesky ordering for both relationships was similar, which implies that the ordering is correct.

6.6. CONCLUSION

In conclusion, the empirical results show that there are significant relationships in the long run and short run of the included variables. The objectives addressing the movement relationships between the variables were the main focus of this chapter. The correlation analysis showed that three sets of variables moved together in a positive manner. The variables that moved together were: jet kerosene and brent oil, jet kerosene and naphtha, brent oil and naphtha, all for spot after the crisis.

Naphtha spot and brent future provided the highest synchronicity for ZAR spot and future respectively. For the FTSE/JSE Top 40 Index, natural gas showed the highest synchronicity for the spot and future combinations.

Several unidirectional relationships were found for ZAR and the FTSE/JSE Top 40 Index after the crisis:

- From brent oil to FTSE/JSE Top 40 Index: spot and future (both tests)
- From brent oil to ZAR: future after (both tests)
- From jet kerosene to FTSE/JSE Top 40 Index: spot (both tests)
- From naphtha to FTSE/JSE Top 40 Index: spot (both tests)
- From FTSE/JSE Top 40 Index to natural gas: spot (Toda Yamamoto test)
- From ZAR to jet kerosene: spot (Toda Yamamoto test)

- From ZAR to FTSE/JSE Top 40 Index: spot and future (both tests).

The remainder of the analysis focused on VAR, Johansen cointegration, VECM and innovation accounting methods. The analysis indicates that there are numerous significant relationships between the six variables.

The VECM results were split into the two main relationships being investigated. The first relationship of the FTSE/JSE Top 40 Index and the four commodities indicated that when considering the cointegrating relationship, jet kerosene, brent oil and naphtha were statistically significant for spot after the crisis when the FTSE/JSE Top 40 Index was the dependent variable. The cointegrating equation normalised for the ZAR indicated that the FTSE/JSE Top 40 Index, jet kerosene, brent oil and naphtha were statistically significant variables for spot after the crisis when the ZAR was the dependent variable.

The short run dynamics of the first relationship of the FTSE/JSE Top 40 Index and the four commodities indicated that no variable entered the cointegrating equation significantly, with a small negative error correction coefficient. For the second relationship between all six variables only jet kerosene was statistically significant, with a small negative error correction coefficient.

The block exogeneity for the first relationship shows that jet kerosene and naphtha were not rejected for spot after crisis, whereas the FTSE/JSE Top 40 Index was not rejected for future after crisis; therefore, they were exogenous. The second relationship shows that jet kerosene was not rejected for spot after crisis, whereas the FTSE/JSE Top 40 Index was not rejected for future after crisis. The results were similar, which indicates that the model is robust.

The empirical results indicate that there is opportunity for further study in other types of commodities and other markets. Energy commodities do not influence the South African market as much as metal commodities and soft commodities, but energy commodities as well as other types of commodities will have different relationships to other financial markets that rely on the production of commodities. Further research can be done related to the forecasting ability of energy commodities as well as the determination of any speculative bubbles that might be present.

Similar to the literature related to metal commodities and soft commodities, the literature related to energy commodities also showed mixed results (Bhunja, 2013; Samanta & Zadeh, 2012; Ziegelbäck and Kastner, 2011; Panagiotidis & Rutledge, 2004). The selection of

commodities as well as the comparative financial variables or other comparative commodities need to be explored further as conclusive results as well as non-conclusive results are found when comparing certain commodities to other variables. The time period selected for the study is also an important consideration as differing results have been found when using different time periods with the same variables.

At this point, relationships between the variables have been identified, but the optimal cross hedging relationships will be explored further in Chapter 7.



CHAPTER 7

ESSAY 4: OPTIMAL CROSS HEDGING RELATIONSHIPS

7.1. INTRODUCTION

In the previous chapters, metal commodities showed the most significant results, followed by the soft commodities. Energy commodities showed the least meaningful results. In the chapter related to metal commodities, platinum, palladium, aluminium and copper showed various long run and short run relationships, but gold did not show significant relationships.

In the soft commodity chapter, corn, cotton and soyabean showed the most significant relationships, followed by sugar and wheat with less noteworthy results. In the energy commodity chapter, crude oil, jet kerosene and naphtha showed the most meaningful results, with natural gas not showing any significant relationships.

The relationships identified in the previous three chapters have focused only on relationships within commodity groups as well as between the FTSE/JSE Top 40 Index and the ZAR, which was done to understand the interrelationships between the variables. These relationships will be further investigated in this chapter to identify the cross hedging relationships within commodity groups and the FTSE/JSE Top 40 Index and ZAR. The research will be taken further to explore the cross hedging relationships across commodity groups as well.

The relationships between variables are a fundamental observation when investigating investment related decisions. These relationships are important to determine possible risk management opportunities by means of cross hedging. In order to investigate cross hedging possibilities, the relationship between variables needed to be determined in order to move forward with identifying optimal ratios.

7.2. REVIEW OF THE LITERATURE

The calculation of cross hedging relationships and optimal hedging relationships and ratios can be done in a number of ways; however, the focus of this study was on the Engle and

Granger two-step process to determine the optimal hedge ratio. Cross hedging is a technique available if no suitable similar asset is available to hedge the current exposure. For example, ethanol can possibly be hedged with corn. Taking the hedging a step further, the optimal hedge ratio provides an estimate of how many units are required from the other asset to hedge the current exposure (Coakley *et al.*, 2008, Eaker & Grant, 1987).

The methods available for estimating the optimal hedge ratio, or minimum variance hedge ratio are by means of the ordinary least squares (OLS) method, the error correction model (ECM) and the generalised autoregressive conditional heteroscedasticity (GARCH) model. The OLS method, which is based on a regression equation, obtains the estimated optimal hedge ratio by means of the slope coefficient that is generated in the results. The second and third methods estimate a time-varying optimal hedge ratio. The literature available as to which method provides the most accurate estimate related to hedging performance is mixed (Coakley *et al.*, 2008; Yang & Allen, 2005; Moosa, 2003; Harris & Shen, 2003; Lien, Tse & Tsui, 2002; Kavussanos & Nomikos, 2000a).

The OLS method has limitations in that it does not take into account time-varying distributions, serial correlation, heteroscedasticity, and cointegration. By not taking into account cointegration, the model produces results that contain a downward bias in the hedge ratio and result in under hedging, therefore the model is also misspecified. The ECM method and GARCH method produce results that perform better than the OLS method (Hatemi & Roca, 2006; Lien *et al.*, 2002; Sim & Zurbruegg, 2001).

7.3. METHODOLOGY

The data methodology applied in this study was explained in Chapter 3, and is based on historical time-series data which is used to explore the cross hedging and optimal hedge ratio relationships that exist between the spot and future variables included. The presence of relationships between the variables was examined using econometric tests applied to the data, namely OLS, ECM, VECM, ECM-GARCH, time-varying hedge ratio estimation based on asymmetric DCC-GARCH with GJR specification. The most reliable optimal hedge ratio is given by the slope coefficient of the model that minimizes the residual standard error (Asteriou & Hall, 2011; Luetkepohl, 2011; Watson, 1994; Johansen, 1991).

In addition, drawdown, Value at Risk on an asset, Value at Risk on a portfolio level between the spot and future variable, and lastly a mean variance comparison of future variables linked to a spot variable will be obtained to evaluate the effectiveness of the hedge under

consideration to determine whether any hedging relationships exist as well as the most optimal hedge ratios between the sixteen variables.

7.4. DATA

All fourteen commodities covered in Chapters 4, 5 and 6 are now included in this chapter. The FTSE/JSE Top 40 Index and ZAR will also be included in the data set. The prices of the datasets are daily spot and future prices available from the commodity benchmarks from the Thomson Reuters DataStream database. The sample period ran from 1 January 2000 to 30 June 2007 as well as from 1 October 2009 to 31 December 2016. These dates were chosen as each dataset was active at this time and to ignore the effects of the 2007 financial crisis. A total of 1954 data points for the time period before the 2007–2009 financial crisis and 1892 data points for the time period after the 2007–2009 financial crisis were included in the study. The data points were cleaned by removing any data that had no value in any of the datasets from all datasets. The data was analysed using financial econometric techniques in EViews and R.

The main research question of the study is related to the optimal hedging relationships between the variables included in the study. The main research question of this study was: What cross hedging relationships and optimal hedge ratios are present within the South African financial market context in relation to a selection of commodities.

For reference purposes, the empirical results are referenced as follows (the code represents the daily spot price):

- South African Rand against the United States Dollar:
 - ZAR: COMRAN\$ (WM/Reuters)
 - ZAR_F: NYRCS00 (FINEX-US\$/SA RAND CONTINUOUS)
- FTSE/JSE Top 40 Index: JSEAL40 (FTSE):
 - FTSE/JSE40: JSEAL40 (FTSE/JSE TOP 40 - PRICE INDEX)
 - FTSE/JSE40_F: SALCS00 (SAFEX-ALL SHARE 40 INDEX CONT. - SETT. PRICE)
- Aluminium:
 - ALUMINIUM: LAHCASH (LME-Aluminium 99.7% Cash U\$/MT)
 - ALUMINIUM_F: LAHCS00 (LME-ALUMINIUM CONTINUOUS - SETT. PRICE)
- Copper:
 - COPPER: LCPCASH (LME-Copper Grade A Cash U\$/MT)

- COPPER_F: LCPCS00 (LME-COPPER CONTINUOUS - SETT. PRICE)
- Gold:
 - GOLD: GOLDBLN (Gold Bullion LBM U\$/Troy Ounce)
 - GOLD_F: NGCCS00 (CMX-GOLD 100 OZ CONTINUOUS - SETT. PRICE)
- Palladium:
 - PALLADIUM: PALLADM (Palladium U\$/Troy Ounce)
 - PALLADIUM_F: NPACS00 (NYM-PALLADIUM CONTINUOUS - SETT. PRICE)
- Platinum:
 - PLATINUM: PLATFRE (London Platinum Free Market \$/Troy oz)
 - PLATINUM_F: NPLCS00 (NYM-PLATINUM CONTINUOUS - SETT. PRICE)
- Corn:
 - CORN: CORNUS2 (Corn No.2 Yellow U\$/Bushel)
 - CORN_F: CCFCS00 (CBT-CORN COMP. CONTINUOUS - SETT. PRICE)
- Cotton:
 - COTTON: COTTONM (Cotton,1 1/16Str Low -Midl,Memph \$/Lb)
 - COTTON_F: NCTCS00 (CSCE-COTTON #2 CONTINUOUS - SETT. PRICE)
- Soyabean:
 - SOYABEAN: SOYBEAN (Soyabeans, No.1 Yellow \$/Bushel)
 - SOYABEAN_F: CS.C.01 (CBT-SOYABEANS TRc1 C.01 - SETT. PRICE)
- Sugar:
 - SUGAR: WSUGDLY (Raw Sugar-ISA Daily Price c/lb)
 - SUGAR_F: NSBCS00 (CSCE-SUGAR #11 CONTINUOUS - SETT. PRICE)
- Wheat:
 - WHEAT: WHEATSF (Wheat No.2, Soft Red U\$/Bu)
 - WHEAT_F: CW.C.01 (CBT-WHEAT C.01 - SETT. PRICE)
- Crude Oil-Brent:
 - BRENT OIL: OILBRNP (Crude Oil-Brent Dated FOB U\$/BBL)
 - BRENT OIL_F: LLCCS00 (ICE-BRENT CRUDE OIL CONTINUOUS - SETT. PRICE)
- Jet Kerosene:
 - JET KEROSENE: JETCIFC U\$ (Jet Kerosene-Cargos CIF NWE U\$/MT)
 - JET KEROSENE_F: None
- Naphtha:
 - NAPHTHA: OILNAPH (Naphtha Europe CIF U\$/MT)
 - NAPHTHA_F: None

- Natural Gas:
 - NATURALGAS: NATGHEN (Natural Gas, Henry Hub U\$/MMBTU)
 - NATURALGAS_F: NNGCS00 (NYM-NATURAL GAS CONTINUOUS - SETT. PRICE)

7.5. EMPIRICAL RESULTS

The empirical results will include static hedge ratios, time-varying hedge ratios, hedging effectiveness and final optimal cross relationships supported with drawdown, mean variance analysis, Value at Risk measures as well as Expected Shortfall measures.

7.5.1. Correlation

The correlation between all variables, both spot and future, is shown in Table 7.1. In Table 7.2 the difference between the correlation values is shown. If the correlation has increased from before crisis to after crisis, the cell is highlighted in green. If the correlation has decreased, the cell is highlighted in red. Cells not highlighted in any colour represent a correlation difference that is between -0.01 and 0.01 from before the crisis to after the crisis. The negative values of ZAR and ZAR_F were reversed to still indicate an increase or decrease in correlation, away from zero and to zero respectively.

Overall, the static correlation indicates that correlation between the majority of the variables has increased; however, the correlations are still low between commodity classes. This still allows for hedging to occur based on the conclusion of Baur and Lucey (2010).

Table 7.1: Correlation summary

| Before Crisis | DLALUMINIUM | DLALUMINIUM_F | DLBRENT OIL | DLBRENT OIL_F | DLCOPPER | DLCOPPER_F | DLCORN | DLCORN_F | DLCOTT ON | DLCOTT ON_F | DLFTSE JSE40 | DLFTSE JSE40_F | DLGOLD | DLGOLD_F | DLJETKE ROSENE | DLNAPHTHA | DLNATURALGAS | DLNATURALGAS_F | DLPALLADIUM | DLPALLADIUM_F | DLPLATINUM | DLPLATINUM_F | DLSOYABEAN | DLSOYABEAN_F | DLSUGAR | DLSUGAR_F | DLWHEAT | DLWHEAT_F | DLZAR | DLZAR_F |
|----------------|-------------|---------------|-------------|---------------|----------|------------|--------|----------|-----------|-------------|--------------|----------------|--------|----------|----------------|-----------|--------------|----------------|-------------|---------------|------------|--------------|------------|--------------|---------|-----------|---------|-----------|--------|---------|
| DLALUMINIUM | 1.000 | 0.988 | 0.071 | 0.091 | 0.726 | 0.689 | 0.075 | 0.082 | 0.063 | 0.081 | 0.216 | 0.219 | 0.264 | 0.268 | 0.056 | 0.075 | 0.030 | 0.085 | 0.130 | 0.216 | 0.135 | 0.178 | 0.064 | 0.076 | 0.082 | 0.048 | 0.074 | 0.084 | -0.175 | -0.145 |
| DLALUMINIUM_F | 0.988 | 1.000 | 0.074 | 0.094 | 0.735 | 0.699 | 0.083 | 0.098 | 0.060 | 0.090 | 0.218 | 0.226 | 0.266 | 0.275 | 0.061 | 0.081 | 0.030 | 0.080 | 0.131 | 0.215 | 0.136 | 0.182 | 0.070 | 0.083 | 0.081 | 0.048 | 0.078 | 0.083 | -0.177 | -0.146 |
| DLBRENT OIL | 0.071 | 0.074 | 1.000 | 0.755 | 0.098 | 0.094 | 0.033 | 0.053 | 0.064 | 0.071 | 0.066 | 0.073 | 0.138 | 0.168 | 0.464 | 0.379 | 0.159 | 0.251 | 0.038 | 0.069 | 0.100 | 0.088 | 0.055 | 0.048 | 0.062 | 0.103 | 0.068 | 0.075 | -0.063 | -0.041 |
| DLBRENT OIL_F | 0.091 | 0.094 | 0.755 | 1.000 | 0.112 | 0.109 | 0.066 | 0.075 | 0.071 | 0.094 | 0.065 | 0.066 | 0.130 | 0.189 | 0.424 | 0.337 | 0.124 | 0.303 | 0.011 | 0.052 | 0.087 | 0.093 | 0.081 | 0.079 | 0.062 | 0.083 | 0.059 | 0.086 | -0.035 | -0.024 |
| DLCOPPER | 0.726 | 0.735 | 0.098 | 0.112 | 1.000 | 0.948 | 0.067 | 0.077 | 0.065 | 0.091 | 0.245 | 0.247 | 0.308 | 0.321 | 0.077 | 0.088 | 0.015 | 0.077 | 0.126 | 0.228 | 0.161 | 0.205 | 0.065 | 0.071 | 0.088 | 0.066 | 0.072 | 0.080 | -0.164 | -0.153 |
| DLCOPPER_F | 0.689 | 0.699 | 0.094 | 0.109 | 0.948 | 1.000 | 0.062 | 0.061 | 0.057 | 0.092 | 0.250 | 0.252 | 0.288 | 0.309 | 0.070 | 0.072 | 0.017 | 0.071 | 0.116 | 0.215 | 0.151 | 0.193 | 0.048 | 0.052 | 0.085 | 0.066 | 0.055 | 0.059 | -0.141 | -0.137 |
| DLCORN | 0.075 | 0.083 | 0.033 | 0.066 | 0.067 | 0.062 | 1.000 | 0.840 | 0.107 | 0.144 | 0.067 | 0.064 | 0.061 | 0.096 | 0.029 | 0.028 | 0.030 | 0.077 | 0.053 | 0.061 | 0.057 | 0.063 | 0.489 | 0.461 | 0.008 | 0.053 | 0.452 | 0.493 | -0.011 | 0.007 |
| DLCORN_F | 0.082 | 0.098 | 0.053 | 0.075 | 0.077 | 0.061 | 0.840 | 1.000 | 0.094 | 0.166 | 0.072 | 0.088 | 0.087 | 0.125 | 0.047 | 0.038 | 0.013 | 0.076 | 0.050 | 0.069 | 0.046 | 0.057 | 0.489 | 0.461 | 0.049 | 0.058 | 0.470 | 0.530 | -0.025 | 0.006 |
| DLCOTT ON | 0.063 | 0.060 | 0.064 | 0.071 | 0.065 | 0.057 | 0.107 | 0.094 | 1.000 | 0.718 | 0.014 | 0.017 | 0.034 | 0.053 | 0.049 | 0.033 | 0.051 | 0.012 | -0.038 | -0.004 | -0.011 | -0.027 | 0.138 | 0.146 | 0.056 | 0.011 | 0.084 | 0.103 | -0.013 | -0.027 |
| DLCOTT ON_F | 0.081 | 0.090 | 0.071 | 0.094 | 0.091 | 0.092 | 0.144 | 0.166 | 0.718 | 1.000 | 0.032 | 0.046 | 0.055 | 0.097 | 0.068 | 0.047 | 0.031 | -0.018 | -0.020 | 0.032 | -0.020 | -0.008 | 0.158 | 0.157 | 0.065 | 0.065 | 0.103 | 0.123 | -0.031 | -0.035 |
| DLFTSE JSE40 | 0.216 | 0.218 | 0.066 | 0.065 | 0.245 | 0.250 | 0.067 | 0.072 | 0.014 | 0.032 | 1.000 | 0.960 | 0.159 | 0.105 | 0.033 | 0.032 | 0.022 | 0.018 | 0.112 | 0.120 | 0.069 | 0.095 | 0.070 | 0.061 | 0.001 | 0.006 | 0.043 | 0.053 | 0.169 | 0.132 |
| DLFTSE JSE40_F | 0.219 | 0.226 | 0.073 | 0.066 | 0.247 | 0.252 | 0.064 | 0.088 | 0.017 | 0.046 | 0.960 | 1.000 | 0.136 | 0.095 | 0.031 | 0.023 | 0.022 | 0.022 | 0.115 | 0.124 | 0.066 | 0.109 | 0.072 | 0.063 | 0.004 | 0.010 | 0.052 | 0.055 | 0.147 | 0.128 |
| DLGOLD | 0.264 | 0.266 | 0.138 | 0.130 | 0.308 | 0.288 | 0.061 | 0.087 | 0.034 | 0.055 | 0.159 | 0.136 | 1.000 | 0.703 | 0.150 | 0.135 | 0.091 | 0.058 | 0.270 | 0.311 | 0.322 | 0.325 | 0.063 | 0.055 | 0.081 | 0.084 | 0.088 | 0.083 | -0.304 | -0.240 |
| DLGOLD_F | 0.268 | 0.275 | 0.168 | 0.189 | 0.321 | 0.309 | 0.096 | 0.125 | 0.053 | 0.097 | 0.105 | 0.095 | 0.703 | 1.000 | 0.125 | 0.105 | 0.072 | 0.101 | 0.183 | 0.320 | 0.212 | 0.356 | 0.083 | 0.099 | 0.071 | 0.089 | 0.090 | 0.089 | -0.275 | -0.283 |
| DLJETKE ROSENE | 0.056 | 0.061 | 0.464 | 0.424 | 0.077 | 0.070 | 0.029 | 0.047 | 0.068 | 0.033 | 0.031 | 0.150 | 0.125 | 1.000 | 0.470 | 0.200 | 0.156 | 0.014 | 0.049 | 0.081 | 0.072 | 0.043 | 0.040 | 0.075 | 0.052 | 0.050 | 0.055 | -0.047 | -0.036 | |
| DLNAPHTHA | 0.075 | 0.081 | 0.379 | 0.337 | 0.088 | 0.072 | 0.028 | 0.038 | 0.033 | 0.047 | 0.032 | 0.023 | 0.135 | 0.105 | 0.470 | 1.000 | 0.143 | 0.084 | 0.064 | 0.075 | 0.110 | 0.098 | 0.042 | 0.042 | 0.008 | 0.069 | 0.046 | 0.044 | -0.018 | 0.012 |
| DLNATURALGAS | 0.030 | 0.030 | 0.159 | 0.124 | 0.015 | 0.017 | 0.030 | 0.013 | 0.051 | 0.031 | 0.022 | 0.022 | 0.091 | 0.072 | 0.200 | 0.143 | 1.000 | 0.286 | 0.031 | 0.028 | 0.060 | 0.025 | 0.024 | 0.028 | 0.054 | 0.066 | -0.016 | -0.008 | -0.041 | -0.027 |
| DLNATURALGAS_F | 0.085 | 0.080 | 0.251 | 0.303 | 0.077 | 0.071 | 0.077 | 0.076 | 0.012 | -0.018 | 0.018 | 0.022 | 0.058 | 0.101 | 0.156 | 0.084 | 0.286 | 1.000 | 0.014 | 0.025 | 0.031 | 0.040 | 0.098 | 0.101 | 0.038 | 0.070 | 0.015 | 0.036 | -0.043 | -0.047 |
| DLPALLADIUM | 0.130 | 0.131 | 0.038 | 0.011 | 0.126 | 0.116 | 0.053 | 0.050 | -0.038 | -0.020 | 0.112 | 0.115 | 0.270 | 0.183 | 0.014 | 0.064 | 0.031 | 0.014 | 1.000 | 0.663 | 0.484 | 0.290 | 0.047 | 0.051 | 0.067 | 0.072 | 0.043 | 0.015 | -0.086 | -0.048 |
| DLPALLADIUM_F | 0.216 | 0.215 | 0.069 | 0.052 | 0.228 | 0.215 | 0.061 | 0.069 | -0.004 | 0.032 | 0.120 | 0.124 | 0.311 | 0.320 | 0.049 | 0.075 | 0.028 | 0.025 | 0.663 | 1.000 | 0.342 | 0.398 | 0.068 | 0.069 | 0.048 | 0.075 | 0.067 | 0.053 | -0.123 | -0.106 |
| DLPLATINUM | 0.135 | 0.136 | 0.100 | 0.087 | 0.161 | 0.151 | 0.057 | 0.046 | -0.011 | -0.020 | 0.069 | 0.066 | 0.322 | 0.212 | 0.081 | 0.110 | 0.060 | 0.031 | 0.484 | 0.342 | 1.000 | 0.533 | 0.017 | 0.011 | 0.055 | 0.059 | 0.050 | 0.035 | -0.096 | -0.069 |
| DLPLATINUM_F | 0.178 | 0.182 | 0.088 | 0.093 | 0.205 | 0.193 | 0.063 | 0.057 | -0.027 | -0.008 | 0.095 | 0.109 | 0.325 | 0.356 | 0.072 | 0.098 | 0.025 | 0.040 | 0.290 | 0.398 | 0.533 | 1.000 | 0.046 | 0.046 | 0.064 | 0.068 | 0.063 | 0.061 | -0.124 | -0.100 |
| DLSOYABEAN | 0.064 | 0.070 | 0.055 | 0.081 | 0.065 | 0.048 | 0.489 | 0.496 | 0.138 | 0.158 | 0.070 | 0.072 | 0.063 | 0.083 | 0.043 | 0.042 | 0.024 | 0.098 | 0.047 | 0.068 | 0.017 | 0.046 | 1.000 | 0.834 | 0.045 | 0.051 | 0.305 | 0.336 | -0.022 | -0.001 |
| DLSOYABEAN_F | 0.076 | 0.083 | 0.048 | 0.079 | 0.071 | 0.052 | 0.461 | 0.497 | 0.146 | 0.157 | 0.061 | 0.063 | 0.055 | 0.099 | 0.040 | 0.042 | 0.028 | 0.101 | 0.051 | 0.069 | 0.011 | 0.046 | 0.834 | 1.000 | 0.055 | 0.065 | 0.305 | 0.347 | -0.017 | -0.006 |
| DLSUGAR | 0.082 | 0.081 | 0.062 | 0.062 | 0.088 | 0.085 | 0.008 | 0.049 | 0.056 | 0.065 | 0.001 | 0.004 | 0.081 | 0.071 | 0.075 | 0.008 | 0.054 | 0.038 | 0.067 | 0.048 | 0.055 | 0.064 | 0.045 | 0.055 | 1.000 | 0.269 | 0.066 | 0.046 | -0.064 | -0.055 |
| DLSUGAR_F | 0.048 | 0.048 | 0.103 | 0.083 | 0.066 | 0.066 | 0.053 | 0.058 | 0.011 | 0.065 | 0.006 | 0.010 | 0.084 | 0.089 | 0.052 | 0.069 | 0.066 | 0.070 | 0.072 | 0.075 | 0.059 | 0.068 | 0.051 | 0.065 | 0.269 | 1.000 | 0.072 | 0.054 | -0.053 | -0.048 |
| DLWHEAT | 0.074 | 0.078 | 0.068 | 0.059 | 0.072 | 0.055 | 0.452 | 0.470 | 0.084 | 0.103 | 0.043 | 0.052 | 0.088 | 0.090 | 0.050 | 0.046 | -0.016 | 0.015 | 0.043 | 0.067 | 0.050 | 0.063 | 0.305 | 0.305 | 0.066 | 0.072 | 1.000 | 0.724 | -0.054 | -0.022 |
| DLWHEAT_F | 0.084 | 0.083 | 0.075 | 0.086 | 0.080 | 0.059 | 0.493 | 0.530 | 0.103 | 0.123 | 0.053 | 0.055 | 0.083 | 0.089 | 0.055 | 0.044 | -0.008 | 0.036 | 0.015 | 0.053 | 0.035 | 0.061 | 0.336 | 0.347 | 0.046 | 0.054 | 0.724 | 1.000 | -0.026 | 0.001 |
| DLZAR | -0.175 | -0.177 | -0.063 | -0.035 | -0.164 | -0.141 | -0.011 | -0.025 | -0.013 | -0.031 | 0.169 | 0.147 | -0.304 | -0.275 | -0.047 | -0.018 | -0.041 | -0.043 | -0.086 | -0.123 | -0.096 | -0.124 | -0.022 | -0.017 | -0.064 | -0.053 | -0.054 | -0.026 | 1.000 | 0.778 |
| DLZAR_F | -0.145 | -0.146 | -0.041 | -0.024 | -0.137 | 0.007 | 0.006 | -0.027 | -0.035 | 0.132 | 0.128 | -0.240 | -0.283 | -0.036 | 0.012 | -0.027 | -0.047 | -0.048 | -0.106 | -0.069 | -0.100 | -0.001 | -0.006 | -0.055 | -0.048 | -0.022 | 0.001 | 0.778 | 1.000 | |
| After crisis | DLALUMINIUM | DLALUMINIUM_F | DLBRENT OIL | DLBRENT OIL_F | DLCOPPER | DLCOPPER_F | DLCORN | DLCORN_F | DLCOTT ON | DLCOTT ON_F | DLFTSE JSE40 | DLFTSE JSE40_F | DLGOLD | DLGOLD_F | DLJETKE ROSENE | DLNAPHTHA | DLNATURALGAS | DLNATURALGAS_F | DLPALLADIUM | DLPALLADIUM_F | DLPLATINUM | DLPLATINUM_F | DLSOYABEAN | DLSOYABEAN_F | DLSUGAR | DLSUGAR_F | DLWHEAT | DLWHEAT_F | DLZAR | DLZAR_F |
| DLALUMINIUM | 1.000 | 0.989 | 0.326 | 0.321 | 0.689 | 0.674 | 0.201 | 0.183 | 0.175 | 0.180 | 0.348 | 0.358 | 0.256 | 0.268 | 0.305 | 0.308 | 0.029 | 0.075 | 0.307 | 0.429 | 0.317 | 0.403 | 0.215 | 0.246 | 0.146 | 0.146 | 0.137 | 0.160 | -0.327 | -0.292 |
| DLALUMINIUM_F | 0.989 | 1.000 | 0.326 | 0.319 | 0.691 | 0.678 | 0.204 | 0.182 | 0.174 | 0.177 | 0.351 | 0.365 | 0.260 | 0.271 | 0.305 | 0.307 | 0.035 | 0.075 | 0.313 | 0.431 | 0.325 | 0.411 | 0.214 | 0.243 | 0.146 | 0.145 | 0.136 | 0.159 | -0.324 | -0.282 |
| DLBRENT OIL | 0.326 | 0.326 | 1.000 | 0.735 | 0.382 | 0.377 | 0.124 | 0.126 | 0.159 | 0.153 | 0.390 | 0.388 | 0.180 | 0.166 | 0.892 | 0.829 | 0.070 | 0.068 | 0.268 | 0.346 | 0.258 | 0.324 | 0.160 | 0.156 | 0.107 | 0.088 | 0.068 | 0.099 | -0.340 | -0.266 |
| DLBRENT OIL_F | 0.321 | 0.319 | 0.735 | 1.000 | 0.356 | 0.355 | 0.170 | 0.183 | 0.175 | 0.151 | 0.313 | 0.314</ | | | | | | | | | | | | | | | | | | |

| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| DLPALLADIUM_F | 0.429 | 0.431 | 0.346 | 0.345 | 0.501 | 0.497 | 0.172 | 0.158 | 0.198 | 0.187 | 0.380 | 0.382 | 0.418 | 0.469 | 0.321 | 0.304 | 0.021 | 0.044 | 0.616 | 1.000 | 0.466 | 0.701 | 0.200 | 0.206 | 0.155 | 0.140 | 0.131 | 0.154 | -0.380 | -0.343 |
| DLPLATINUM | 0.317 | 0.325 | 0.258 | 0.176 | 0.331 | 0.326 | 0.105 | 0.076 | 0.143 | 0.138 | 0.295 | 0.294 | 0.531 | 0.433 | 0.254 | 0.227 | 0.064 | 0.008 | 0.690 | 0.466 | 1.000 | 0.647 | 0.150 | 0.135 | 0.064 | 0.043 | 0.091 | 0.083 | -0.329 | -0.225 |
| DLPLATINUM_F | 0.403 | 0.411 | 0.324 | 0.301 | 0.448 | 0.444 | 0.157 | 0.152 | 0.164 | 0.146 | 0.294 | 0.295 | 0.619 | 0.699 | 0.295 | 0.269 | 0.036 | 0.050 | 0.460 | 0.701 | 0.647 | 1.000 | 0.202 | 0.210 | 0.124 | 0.108 | 0.137 | 0.157 | -0.405 | -0.363 |
| DLSOYABEAN | 0.215 | 0.214 | 0.160 | 0.198 | 0.230 | 0.227 | 0.518 | 0.464 | 0.180 | 0.151 | 0.150 | 0.149 | 0.100 | 0.139 | 0.148 | 0.160 | 0.041 | 0.066 | 0.152 | 0.200 | 0.150 | 0.202 | 1.000 | 0.754 | 0.141 | 0.077 | 0.340 | 0.399 | -0.174 | -0.171 |
| DLSOYABEAN_F | 0.246 | 0.243 | 0.156 | 0.214 | 0.265 | 0.261 | 0.501 | 0.490 | 0.192 | 0.166 | 0.157 | 0.157 | 0.106 | 0.135 | 0.151 | 0.149 | 0.049 | 0.052 | 0.133 | 0.206 | 0.135 | 0.210 | 0.754 | 1.000 | 0.132 | 0.114 | 0.368 | 0.409 | -0.186 | -0.183 |
| DLUGAR | 0.146 | 0.146 | 0.107 | 0.134 | 0.160 | 0.157 | 0.148 | 0.148 | 0.127 | 0.141 | 0.115 | 0.116 | 0.038 | 0.088 | 0.084 | 0.085 | 0.045 | 0.045 | 0.101 | 0.155 | 0.064 | 0.124 | 0.141 | 0.132 | 1.000 | 0.735 | 0.099 | 0.148 | -0.122 | -0.144 |
| DLUGAR_F | 0.146 | 0.145 | 0.088 | 0.132 | 0.171 | 0.167 | 0.120 | 0.129 | 0.121 | 0.175 | 0.119 | 0.120 | 0.040 | 0.072 | 0.084 | 0.093 | 0.028 | 0.034 | 0.079 | 0.140 | 0.043 | 0.108 | 0.077 | 0.114 | 0.735 | 1.000 | 0.090 | 0.143 | -0.140 | -0.155 |
| DLWHEAT | 0.137 | 0.136 | 0.068 | 0.132 | 0.141 | 0.137 | 0.539 | 0.513 | 0.159 | 0.153 | 0.096 | 0.102 | 0.061 | 0.119 | 0.060 | 0.053 | 0.069 | 0.083 | 0.081 | 0.131 | 0.091 | 0.137 | 0.340 | 0.368 | 0.099 | 0.090 | 1.000 | 0.755 | -0.132 | -0.142 |
| DLWHEAT_F | 0.160 | 0.159 | 0.099 | 0.160 | 0.169 | 0.166 | 0.631 | 0.643 | 0.190 | 0.163 | 0.079 | 0.082 | 0.075 | 0.128 | 0.088 | 0.078 | 0.076 | 0.098 | 0.063 | 0.154 | 0.083 | 0.157 | 0.399 | 0.409 | 0.148 | 0.143 | 0.755 | 1.000 | -0.140 | -0.148 |
| DLZAR | -0.327 | -0.324 | -0.340 | -0.317 | -0.377 | -0.370 | -0.127 | -0.125 | -0.188 | -0.177 | -0.283 | -0.290 | -0.295 | -0.285 | -0.307 | -0.298 | -0.051 | -0.039 | -0.319 | -0.380 | -0.329 | -0.405 | -0.174 | -0.186 | -0.122 | -0.140 | -0.132 | -0.140 | 1.000 | 0.811 |
| DLZAR_F | -0.292 | -0.282 | -0.266 | -0.345 | -0.346 | -0.346 | -0.132 | -0.130 | -0.188 | -0.175 | -0.204 | -0.196 | -0.219 | -0.261 | -0.227 | -0.229 | -0.008 | -0.043 | -0.237 | -0.343 | -0.225 | -0.363 | -0.171 | -0.183 | -0.144 | -0.155 | -0.142 | -0.148 | 0.811 | 1.000 |

Source: Thomson Reuters DataStream and EViews.

Table 7.2: Correlation change summary

| | DLALUMI NUM | DLALUMI NUM_F | DLBRENT TOIL | DLBRENT TOIL_F | DLCOPE R | DLCOPE R_F | DLCOR N | DLCOR N_F | DLCOTT ON | DLCOTT ON_F | DLFTSE JSE40 | DLFTSE JSE40_F | DLGOLD | DLGOLD _F | DLJETKE ROSENE | DLNAPH THA | DLNATU RALGAS | DLNATU RALGAS _F | DLPALLA DIUM | DLPALLA DIUM_F | DLPLATI NUM | DLPLATI NUM_F | DLSOYA BEAN | DLSOYA BEAN_F | DLSUGA R | DLSUGA R_F | DLWHEA T | DLWHEA T_F | DLZAR | DLZAR_F | |
|----------------|----------------|------------------|-----------------|-------------------|-------------|---------------|------------|--------------|--------------|----------------|-----------------|-------------------|--------|--------------|-------------------|---------------|------------------|------------------------|-----------------|-------------------|----------------|------------------|----------------|------------------|-------------|---------------|-------------|---------------|--------|---------|--------|
| DLALUMINIUM | 0.000 | 0.001 | 0.255 | 0.230 | -0.037 | -0.015 | 0.126 | 0.101 | 0.112 | 0.099 | 0.132 | 0.139 | -0.008 | 0.000 | 0.249 | 0.233 | -0.001 | -0.010 | 0.177 | 0.213 | 0.182 | 0.225 | 0.151 | 0.170 | 0.064 | 0.098 | 0.063 | 0.076 | -0.152 | -0.147 | |
| DLALUMINIUM_F | 0.001 | 0.000 | 0.252 | 0.225 | -0.044 | -0.021 | 0.121 | 0.084 | 0.114 | 0.087 | 0.133 | 0.139 | -0.006 | -0.004 | 0.244 | 0.226 | 0.005 | -0.005 | 0.182 | 0.216 | 0.189 | 0.229 | 0.144 | 0.160 | 0.065 | 0.097 | 0.058 | 0.076 | -0.147 | -0.136 | |
| DLBRENTTOIL | 0.255 | 0.252 | 0.000 | -0.020 | 0.284 | 0.283 | 0.091 | 0.073 | 0.095 | 0.082 | 0.324 | 0.315 | 0.042 | -0.002 | 0.428 | 0.450 | -0.089 | -0.183 | 0.230 | 0.277 | 0.158 | 0.236 | 0.105 | 0.108 | 0.045 | -0.015 | 0.000 | 0.024 | -0.277 | -0.225 | |
| DLBRENTTOIL_F | 0.230 | 0.225 | -0.020 | 0.000 | 0.244 | 0.246 | 0.104 | 0.108 | 0.104 | 0.057 | 0.248 | 0.248 | 0.002 | -0.023 | 0.249 | 0.318 | -0.102 | -0.182 | 0.197 | 0.293 | 0.089 | 0.208 | 0.117 | 0.135 | 0.072 | 0.049 | 0.073 | 0.074 | -0.282 | -0.321 | |
| DLCOPPER | -0.037 | -0.044 | 0.284 | 0.244 | 0.000 | 0.030 | 0.112 | 0.095 | 0.144 | 0.114 | 0.174 | 0.183 | -0.003 | -0.003 | 0.274 | 0.271 | -0.014 | -0.036 | 0.236 | 0.273 | 0.170 | 0.243 | 0.165 | 0.194 | 0.072 | 0.105 | 0.069 | 0.089 | -0.213 | -0.193 | |
| DLCOPPER_F | -0.015 | -0.021 | 0.283 | 0.246 | 0.030 | 0.000 | 0.116 | 0.110 | 0.141 | 0.105 | 0.160 | 0.168 | 0.015 | 0.007 | 0.277 | 0.279 | -0.006 | -0.017 | 0.243 | 0.282 | 0.175 | 0.251 | 0.179 | 0.209 | 0.072 | 0.101 | 0.082 | 0.107 | -0.229 | -0.209 | |
| DLCORN | 0.126 | 0.121 | 0.091 | 0.104 | 0.112 | 0.116 | 0.000 | 0.040 | 0.083 | 0.063 | 0.025 | 0.026 | 0.021 | 0.039 | 0.077 | 0.076 | 0.028 | 0.014 | 0.046 | 0.111 | 0.048 | 0.094 | 0.029 | 0.040 | 0.140 | 0.067 | 0.087 | 0.138 | -0.116 | -0.139 | |
| DLCORN_F | 0.101 | 0.084 | 0.073 | 0.108 | 0.095 | 0.110 | 0.040 | 0.000 | 0.083 | 0.000 | 0.007 | -0.004 | -0.027 | 0.003 | 0.067 | 0.074 | 0.049 | 0.016 | 0.019 | 0.089 | 0.030 | 0.095 | -0.032 | -0.007 | 0.099 | 0.071 | 0.043 | 0.113 | -0.100 | -0.136 | |
| DLCOTTON | 0.112 | 0.114 | 0.095 | 0.104 | 0.144 | 0.141 | 0.083 | 0.083 | 0.000 | 0.042 | 0.142 | 0.139 | 0.074 | 0.050 | 0.106 | 0.104 | -0.035 | -0.006 | 0.196 | 0.202 | 0.154 | 0.191 | 0.042 | 0.046 | 0.071 | 0.110 | 0.075 | 0.087 | -0.175 | -0.161 | |
| DLCOTTON_F | 0.099 | 0.087 | 0.082 | 0.057 | 0.114 | 0.105 | 0.063 | 0.000 | 0.042 | 0.000 | 0.116 | 0.103 | 0.058 | 0.007 | 0.081 | 0.090 | -0.017 | 0.005 | 0.192 | 0.155 | 0.158 | 0.154 | -0.007 | 0.009 | 0.076 | 0.110 | 0.050 | 0.040 | -0.146 | -0.140 | |
| DLFTSE_JSE40 | 0.132 | 0.133 | 0.324 | 0.248 | 0.174 | 0.160 | 0.025 | 0.007 | 0.142 | 0.116 | 0.000 | 0.026 | -0.032 | -0.005 | 0.344 | 0.321 | 0.011 | 0.009 | 0.243 | 0.260 | 0.226 | 0.199 | 0.080 | 0.096 | 0.114 | 0.113 | 0.053 | 0.026 | -0.452 | -0.336 | |
| DLFTSE_JSE40_F | 0.139 | 0.139 | 0.315 | 0.248 | 0.183 | 0.168 | 0.026 | -0.004 | 0.139 | 0.103 | 0.026 | 0.000 | -0.008 | 0.008 | 0.342 | 0.329 | 0.012 | 0.008 | 0.245 | 0.258 | 0.228 | 0.186 | 0.077 | 0.094 | 0.112 | 0.110 | 0.050 | 0.027 | -0.437 | -0.324 | |
| DLGOLD | -0.008 | -0.006 | 0.042 | 0.002 | -0.003 | 0.015 | 0.021 | -0.027 | 0.074 | 0.058 | -0.032 | -0.008 | 0.000 | 0.137 | 0.030 | 0.028 | -0.048 | -0.060 | 0.092 | 0.107 | 0.209 | 0.294 | 0.037 | 0.051 | -0.043 | -0.044 | -0.027 | -0.008 | 0.009 | 0.021 | |
| DLGOLD_F | 0.000 | -0.004 | -0.002 | -0.023 | -0.003 | 0.007 | 0.039 | 0.003 | 0.050 | 0.007 | -0.005 | 0.008 | 0.137 | 0.000 | 0.030 | 0.045 | -0.051 | -0.080 | 0.101 | 0.149 | 0.221 | 0.343 | 0.056 | 0.036 | 0.017 | -0.017 | 0.029 | 0.039 | -0.010 | 0.022 | |
| DLJETKEROSENE | 0.249 | 0.244 | 0.428 | 0.249 | 0.274 | 0.277 | 0.077 | 0.067 | 0.106 | 0.081 | 0.344 | 0.342 | 0.030 | 0.030 | 0.000 | 0.319 | 0.000 | -0.118 | -0.091 | 0.248 | 0.272 | 0.173 | 0.223 | 0.105 | 0.111 | 0.009 | 0.032 | 0.010 | 0.033 | -0.260 | -0.191 |
| DLNAPHTHA | 0.233 | 0.226 | 0.450 | 0.318 | 0.271 | 0.279 | 0.076 | 0.074 | 0.104 | 0.090 | 0.321 | 0.329 | 0.028 | 0.045 | 0.319 | 0.000 | -0.102 | -0.034 | 0.183 | 0.229 | 0.117 | 0.171 | 0.118 | 0.107 | 0.077 | 0.024 | 0.007 | 0.034 | -0.280 | -0.241 | |
| DLNATURALGAS | -0.001 | 0.005 | -0.089 | -0.102 | -0.014 | -0.006 | 0.028 | 0.049 | -0.035 | -0.017 | 0.011 | 0.012 | -0.048 | -0.051 | -0.118 | -0.102 | 0.000 | -0.092 | 0.031 | -0.007 | 0.004 | 0.011 | 0.017 | 0.021 | -0.009 | -0.038 | 0.085 | 0.084 | -0.010 | 0.019 | |
| DLNATURALGAS_F | -0.010 | -0.005 | -0.183 | -0.182 | -0.036 | -0.017 | 0.014 | 0.016 | -0.006 | 0.005 | 0.009 | 0.008 | -0.060 | -0.080 | -0.091 | -0.034 | -0.092 | 0.000 | -0.010 | 0.019 | -0.023 | 0.010 | -0.032 | -0.049 | 0.007 | -0.036 | 0.068 | 0.062 | 0.004 | 0.004 | |
| DLPALLADIUM | 0.177 | 0.182 | 0.230 | 0.197 | 0.236 | 0.243 | 0.046 | 0.019 | 0.196 | 0.192 | 0.243 | 0.245 | 0.092 | 0.101 | 0.248 | 0.183 | 0.031 | -0.010 | 0.000 | 0.000 | -0.047 | 0.206 | 0.170 | 0.105 | 0.082 | 0.034 | 0.007 | 0.038 | 0.048 | -0.233 | -0.189 |
| DLPALLADIUM_F | 0.213 | 0.216 | 0.277 | 0.293 | 0.273 | 0.282 | 0.111 | 0.089 | 0.202 | 0.155 | 0.260 | 0.258 | 0.107 | 0.149 | 0.272 | 0.229 | -0.007 | 0.019 | -0.047 | 0.000 | 0.124 | 0.303 | 0.132 | 0.137 | 0.107 | 0.065 | 0.064 | 0.101 | -0.257 | -0.237 | |
| DLPLATINUM | 0.182 | 0.189 | 0.158 | 0.089 | 0.170 | 0.175 | 0.048 | 0.030 | 0.154 | 0.158 | 0.226 | 0.228 | 0.209 | 0.221 | 0.173 | 0.117 | 0.004 | -0.023 | 0.206 | 0.124 | 0.000 | 0.114 | 0.133 | 0.124 | 0.009 | -0.016 | 0.041 | 0.048 | -0.233 | -0.156 | |
| DLPLATINUM_F | 0.225 | 0.229 | 0.236 | 0.208 | 0.243 | 0.251 | 0.094 | 0.095 | 0.191 | 0.154 | 0.199 | 0.186 | 0.294 | 0.343 | 0.223 | 0.171 | 0.011 | 0.010 | 0.170 | 0.303 | 0.114 | 0.000 | 0.156 | 0.164 | 0.060 | 0.040 | 0.074 | 0.096 | -0.281 | -0.263 | |
| DLSOYABEAN | 0.151 | 0.144 | 0.105 | 0.117 | 0.165 | 0.179 | 0.029 | -0.032 | 0.042 | -0.007 | 0.080 | 0.077 | 0.037 | 0.056 | 0.105 | 0.118 | 0.017 | -0.032 | 0.105 | 0.132 | 0.133 | 0.156 | 0.000 | -0.080 | 0.096 | 0.026 | 0.035 | 0.063 | -0.152 | -0.170 | |
| DLSOYABEAN_F | 0.170 | 0.160 | 0.108 | 0.135 | 0.194 | 0.209 | 0.040 | -0.007 | 0.046 | 0.009 | 0.096 | 0.094 | 0.051 | 0.036 | 0.111 | 0.107 | 0.021 | -0.049 | 0.082 | 0.137 | 0.124 | 0.164 | -0.080 | 0.000 | 0.077 | 0.049 | 0.063 | 0.062 | -0.169 | -0.177 | |
| DLUGAR | 0.064 | 0.065 | 0.045 | 0.072 | 0.072 | 0.072 | 0.140 | 0.099 | 0.071 | 0.076 | 0.114 | 0.112 | -0.043 | 0.017 | 0.009 | 0.077 | -0.009 | 0.007 | 0.034 | 0.107 | 0.009 | 0.060 | 0.096 | 0.077 | 0.000 | 0.466 | 0.033 | 0.102 | -0.058 | -0.089 | |
| DLUGAR_F | 0.098 | 0.097 | -0.015 | 0.049 | 0.105 | 0.101 | 0.067 | 0.110 | 0.110 | 0.110 | 0.113 | 0.110 | -0.044 | -0.017 | 0.032 | 0.024 | -0.038 | -0.036 | 0.007 | 0.065 | -0.016 | 0.040 | 0.026 | 0.049 | 0.466 | 0.000 | 0.018 | 0.089 | -0.087 | -0.107 | |
| DLWHEAT | 0.063 | 0.058 | 0.000 | 0.073 | 0.069 | 0.082 | 0.087 | 0.043 | 0.075 | 0.050 | 0.053 | 0.050 | | | | | | | | | | | | | | | | | | | |

7.5.2. Granger causality

The Granger causality results are shown in Table 7.3 as an indication only to highlight the Granger causal relationships between commodity classes. The number of relationships between commodity classes are as follows:

- From metal to soft commodities (darker yellow): 14
- From metal to energy commodities (lighter yellow/green): 8
- From energy to metal commodities (bright aqua): 23
- From energy to soft commodities (light blue): 13
- From soft to metal commodities (light purple): 45
- From soft to energy commodities (light pink): 19.

Overall, the relationships from soft commodities to metal commodities are the highest, followed by energy commodities to metal commodities. The probabilities are highlighted in colours as well to easily distinguish the level of significance. A 99% level of significance is highlighted in green, 95% in red, and 90% in blue.

Table 7.3: Granger causality

| Null Hypothesis: | Before crisis | | | After crisis | | |
|---|---------------|-------------|-------|--------------|-------------|-------|
| | Obs | F-Statistic | Prob. | Obs | F-Statistic | Prob. |
| DLALUMINIUM does not Granger Cause DLCORN | | 0.303 | 0.739 | | 2.675 | 0.069 |
| DLALUMINIUM does not Granger Cause DLCORN_F | | 0.092 | 0.912 | | 3.298 | 0.037 |
| DLNATURALGAS does not Granger Cause DLALUMINIUM | 1952 | 4.052 | 0.018 | 1892 | 3.479 | 0.031 |
| DLNATURALGAS_F does not Granger Cause DLALUMINIUM | 1952 | 3.968 | 0.019 | 1892 | 0.011 | 0.989 |
| DLSOYABEAN does not Granger Cause DLALUMINIUM | 1952 | 2.866 | 0.057 | 1892 | 1.594 | 0.203 |
| DLSUGAR does not Granger Cause DLALUMINIUM | 1952 | 1.360 | 0.257 | 1892 | 2.472 | 0.085 |
| DLALUMINIUM_F does not Granger Cause DLCORN | | 0.268 | 0.765 | | 2.564 | 0.077 |
| DLALUMINIUM_F does not Granger Cause DLCORN_F | | 0.073 | 0.930 | | 3.305 | 0.037 |
| DLNATURALGAS does not Granger Cause DLALUMINIUM_F | 1952 | 4.577 | 0.010 | 1892 | 3.595 | 0.028 |
| DLNATURALGAS_F does not Granger Cause DLALUMINIUM_F | 1952 | 5.370 | 0.005 | 1892 | 0.150 | 0.861 |
| DLSOYABEAN does not Granger Cause DLALUMINIUM_F | 1952 | 3.403 | 0.034 | 1892 | 1.650 | 0.192 |
| DLSOYABEAN_F does not Granger Cause DLALUMINIUM_F | 1952 | 2.611 | 0.074 | 1892 | 0.318 | 0.728 |
| DLSUGAR does not Granger Cause DLALUMINIUM_F | 1952 | 1.372 | 0.254 | 1892 | 2.600 | 0.075 |
| DLCOPPER does not Granger Cause DLBRENTAOL | 1952 | 3.232 | 0.040 | 1892 | 0.361 | 0.697 |
| DLCOPPER_F does not Granger Cause DLBRENTAOL | 1952 | 3.855 | 0.021 | 1892 | 0.787 | 0.455 |
| DLCORN does not Granger Cause DLBRENTAOL | 1952 | 0.996 | 0.370 | 1892 | 2.529 | 0.080 |
| DLBRENTAOL does not Granger Cause DLGOLD | | 3.279 | 0.038 | | 1.806 | 0.165 |
| DLBRENTAOL does not Granger Cause DLPALLADIUM | | 3.202 | 0.041 | | 13.163 | 0.000 |
| DLBRENTAOL does not Granger Cause DLPLATINUM | | 6.163 | 0.002 | | 20.474 | 0.000 |
| DLBRENTAOL_F does not Granger Cause DLPLATINUM_F | | 3.690 | 0.025 | | 2.800 | 0.061 |
| DLSOYABEAN does not Granger Cause DLBRENTAOL | 1952 | 0.238 | 0.788 | 1892 | 4.287 | 0.014 |
| DLSOYABEAN_F does not Granger Cause DLBRENTAOL | 1952 | 0.849 | 0.428 | 1892 | 4.668 | 0.010 |
| DLSUGAR does not Granger Cause DLBRENTAOL | 1952 | 2.946 | 0.053 | 1892 | 1.225 | 0.294 |
| DLBRENTAOL does not Granger Cause DLSUGAR | | 3.861 | 0.021 | | 1.568 | 0.209 |
| DLSUGAR_F does not Granger Cause DLBRENTAOL | 1952 | 2.033 | 0.131 | 1892 | 2.339 | 0.097 |
| DLBRENTAOL does not Granger Cause DLSUGAR_F | | 0.013 | 0.987 | | 2.570 | 0.077 |
| DLBRENTAOL_F does not Granger Cause DLGOLD | | 6.361 | 0.002 | | 3.461 | 0.032 |
| DLBRENTAOL_F does not Granger Cause DLPALLADIUM | | 3.120 | 0.044 | | 25.196 | 0.000 |
| DLBRENTAOL_F does not Granger Cause DLPLATINUM | | 8.202 | 0.000 | | 31.061 | 0.000 |
| DLBRENTAOL_F does not Granger Cause DLPLATINUM_F | | 2.808 | 0.061 | | 3.767 | 0.023 |
| DLSUGAR does not Granger Cause DLBRENTAOL_F | 1952 | 4.427 | 0.012 | 1892 | 0.288 | 0.750 |
| DLBRENTAOL_F does not Granger Cause DLSUGAR | | 3.406 | 0.033 | | 1.062 | 0.346 |
| DLBRENTAOL_F does not Granger Cause DLWHEAT | | 0.068 | 0.934 | | 4.041 | 0.018 |
| DLBRENTAOL_F does not Granger Cause DLWHEAT_F | | 0.140 | 0.870 | | 4.062 | 0.017 |
| DLCOPPER does not Granger Cause DLJETKEROSENE | | 3.993 | 0.019 | | 0.314 | 0.731 |
| DLSOYABEAN does not Granger Cause DLCOPPER | 1952 | 3.653 | 0.026 | 1892 | 1.620 | 0.198 |
| DLSOYABEAN_F does not Granger Cause DLCOPPER | 1952 | 2.432 | 0.088 | 1892 | 0.360 | 0.698 |

| | Before crisis | | After crisis | | | |
|---|---------------|--------|--------------|------|--------|-------|
| DLWHEAT does not Granger Cause DLCOPPER | 1952 | 1.533 | 0.216 | 1892 | 2.493 | 0.083 |
| DLCOPPER_F does not Granger Cause DLJETKEROSENE | | 4.344 | 0.013 | | 1.105 | 0.332 |
| DLSOYABEAN does not Granger Cause DLCOPPER_F | 1952 | 5.478 | 0.004 | 1892 | 1.713 | 0.181 |
| DLSOYABEAN_F does not Granger Cause DLCOPPER_F | 1952 | 3.608 | 0.027 | 1892 | 0.218 | 0.804 |
| DLCOPPER_F does not Granger Cause DLSUGAR | | 2.864 | 0.057 | | 0.209 | 0.812 |
| DLWHEAT does not Granger Cause DLCOPPER_F | 1952 | 2.469 | 0.085 | 1892 | 2.079 | 0.125 |
| DLWHEAT_F does not Granger Cause DLCOPPER_F | 1952 | 3.018 | 0.049 | 1892 | 1.022 | 0.360 |
| DLCORN does not Granger Cause DLGOLD | | 5.887 | 0.003 | | 3.527 | 0.030 |
| DLJETKEROSENE does not Granger Cause DLCORN | 1952 | 2.605 | 0.074 | 1892 | 0.655 | 0.520 |
| DLCORN does not Granger Cause DLJETKEROSENE | | 0.540 | 0.583 | | 3.411 | 0.033 |
| DLCORN does not Granger Cause DLNATURALGAS | | 1.936 | 0.145 | | 4.183 | 0.015 |
| DLCORN does not Granger Cause DLPALLADIUM | | 1.974 | 0.139 | | 11.135 | 0.000 |
| DLCORN does not Granger Cause DLPALLADIUM_F | | 2.428 | 0.089 | | 1.175 | 0.309 |
| DLCORN does not Granger Cause DLPLATINUM | | 4.750 | 0.009 | | 10.045 | 0.000 |
| DLCORN does not Granger Cause DLPLATINUM_F | | 1.507 | 0.222 | | 2.682 | 0.069 |
| DLCORN_F does not Granger Cause DLGOLD | | 2.651 | 0.071 | | 4.818 | 0.008 |
| DLCORN_F does not Granger Cause DLJETKEROSENE | | 1.274 | 0.280 | | 3.022 | 0.049 |
| DLNATURALGAS does not Granger Cause DLCORN_F | 1952 | 0.553 | 0.575 | 1892 | 2.638 | 0.072 |
| DLCORN_F does not Granger Cause DLNATURALGAS | | 2.848 | 0.058 | | 3.711 | 0.025 |
| DLCORN_F does not Granger Cause DLPALLADIUM | | 2.080 | 0.125 | | 12.658 | 0.000 |
| DLCORN_F does not Granger Cause DLPALLADIUM_F | | 4.011 | 0.018 | | 1.804 | 0.165 |
| DLCORN_F does not Granger Cause DLPLATINUM | | 5.273 | 0.005 | | 12.274 | 0.000 |
| DLCORN_F does not Granger Cause DLPLATINUM_F | | 1.626 | 0.197 | | 3.389 | 0.034 |
| DLPALLADIUM does not Granger Cause DLCOTTON | 1952 | 0.885 | 0.413 | 1892 | 3.085 | 0.046 |
| DLCOTTON does not Granger Cause DLPALLADIUM | | 1.965 | 0.141 | | 5.244 | 0.005 |
| DLPALLADIUM_F does not Granger Cause DLCOTTON | 1952 | 2.243 | 0.107 | 1892 | 2.734 | 0.065 |
| DLGOLD_F does not Granger Cause DLCOTTON_F | 1952 | 2.774 | 0.063 | 1892 | 0.154 | 0.857 |
| DLNATURALGAS_F does not Granger Cause DLCOTTON_F | 1952 | 2.598 | 0.075 | 1892 | 0.693 | 0.500 |
| DLCOTTON_F does not Granger Cause DLPALLADIUM | | 2.455 | 0.086 | | 1.553 | 0.212 |
| DLPALLADIUM_F does not Granger Cause DLCOTTON_F | 1952 | 2.779 | 0.062 | 1892 | 1.216 | 0.297 |
| DLJETKEROSENE does not Granger Cause DLGOLD | 1952 | 0.911 | 0.402 | 1892 | 2.484 | 0.084 |
| DLNATURALGAS_F does not Granger Cause DLGOLD | 1952 | 6.403 | 0.002 | 1892 | 0.409 | 0.665 |
| DLSOYABEAN does not Granger Cause DLGOLD | 1952 | 2.474 | 0.085 | 1892 | 0.955 | 0.385 |
| DLSOYABEAN_F does not Granger Cause DLGOLD | 1952 | 2.957 | 0.052 | 1892 | 2.096 | 0.123 |
| DLWHEAT does not Granger Cause DLGOLD | 1952 | 1.974 | 0.139 | 1892 | 4.363 | 0.013 |
| DLWHEAT_F does not Granger Cause DLGOLD | 1952 | 3.049 | 0.048 | 1892 | 3.736 | 0.024 |
| DLNATURALGAS_F does not Granger Cause DLGOLD_F | 1952 | 2.770 | 0.063 | 1892 | 0.069 | 0.933 |
| DLGOLD_F does not Granger Cause DLNATURALGAS_F | | 2.441 | 0.087 | | 0.662 | 0.516 |
| DLGOLD_F does not Granger Cause DLSUGAR | | 4.080 | 0.017 | | 0.062 | 0.940 |
| DLJETKEROSENE does not Granger Cause DLPALLADIUM | | 1.527 | 0.218 | | 11.576 | 0.000 |
| DLJETKEROSENE does not Granger Cause DLPLATINUM | | 0.233 | 0.792 | | 17.365 | 0.000 |
| DLJETKEROSENE does not Granger Cause DLPLATINUM_F | | 0.882 | 0.414 | | 3.157 | 0.043 |
| DLSOYABEAN does not Granger Cause DLJETKEROSENE | 1952 | 0.362 | 0.697 | 1892 | 5.535 | 0.004 |
| DLSOYABEAN_F does not Granger Cause DLJETKEROSENE | 1952 | 0.274 | 0.760 | 1892 | 5.942 | 0.003 |
| DLSUGAR does not Granger Cause DLJETKEROSENE | 1952 | 4.095 | 0.017 | 1892 | 1.592 | 0.204 |
| DLJETKEROSENE does not Granger Cause DLSUGAR | | 0.015 | 0.985 | | 2.366 | 0.094 |
| DLSUGAR_F does not Granger Cause DLJETKEROSENE | 1952 | 4.872 | 0.008 | 1892 | 2.620 | 0.073 |
| DLJETKEROSENE does not Granger Cause DLSUGAR_F | | 0.387 | 0.679 | | 4.916 | 0.007 |
| DLNAPHTHA does not Granger Cause DLPALLADIUM | | 2.160 | 0.116 | | 9.194 | 0.000 |
| DLPALLADIUM_F does not Granger Cause DLNAPHTHA | 1952 | 0.006 | 0.994 | 1892 | 2.628 | 0.073 |
| DLNAPHTHA does not Granger Cause DLPLATINUM | | 3.243 | 0.039 | | 14.070 | 0.000 |
| DLNAPHTHA does not Granger Cause DLPLATINUM_F | | 1.698 | 0.183 | | 2.561 | 0.078 |
| DLSOYABEAN does not Granger Cause DLNAPHTHA | 1952 | 0.524 | 0.593 | 1892 | 4.678 | 0.009 |
| DLSOYABEAN_F does not Granger Cause DLNAPHTHA | 1952 | 0.513 | 0.599 | 1892 | 4.950 | 0.007 |
| DLSUGAR does not Granger Cause DLNAPHTHA | 1952 | 11.705 | 0.000 | 1892 | 0.998 | 0.369 |
| DLNATURALGAS does not Granger Cause DLSOYABEAN | | 0.081 | 0.922 | | 3.758 | 0.024 |
| DLNATURALGAS does not Granger Cause DLSOYABEAN_F | | 0.189 | 0.828 | | 2.894 | 0.056 |
| DLNATURALGAS does not Granger Cause DLSUGAR | | 3.154 | 0.043 | | 0.846 | 0.429 |
| DLSUGAR_F does not Granger Cause DLNATURALGAS | 1952 | 3.150 | 0.043 | 1892 | 0.698 | 0.498 |
| DLWHEAT_F does not Granger Cause DLNATURALGAS | 1952 | 0.767 | 0.465 | 1892 | 3.816 | 0.022 |
| DLPALLADIUM does not Granger Cause DLNATURALGAS_F | 1952 | 2.883 | 0.056 | 1892 | 0.377 | 0.686 |
| DLNATURALGAS_F does not Granger Cause DLPALLADIUM | | 3.187 | 0.042 | | 3.772 | 0.023 |
| DLPALLADIUM_F does not Granger Cause DLNATURALGAS_F | 1952 | 2.961 | 0.052 | 1892 | 0.173 | 0.841 |
| DLNATURALGAS_F does not Granger Cause DLPLATINUM | | 2.368 | 0.094 | | 3.130 | 0.044 |
| DLSOYABEAN does not Granger Cause DLPALLADIUM | 1952 | 0.593 | 0.553 | 1892 | 12.715 | 0.000 |
| DLSOYABEAN_F does not Granger Cause DLPALLADIUM | 1952 | 0.212 | 0.809 | 1892 | 12.132 | 0.000 |
| DLSUGAR does not Granger Cause DLPALLADIUM | 1952 | 4.212 | 0.015 | 1892 | 6.565 | 0.001 |
| DLSUGAR_F does not Granger Cause DLPALLADIUM | 1952 | 0.969 | 0.380 | 1892 | 4.364 | 0.013 |
| DLWHEAT does not Granger Cause DLPALLADIUM | 1952 | 0.416 | 0.660 | 1892 | 7.515 | 0.001 |
| DLWHEAT_F does not Granger Cause DLPALLADIUM | 1952 | 1.457 | 0.233 | 1892 | 12.413 | 0.000 |
| DLSUGAR does not Granger Cause DLPALLADIUM_F | 1952 | 3.794 | 0.023 | 1892 | 2.054 | 0.129 |
| DLPALLADIUM_F does not Granger Cause DLSUGAR | | 3.177 | 0.042 | | 0.656 | 0.519 |
| DLSUGAR_F does not Granger Cause DLPALLADIUM_F | 1952 | 0.754 | 0.471 | 1892 | 3.945 | 0.020 |
| DLWHEAT does not Granger Cause DLPALLADIUM_F | 1952 | 0.842 | 0.431 | 1892 | 2.584 | 0.076 |
| DLPALLADIUM_F does not Granger Cause DLWHEAT_F | | 3.391 | 0.034 | | 1.262 | 0.283 |
| DLSOYABEAN does not Granger Cause DLPLATINUM | 1952 | 1.850 | 0.157 | 1892 | 10.770 | 0.000 |
| DLSOYABEAN_F does not Granger Cause DLPLATINUM | 1952 | 2.252 | 0.105 | 1892 | 16.098 | 0.000 |
| DLSUGAR does not Granger Cause DLPLATINUM | 1952 | 5.187 | 0.006 | 1892 | 7.057 | 0.001 |
| DLPLATINUM does not Granger Cause DLSUGAR | | 3.581 | 0.028 | | 0.476 | 0.621 |

| | Before crisis | | | After crisis | | |
|---|---------------|-------|-------|--------------|-------|-------|
| DLSUGAR_F does not Granger Cause DLPLATINUM | 1952 | 3.917 | 0.020 | 1892 | 4.178 | 0.016 |
| DLWHEAT does not Granger Cause DLPLATINUM | 1952 | 3.454 | 0.032 | 1892 | 4.358 | 0.013 |
| DLWHEAT_F does not Granger Cause DLPLATINUM | 1952 | 3.912 | 0.020 | 1892 | 8.940 | 0.000 |
| DLSUGAR does not Granger Cause DLPLATINUM_F | 1952 | 2.581 | 0.076 | 1892 | 2.539 | 0.079 |
| DLSUGAR_F does not Granger Cause DLPLATINUM_F | 1952 | 0.901 | 0.407 | 1892 | 2.484 | 0.084 |
| DLPLATINUM_F does not Granger Cause DLSUGAR_F | | 1.113 | 0.329 | | 2.577 | 0.076 |

Source: Thomson Reuters DataStream and EViews.

7.5.3. Static hedge ratio estimation

The static hedge ratio analysis will be comprised of OLS, ECM, VECM, and ECM-GARCH estimation. The results displayed in the proceeding section will only include the final hedge ratio. The analysis prior to the hedge ratio analysis will not be included due to the substantial extent of analysis that had to be done in order to obtain the final hedge ratios.

7.5.3.1. OLS

The OLS hedge ratio estimation shown in Table 7.4 was done based on regression analysis. The beta obtained when comparing the bivariate spot and future price combination represents the optimal hedge ratio. The OLS analysis was based on log returns in order to obtain a "standardised" hedge ratio.

Overall, the hedge ratio improved after the crisis as compared to before the crisis; however, some combinations did return a lower hedge ratio. The improved hedge ratio is most likely due to the financialisation of commodities. Gold future provides the lowest negative hedge ratio among all the variables after the crisis, whereas platinum provides the lowest negative hedge ratio after the crisis for ZAR spot. After the crisis, platinum future is a better hedge for palladium than palladium future.

Table 7.4: OLS hedge ratio

| Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|------------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|---------|---------|--------|
| Aluminium | 1.010 | 0.053 | 0.569 | 0.065 | 0.054 | 0.216 | 0.330 | 0.028 | 0.125 | 0.152 | 0.063 | 0.021 | 0.062 | -0.167 |
| Brentoil | 0.138 | 0.807 | 0.142 | 0.076 | 0.087 | 0.131 | 0.378 | 0.153 | 0.073 | 0.137 | 0.073 | 0.083 | 0.102 | -0.086 |
| Copper | 0.922 | 0.080 | 0.960 | 0.075 | 0.075 | 0.299 | 0.485 | 0.032 | 0.162 | 0.216 | 0.072 | 0.036 | 0.072 | -0.215 |
| Corn | 0.113 | 0.052 | 0.069 | 0.888 | 0.129 | 0.085 | 0.158 | 0.034 | 0.047 | 0.072 | 0.507 | 0.031 | 0.487 | 0.011 |
| Cotton | 0.102 | 0.070 | 0.078 | 0.124 | 0.803 | 0.028 | 0.110 | 0.007 | -0.003 | -0.038 | 0.201 | 0.008 | 0.127 | -0.051 |
| FTSE/JSE40 | 0.220 | 0.038 | 0.204 | 0.056 | 0.021 | 0.932 | 0.127 | 0.006 | 0.068 | 0.080 | 0.049 | 0.003 | 0.039 | 0.15 |
| Gold | 0.209 | 0.059 | 0.183 | 0.053 | 0.028 | 0.103 | 0.667 | 0.015 | 0.139 | 0.214 | 0.035 | 0.029 | 0.047 | -0.212 |
| Jet Kerosene | 0.108 | 0.425 | 0.099 | 0.064 | 0.078 | 0.052 | 0.264 | 0.089 | 0.049 | 0.106 | 0.057 | 0.040 | 0.070 | -0.070 |
| Naphtha | 0.154 | 0.365 | 0.110 | 0.056 | 0.059 | 0.042 | 0.241 | 0.052 | 0.080 | 0.156 | 0.064 | 0.057 | 0.060 | 0.026 |
| Natural Gas | 0.111 | 0.259 | 0.050 | 0.037 | 0.074 | 0.079 | 0.318 | 0.343 | 0.059 | 0.076 | 0.083 | 0.104 | -0.022 | -0.111 |
| Palladium | 0.237 | 0.012 | 0.169 | 0.070 | -0.023 | 0.201 | 0.398 | 0.008 | 0.679 | 0.439 | 0.074 | 0.056 | 0.020 | -0.096 |
| Platinum | 0.154 | 0.056 | 0.139 | 0.041 | -0.015 | 0.073 | 0.291 | 0.012 | 0.221 | 0.508 | 0.010 | 0.029 | 0.029 | -0.088 |
| Soyabean | 0.089 | 0.059 | 0.050 | 0.488 | 0.132 | 0.088 | 0.128 | 0.040 | 0.049 | 0.049 | 0.855 | 0.028 | 0.309 | -0.001 |
| Sugar | 0.146 | 0.065 | 0.124 | 0.069 | 0.077 | 0.008 | 0.157 | 0.022 | 0.049 | 0.097 | 0.081 | 0.211 | 0.060 | -0.113 |
| Wheat | 0.131 | 0.057 | 0.075 | 0.607 | 0.113 | 0.083 | 0.181 | 0.008 | 0.063 | 0.088 | 0.410 | 0.052 | 0.875 | -0.041 |
| ZAR | -0.146 | -0.017 | -0.094 | -0.016 | -0.017 | 0.117 | -0.273 | -0.012 | -0.058 | -0.085 | -0.011 | -0.019 | -0.016 | 0.720 |
| OLS After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | 0.998 | 0.214 | 0.596 | 0.129 | 0.126 | 0.426 | 0.317 | 0.034 | 0.296 | 0.406 | 0.219 | 0.091 | 0.106 | -0.382 |
| Brentoil | 0.478 | 0.712 | 0.486 | 0.130 | 0.155 | 0.672 | 0.287 | 0.046 | 0.348 | 0.475 | 0.203 | 0.079 | 0.095 | -0.510 |
| Copper | 0.776 | 0.265 | 0.963 | 0.135 | 0.160 | 0.570 | 0.418 | 0.019 | 0.385 | 0.502 | 0.262 | 0.119 | 0.124 | -0.503 |
| Corn | 0.286 | 0.159 | 0.219 | 0.866 | 0.203 | 0.150 | 0.223 | 0.057 | 0.165 | 0.220 | 0.623 | 0.104 | 0.584 | -0.240 |
| Cotton | 0.248 | 0.166 | 0.247 | 0.177 | 0.757 | 0.264 | 0.173 | 0.002 | 0.193 | 0.234 | 0.242 | 0.108 | 0.179 | -0.347 |
| FTSE/JSE40 | 0.290 | 0.171 | 0.297 | 0.046 | 0.085 | 0.961 | 0.097 | 0.010 | 0.215 | 0.242 | 0.115 | 0.061 | 0.043 | -0.220 |
| Gold | 0.218 | 0.073 | 0.224 | 0.035 | 0.066 | 0.127 | 0.828 | 0.000 | 0.241 | 0.519 | 0.079 | 0.021 | 0.041 | -0.240 |
| Jet Kerosene | 0.382 | 0.555 | 0.382 | 0.100 | 0.129 | 0.550 | 0.229 | 0.038 | 0.275 | 0.368 | 0.167 | 0.065 | 0.073 | -0.373 |
| Naphtha | 0.465 | 0.654 | 0.468 | 0.119 | 0.143 | 0.629 | 0.267 | 0.037 | 0.316 | 0.406 | 0.199 | 0.087 | 0.078 | -0.457 |
| Natural Gas | 0.101 | 0.044 | 0.022 | 0.129 | 0.029 | 0.120 | 0.071 | 0.260 | 0.041 | 0.105 | 0.127 | 0.052 | 0.149 | -0.015 |
| Palladium | 0.457 | 0.200 | 0.460 | 0.070 | 0.174 | 0.620 | 0.487 | 0.002 | 0.616 | 0.672 | 0.171 | 0.071 | 0.060 | -0.451 |
| Platinum | 0.313 | 0.112 | 0.275 | 0.051 | 0.092 | 0.334 | 0.490 | 0.004 | 0.308 | 0.623 | 0.115 | 0.026 | 0.052 | -0.282 |
| Soyabean | 0.246 | 0.151 | 0.230 | 0.375 | 0.121 | 0.202 | 0.188 | 0.034 | 0.158 | 0.233 | 0.769 | 0.055 | 0.303 | -0.256 |
| Sugar | 0.217 | 0.133 | 0.205 | 0.155 | 0.147 | 0.206 | 0.154 | 0.029 | 0.159 | 0.185 | 0.174 | 0.681 | 0.146 | -0.277 |
| Wheat | 0.257 | 0.165 | 0.227 | 0.680 | 0.202 | 0.227 | 0.265 | 0.071 | 0.170 | 0.259 | 0.615 | 0.105 | 0.939 | -0.348 |
| ZAR | -0.250 | -0.162 | -0.25 | -0.068 | -0.095 | -0.265 | -0.258 | -0.013 | -0.201 | -0.313 | -0.127 | -0.067 | -0.071 | 0.814 |

Source: Thomson Reuters DataStream and EViews.

7.5.3.2. ECM

In order to obtain the hedge ratios using the ECM model, cointegration needs to be present, this is tested using the Engle Granger approach. The first step of the analysis is based on the differenced spot prices, by estimating the following model:

$$\Delta Y_t = \beta \Delta X_t \quad [7.1]$$

where ΔY_t is the dependent variable (differenced log spot price), ΔX_t is the independent variable (differenced log futures price) and β is the optimal hedge ratio. No intercept is included in this model as we assume no cash holdings. A shortcoming of this method of estimating the hedge ratio is that it takes only the short run effects into account. The next step is the cointegration test, which is done by estimating the following model:

$$Y_t = \alpha + \delta X_t + u_t \quad [7.2]$$

where u_t is the error term. If u_t is stationary ($u_t \sim I(0)$), it implies that Y_t and X_t are cointegrated and have a long run linear relationship. Cointegration based on Engle and Granger (1987) cointegration and not Johansen cointegration is used, as the relationship of interest is bivariate. Engle and Granger (1987) have the objective of finding a linear combination between nonstationary time series variables that form a stationary time series when combined. It is therefore possible to identify stable long run relationships between stationary time series. By assuming that variables are integrated of order one, the Engle and Granger two step estimation technique is used to test for cointegration by means of the augmented Dickey-Fuller test of the error terms (Dickey & Fuller, 1981). The unit root test will be verified by the Phillips-Perron test. The augmented Dickey-Fuller test is done to determine the long run relationships between the variables.

In order to estimate the optimal hedge ratio using an ECM, the variables included should be cointegrated. This implies that stationarity of the error term is required. The critical values used to determine whether the null hypothesis is rejected or not rejected is based on the Engle and Yoo (1987) critical values as the series is now an estimated one. In this step we aim to reject the null hypothesis of non-stationarity to obtain two cointegrated variables. If the variables are cointegrated, the next step is the estimation of the ECM which takes feedback effects into account (Puhle, 2013; Alexander, 1999).

This is done by estimating the following model:

$$\Delta Y_t = \beta^* \Delta X_t + \gamma u_{t-1} \quad [7.3]$$

where β^* is the hedge ratio based on the ECM, γ is the feedback coefficient, and δ is the long run coefficient. The error correction model (Equation 7.3) can be estimated if, and only if Y_t and X_t are cointegrated. The ADRL approach is utilised for the ECM analysis in order to take lags into account.

In the first step, the optimal hedge ratios are calculated by regressing the spot prices without considering the feedback effects between the variables. The first step is based on the classical approach (Equation 7.1) of only taking into account the short run fluctuations between two time series, therefore ignoring the long run relationships and feedback effects between variables. The objective of the classical approach is to derive the minimum variance hedge by fitting a linear model that explains the changes in one variable by changes in another variable. The β that is obtained in the analysis is defined as the optimal hedge ratio which is linked to a residual standard error, which is shown in Table 7.5. No intercept was included as it was assumed that there is a zero initial cash budget. The top value in each cell is the coefficient and the value at the bottom of each cell is the residual standard error. In this approach the cross hedge is viewed as not perfect, which results in a hedged portfolio that still contains risk (Puhle, 2013).

The second part of the analysis builds on the classical approach of obtaining a hedge ratio and improves it by taking into account the long run stable relationship between the two time series in order to improve the residual standard error and improve the hedged portfolio. The unit root test results of ADF and PP are shown in Table 7.5. The hedge ratios are calculated based on the residuals of the time series that are stationary and statistically significant at a 95% confidence level. At that point, the residuals are cointegrated, and a long run relationship exists. The analysis following the unit root tests is based on the ADF cointegration matrix with the PP cointegration matrix used as a confirmation tool.

In Table 7.6 the hedge ratios based on the ECM are shown. Similar to the OLS results, the hedge ratio improved overall after the crisis as compared to before the crisis; however, some combinations did return a lower hedge ratio. The improved hedge ratio is most likely due to the financialisation of commodities. Platinum provides the lowest negative hedge ratio after the crisis for ZAR spot. After the crisis, platinum future is a better hedge for palladium than palladium future.

Table 7.5: Cointegration analysis

| ADF Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|-------------------|-------------|------------|------------|-----------|------------|--------------|------------|---------------|-------------|------------|------------|------------|-----------|------------|
| Aluminium | -7.063*** | -3.390*** | -3.442*** | -1.621* | -0.524 | -2.837*** | -2.727*** | -1.749* | -0.358 | -3.247*** | -1.160 | -2.055** | -2.270** | -1.043 |
| Brentoil | -3.720*** | -8.005*** | -3.985*** | -1.422 | -1.030 | -2.641*** | -3.111*** | -2.356** | -0.869 | -3.998*** | -1.472 | -2.126** | -2.094** | -1.896* |
| Copper | -3.372*** | -3.755*** | -2.512** | -1.055 | 0.297 | -2.122** | -2.425** | -1.508 | 0.612 | -3.274*** | -0.767 | -1.300 | -2.042** | -0.491 |
| Corn | -1.979** | -1.690* | -1.915* | -4.608*** | -1.537 | -2.035** | -2.055** | -1.477 | -1.444 | -1.944** | -2.275** | -1.447 | -2.945*** | -1.448 |
| Cotton | -2.088** | -2.094** | -2.089** | -2.099** | -8.631*** | -1.985** | -2.087** | -2.611*** | -2.007** | -2.229** | -2.491** | -2.018** | -2.091** | -2.791*** |
| JSE | -2.554** | -2.123** | -2.033** | -1.162 | 0.735 | -6.455*** | -2.031** | -0.718 | 0.548 | -1.881* | -0.328 | -0.869 | -2.318** | 0.155 |
| Gold | -2.645*** | -2.597*** | -2.380** | -1.517 | -0.231 | -2.171** | -26.963*** | -1.567 | -0.176 | -3.189*** | -1.342 | -45.970*** | -2.728*** | -0.820 |
| Jet Kerosene | -3.132*** | -6.028*** | -3.428*** | -1.260 | -0.934 | -2.254** | -2.684*** | -2.494** | -0.724 | -3.819*** | -1.365 | -2.209** | -1.912* | -1.851* |
| Naphtha | -3.811*** | -4.129*** | -3.960*** | -1.549 | -1.183 | -2.587*** | -3.233*** | -2.568*** | -0.872 | -4.169*** | -1.617* | -1.934* | -2.225** | -2.162** |
| Natural Gas | -3.195*** | -3.349*** | -3.125*** | -2.631*** | -3.060*** | -2.806*** | -3.017*** | -9.077*** | -2.667*** | -3.419*** | -2.799*** | -3.005*** | -2.679*** | -3.861*** |
| Palladium | -1.134 | -1.067 | -1.056 | -1.120 | -1.145 | -1.036 | -1.159 | -1.309 | -23.988*** | -1.247 | -1.316 | -1.199 | -1.003 | -1.327 |
| Platinum | -3.689*** | -3.519*** | -3.787*** | -1.811* | -1.358 | -2.433** | -3.421*** | -2.623*** | -0.926 | -7.058*** | -1.893* | -1.586 | -2.638*** | -2.221** |
| Soyabean | -1.654* | -1.623* | -1.710* | -2.098** | -2.106** | -1.616 | -1.8230* | -1.748* | -1.713* | -1.909* | -6.593*** | -1.397 | -2.371** | -1.818* |
| Sugar | -2.347** | -2.181** | -2.020** | -1.736* | -1.748* | -1.909* | -1.834* | -2.182** | -1.789* | -1.859* | -1.783* | -7.771*** | -1.701* | -2.045** |
| Wheat | -2.635*** | -2.232** | -2.708*** | -3.000*** | -1.880* | -2.874*** | -3.260*** | -2.045** | -2.176** | -2.897*** | -3.003*** | -1.631* | -3.550*** | -1.932* |
| ZAR | -1.778* | -2.281** | -1.838* | -1.532 | -2.351** | -1.668* | -1.864* | -3.186*** | -1.630* | -2.459** | -2.060** | -1.930* | -1.636* | -15.381*** |
| PP Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | -6.649*** | -3.333*** | -3.506*** | -1.503 | -0.445 | -2.547** | -2.397** | -1.713* | -0.266 | -3.056*** | -1.035 | -1.549 | -2.042** | -0.773 |
| Brentoil | -3.598*** | -16.889*** | -4.098*** | -1.530 | -1.034 | -2.697*** | -3.285*** | -2.351** | -0.989 | -3.921*** | -1.625* | -2.167** | -2.130** | -1.930* |
| Copper | -3.233*** | -3.648*** | -15.942*** | -1.064 | 0.366 | -1.990** | -2.163** | -1.430 | 0.683 | -3.143*** | -0.756 | -1.296 | -1.958** | -0.437 |
| Corn | -1.974** | -1.752* | -1.953** | -4.703*** | -1.577 | -2.038** | -2.088** | -1.525 | -1.470 | -1.976** | -2.306** | -1.467 | -3.191*** | -1.466 |
| Cotton | -2.013** | -2.009** | -2.020** | -2.017** | -10.558*** | -1.905* | -2.013** | -2.731*** | -1.933** | -2.152** | -2.387** | -1.945** | -2.014** | -2.821*** |
| JSE | -2.261** | -2.044** | -1.927* | -1.188 | 0.756 | -11.535*** | -1.945** | -0.663 | 0.594 | -1.533 | -0.409 | -0.927 | -2.296** | 0.093 |
| Gold | -2.328** | -2.719*** | -2.273** | -1.499 | -0.207 | -2.178** | -39.823*** | -1.489 | -0.193 | -3.136*** | -1.315 | -45.932*** | -2.683*** | -0.724 |
| Jet Kerosene | -3.129*** | -7.617*** | -3.292*** | -1.282 | -0.851 | -2.261** | -2.585*** | -2.476** | -0.664 | -3.599*** | -1.367 | -2.143** | -1.901* | -1.780* |
| Naphtha | -3.710*** | -5.900*** | -3.904*** | -1.558 | -1.099 | -2.506** | -3.225*** | -2.528*** | -0.904 | -4.298*** | -1.699* | -1.863* | -2.210** | -2.146** |
| Natural Gas | -3.284*** | -3.638*** | -3.302*** | -2.859*** | -3.180*** | -2.951*** | -3.377*** | -22.713*** | -2.737*** | -3.630*** | -2.878*** | -3.215*** | -2.963*** | -3.872*** |
| Palladium | -1.243 | -1.238 | -1.180 | -1.212 | -1.242 | -1.169 | -1.202 | -1.378 | -43.812*** | -1.295 | -1.300 | -1.252 | -1.144 | -1.362 |
| Platinum | -3.339*** | -3.622*** | -3.504*** | -1.751* | -1.261 | -2.184** | -3.524*** | -2.623*** | -0.921 | -16.182*** | -1.898* | -1.357 | -2.492** | -2.123** |
| Soyabean | -1.900* | -1.971** | -2.000** | -2.129** | -2.037** | -1.890* | -2.141** | -1.931* | -1.743* | -2.254** | -8.724*** | -1.649* | -2.676*** | -2.052** |
| Sugar | -2.277** | -2.332** | -2.014** | -1.746* | -1.748* | -1.963** | -1.915* | -2.306** | -1.774* | -2.176** | -1.771* | -11.019*** | -1.696* | -2.000** |
| Wheat | -2.495** | -2.257** | -2.550** | -3.000*** | -1.760* | -2.748*** | -3.160*** | -1.920* | -2.009** | -2.681*** | -3.023*** | -1.677* | -3.823*** | -1.810* |
| ZAR | -1.742* | -2.265** | -1.821* | -1.517 | -2.304** | -1.659* | -1.860* | -3.158*** | -1.641* | -2.453** | -2.031** | -1.910* | -1.631* | -30.536*** |
| ADF After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | -8.434*** | -2.382** | -2.974*** | -2.343** | -3.075*** | -3.858*** | -2.111** | -2.561** | -1.732* | -3.009*** | -1.979** | -3.050*** | -2.431** | -4.329*** |
| Brentoil | -1.802* | -9.809*** | -2.936*** | -2.020** | -1.548 | -1.887* | -1.927* | -1.823* | -0.968 | -2.430** | -2.783*** | -1.436 | -2.776*** | -2.068** |
| Copper | -3.022*** | -3.187*** | -7.249*** | -2.543** | -2.450** | -3.208*** | -1.939* | -2.282** | -1.174 | -3.984*** | -2.193** | -2.281** | -3.161*** | -4.075*** |
| Corn | -1.811* | -2.133** | -2.298** | -3.636*** | -1.630* | -2.202** | -3.340*** | -1.351 | -1.091 | -2.051** | -2.548** | -2.009** | -2.676*** | -2.227** |
| Cotton | -2.940*** | -1.993** | -2.543** | -1.996** | -8.508*** | -2.724*** | -1.737* | -2.339** | -1.507 | -2.202** | -1.838* | -2.962*** | -1.992** | -2.617*** |
| JSE | -3.786*** | -2.429** | -3.353*** | -2.746*** | -2.866*** | -6.339*** | -2.651*** | -1.871* | -0.879 | -3.305*** | -2.178** | -2.352** | -2.681*** | -3.607*** |
| Gold | -2.308** | -2.687*** | -2.439** | -3.913*** | -2.079** | -2.707*** | -41.908*** | -2.001** | -1.382 | -2.277** | -2.947*** | -2.892*** | -2.893*** | -2.723*** |
| Jet Kerosene | -1.763* | -3.904*** | -2.908*** | -2.001** | -1.330 | -1.791* | -1.906* | -1.711** | -0.981 | -2.326** | -2.727** | -1.344 | -2.830*** | -2.036** |
| Naphtha | -1.987** | -4.221*** | -3.280*** | -2.097** | -1.616 | -2.059** | -1.904* | -1.982** | -1.028 | -2.798*** | -2.729*** | -1.577 | -2.881*** | -2.310** |
| Natural Gas | -2.982*** | -2.923*** | -2.925*** | -2.500** | -3.042*** | -3.115*** | -2.687*** | -12.609*** | -2.667*** | -3.195*** | -2.581*** | -2.706*** | -2.558** | -2.998*** |
| Palladium | -3.845*** | -3.905*** | -3.801*** | -3.670*** | -3.722*** | -3.414*** | -3.392*** | -3.836*** | -37.871*** | -3.835*** | -3.688*** | -3.797*** | -3.632*** | -3.789*** |
| Platinum | -2.491** | -2.201** | -3.643*** | -1.782* | -1.576 | -2.638*** | -0.851 | -1.712* | -0.303 | -26.861*** | -1.664* | -1.423 | -2.604*** | -3.535*** |
| Soyabean | -1.939* | -3.150*** | -2.290** | -2.650*** | -1.946** | -2.077** | -2.688*** | -1.997** | -1.747* | -2.378** | -9.702*** | -2.135** | -3.174*** | -2.286** |
| Sugar | -3.055*** | -2.347** | -2.810*** | -2.499** | -2.922*** | -2.626*** | -2.954*** | -2.015** | -1.946** | -2.476** | -2.304** | -4.571*** | -2.232** | -2.402** |

| | | | | | | | | | | | | | | |
|-----------------|-------------|------------|-----------|-----------|-----------|--------------|------------|---------------|-------------|------------|------------|-----------|-----------|------------|
| Wheat | -3.394*** | -4.225*** | -3.987*** | -4.457*** | -3.284*** | -3.55*** | -3.504*** | -3.141*** | -2.353** | -4.023*** | -4.908*** | -3.361*** | -5.228*** | -4.009*** |
| ZAR | -4.034*** | -1.900* | -3.815*** | -2.060** | -2.109** | -3.433*** | -1.843* | -1.476 | -0.548 | -3.566*** | -1.553 | -1.408 | -2.467** | -13.295*** |
| PP After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | -8.444*** | -2.325** | -3.239*** | -2.353** | -3.184*** | -3.858*** | -2.091** | -2.510** | -1.697* | -3.204*** | -1.956** | -3.111*** | -2.426** | -4.205*** |
| Brentoil | -1.791* | -37.052*** | -2.897*** | -2.025** | -1.583 | -1.944** | -2.058** | -1.722* | -1.049 | -2.813*** | -2.619*** | -1.493 | -2.782*** | -2.086** |
| Copper | -2.997*** | -3.018*** | -8.855*** | -2.507** | -2.437** | -3.155*** | -1.951** | -2.212** | -1.020 | -3.938*** | -2.121** | -2.240** | -3.099*** | -4.075*** |
| Corn | -1.876* | -2.111** | -2.232** | -4.205*** | -1.629* | -2.219** | -3.31*** | -1.377 | -1.104 | -2.095** | -2.189** | -1.996** | -2.670*** | -2.254** |
| Cotton | -2.915*** | -2.021** | -2.390** | -1.913* | -9.096*** | -2.754*** | -1.771* | -2.362** | -1.499 | -2.224** | -1.812* | -3.035*** | -1.991** | -2.613*** |
| JSE | -3.727*** | -2.414** | -3.282*** | -2.762*** | -2.859*** | -8.996*** | -2.699*** | -1.725* | -0.934 | -3.327*** | -2.189** | -2.348** | -2.675*** | -3.428*** |
| Gold | -2.294** | -2.671*** | -2.422** | -3.774*** | -2.083** | -2.694*** | -41.913*** | -1.984** | -1.363 | -2.237** | -2.923*** | -2.875*** | -2.827*** | -2.694*** |
| Jet Kerosene | -1.722* | -7.700*** | -2.795*** | -1.992** | -1.443 | -1.830* | -1.996** | -1.587 | -1.041 | -2.590*** | -2.574*** | -1.383 | -2.797*** | -2.034** |
| Naphtha | -1.941** | -6.012*** | -3.147*** | -2.043** | -1.700* | -2.069** | -1.966** | -1.856* | -1.013 | -3.106*** | -2.539** | -1.581 | -2.881*** | -2.273** |
| Natural Gas | -3.337*** | -3.223*** | -3.282*** | -2.685*** | -3.139*** | -3.178*** | -2.697*** | -16.296*** | -2.705*** | -3.338*** | -2.771*** | -2.923*** | -2.820*** | -3.335*** |
| Palladium | -3.845*** | -3.904*** | -3.803*** | -3.667*** | -3.722*** | -3.407*** | -3.380*** | -3.837*** | -38.444*** | -3.835*** | -3.672*** | -3.798*** | -3.627*** | -3.793*** |
| Platinum | -2.788*** | -2.674*** | -3.878*** | -1.849* | -1.729* | -2.730*** | -0.907 | -1.856* | -0.375 | -39.438*** | -1.707* | -1.513 | -2.648*** | -3.646*** |
| Soyabean | -1.922* | -3.047*** | -2.305** | -2.517** | -1.882* | -2.074** | -2.696*** | -1.964** | -1.700* | -2.353** | -11.969*** | -2.108** | -3.174*** | -2.252** |
| Sugar | -3.194*** | -2.272** | -2.703*** | -2.564** | -3.131*** | -2.524** | -2.902*** | -2.098** | -1.875* | -2.432** | -2.354** | -9.844*** | -2.297** | -2.295** |
| Wheat | -3.304*** | -4.135*** | -3.963*** | -4.452*** | -3.186*** | -3.505*** | -3.472*** | -3.067*** | -2.111** | -3.930*** | -4.561*** | -3.374*** | -5.476*** | -3.968*** |
| ZAR | -3.887*** | -1.833* | -3.713*** | -2.058** | -2.109** | -3.079*** | -1.827* | -1.306 | -0.415 | -3.703*** | -1.493 | -1.435 | -2.433** | -32.125*** |

*, **, *** indicate significance at a 10%, 5% and 1% level of significance respectively

Source: Thomson Reuters DataStream and EViews.

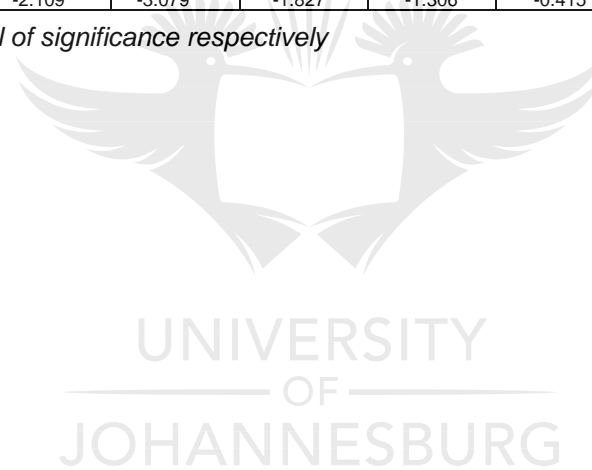


Table 7.6: ECM hedge ratio

| ECM Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|-------------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|----------------------|---------|--------|
| Aluminium | 1.010 | 0.055 | 0.567 | N/A | N/A | 0.224 | 0.331 | N/A | N/A | 0.157 | N/A | 0.022 | 0.062 | N/A |
| Brentoil | 0.155 | 0.846 | 0.154 | N/A | N/A | 0.135 | 0.378 | 0.152 | N/A | 0.143 | N/A | 0.084 | 0.108 | N/A |
| Copper | 0.923 | 0.082 | 0.990 | N/A | N/A | 0.304 | 0.488 | N/A | N/A | 0.221 | N/A | N/A | 0.070 | N/A |
| Corn | 0.113 | N/A | 0.068 | 0.895 | N/A | 0.084 | 0.162 | N/A | N/A | 0.073 | 0.509 | N/A | 0.490 | N/A |
| Cotton | 0.103 | 0.071 | 0.079 | 0.120 | 0.817 | 0.034 | 0.107 | 0.004 | 0.003 | -0.026 | 0.208 | 0.012 | 0.127 | -0.065 |
| FTSE/JSE40 | 0.229 | 0.040 | 0.210 | N/A | N/A | 0.935 | 0.130 | N/A | N/A | N/A | N/A | N/A | 0.040 | N/A |
| Gold | 0.215 | 0.059 | 0.187 | N/A | N/A | 0.101 | 0.701 | N/A | N/A | 0.218 | N/A | NEAR SINGULAR MATRIX | 0.047 | N/A |
| Jet Kerosene | 0.118 | 0.442 | 0.107 | N/A | N/A | 0.047 | 0.261 | 0.091 | N/A | 0.111 | N/A | 0.037 | N/A | N/A |
| Naphtha | 0.160 | 0.392 | 0.115 | N/A | N/A | 0.038 | 0.248 | 0.056 | N/A | 0.170 | N/A | N/A | 0.066 | 0.026 |
| Natural Gas | 0.144 | 0.272 | 0.070 | 0.024 | 0.078 | 0.095 | 0.341 | 0.369 | 0.063 | 0.078 | 0.070 | 0.100 | -0.032 | -0.135 |
| Palladium | N/A | N/A | N/A | N/A | N/A | N/A | N/A | N/A | 0.670 | N/A | N/A | N/A | N/A | N/A |
| Platinum | 0.169 | 0.056 | 0.148 | N/A | N/A | 0.072 | 0.301 | 0.012 | N/A | 0.537 | N/A | N/A | 0.032 | -0.089 |
| Soyabean | N/A | 0.061 | 0.055 | 0.488 | 0.132 | N/A | 0.132 | N/A | N/A | 0.050 | 0.852 | N/A | 0.305 | -0.007 |
| Sugar | 0.162 | 0.073 | 0.133 | N/A | N/A | 0.005 | N/A | 0.024 | N/A | 0.102 | N/A | 0.236 | N/A | -0.115 |
| Wheat | 0.134 | 0.060 | 0.078 | 0.609 | N/A | 0.083 | 0.186 | 0.009 | 0.065 | 0.091 | 0.412 | N/A | 0.876 | N/A |
| ZAR | N/A | -0.017 | N/A | N/A | -0.018 | N/A | N/A | -0.012 | N/A | -0.084 | -0.012 | N/A | N/A | 0.776 |
| ECM After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | 0.999 | 0.216 | 0.598 | 0.129 | 0.127 | 0.424 | 0.318 | 0.036 | N/A | 0.407 | 0.218 | 0.090 | 0.105 | -0.381 |
| Brentoil | N/A | 0.750 | 0.488 | 0.129 | N/A | 0.672 | 0.286 | N/A | N/A | 0.476 | 0.206 | N/A | 0.097 | -0.510 |
| Copper | 0.775 | 0.268 | 0.961 | 0.134 | 0.161 | 0.572 | 0.419 | 0.021 | N/A | 0.508 | 0.263 | 0.118 | 0.125 | -0.499 |
| Corn | N/A | 0.160 | 0.220 | 0.868 | N/A | 0.149 | 0.228 | N/A | N/A | 0.221 | 0.625 | 0.105 | 0.584 | -0.243 |
| Cotton | 0.250 | 0.167 | 0.250 | 0.177 | 0.760 | 0.260 | N/A | 0.004 | N/A | 0.235 | N/A | 0.109 | 0.178 | -0.348 |
| FTSE/JSE40 | 0.288 | 0.176 | 0.297 | 0.044 | 0.083 | 0.960 | 0.094 | N/A | N/A | 0.241 | 0.114 | 0.059 | 0.040 | -0.215 |
| Gold | 0.218 | 0.076 | 0.224 | 0.036 | 0.067 | 0.126 | 0.841 | -0.000 | N/A | 0.515 | 0.081 | 0.021 | 0.042 | -0.235 |
| Jet Kerosene | N/A | 0.572 | 0.383 | 0.099 | N/A | N/A | 0.230 | N/A | N/A | 0.361 | 0.170 | N/A | 0.074 | -0.367 |
| Naphtha | 0.470 | 0.680 | 0.472 | 0.119 | N/A | 0.634 | 0.269 | 0.037 | N/A | 0.408 | 0.204 | N/A | 0.081 | -0.457 |
| Natural Gas | 0.060 | 0.033 | -0.003 | 0.067 | 0.002 | 0.097 | 0.015 | 0.308 | 0.025 | 0.068 | 0.070 | 0.037 | 0.115 | -0.001 |
| Palladium | 0.463 | 0.207 | 0.465 | 0.065 | 0.168 | 0.636 | 0.490 | 0.005 | 0.582 | 0.652 | 0.169 | 0.070 | 0.056 | -0.432 |
| Platinum | 0.322 | 0.120 | 0.282 | N/A | N/A | 0.337 | N/A | N/A | N/A | 0.621 | N/A | N/A | 0.052 | -0.276 |
| Soyabean | N/A | 0.153 | 0.233 | 0.373 | 0.119 | 0.210 | 0.192 | 0.036 | N/A | 0.235 | 0.779 | 0.060 | 0.302 | -0.255 |
| Sugar | 0.227 | 0.131 | 0.207 | 0.157 | 0.138 | 0.204 | 0.164 | 0.032 | 0.164 | 0.190 | 0.185 | 0.692 | 0.142 | -0.275 |
| Wheat | 0.258 | 0.164 | 0.230 | 0.683 | 0.203 | 0.234 | 0.278 | 0.072 | 0.179 | 0.269 | 0.626 | 0.108 | 0.940 | -0.355 |
| ZAR | -0.254 | N/A | -0.250 | -0.067 | -0.093 | -0.264 | N/A | N/A | N/A | -0.314 | N/A | N/A | -0.070 | 0.822 |

Source: Thomson Reuters DataStream and EViews.

7.5.3.3. VECM

For the VECM analysis, the same cointegration analysis applies. Therefore, hedge ratios based on the VECM methodology are only done for the combination of variables that are cointegrated according to the Engle and Granger cointegration methodology. In Table 7.7, the hedge ratios based on the VECM are shown. The aspects highlighted in ECM apply to VECM as well.



Table 7.7: VECM hedge ratio

| VECM Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|--------------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|---------|---------|--------|
| Aluminium | 1.010 | 0.056 | 0.567 | N/A | N/A | 0.222 | 0.330 | N/A | N/A | 0.159 | N/A | 0.023 | 0.061 | N/A |
| Brentoil | 0.149 | 0.846 | 0.151 | N/A | N/A | 0.128 | 0.374 | 0.154 | N/A | 0.144 | N/A | 0.081 | 0.104 | N/A |
| Copper | 0.923 | 0.083 | 0.985 | N/A | N/A | 0.304 | 0.489 | N/A | N/A | 0.224 | N/A | N/A | 0.071 | N/A |
| Corn | 0.114 | N/A | 0.068 | 0.896 | N/A | 0.085 | 0.163 | N/A | N/A | 0.075 | 0.508 | N/A | 0.489 | N/A |
| Cotton | 0.102 | 0.071 | 0.081 | 0.121 | 0.818 | 0.036 | 0.105 | 0.006 | 0.002 | -0.024 | 0.206 | 0.011 | 0.129 | -0.066 |
| FTSE/JSE40 | 0.226 | 0.040 | 0.208 | N/A | N/A | 0.936 | 0.131 | N/A | N/A | N/A | N/A | N/A | 0.038 | N/A |
| Gold | 0.214 | 0.059 | 0.188 | N/A | N/A | 0.101 | 0.701 | N/A | N/A | 0.216 | N/A | 0.028 | 0.047 | N/A |
| Jet Kerosene | 0.116 | 0.444 | 0.107 | N/A | N/A | 0.048 | 0.261 | 0.092 | N/A | 0.112 | N/A | 0.307 | N/A | N/A |
| Naphtha | 0.161 | 0.393 | 0.117 | N/A | N/A | 0.038 | 0.248 | 0.055 | N/A | 0.170 | N/A | N/A | 0.063 | 0.023 |
| Natural Gas | 0.133 | 0.274 | 0.065 | 0.025 | 0.085 | 0.075 | 0.327 | 0.371 | 0.058 | 0.070 | 0.076 | 0.098 | -0.022 | -0.136 |
| Palladium | N/A | N/A | N/A | N/A | N/A | N/A | N/A | N/A | 0.669 | N/A | N/A | N/A | N/A | N/A |
| Platinum | 0.168 | 0.056 | 0.149 | N/A | N/A | 0.072 | 0.301 | 0.011 | N/A | 0.536 | N/A | N/A | 0.031 | -0.087 |
| Soyabean | N/A | 0.060 | 0.055 | 0.489 | 0.130 | N/A | 0.134 | N/A | N/A | 0.052 | 0.851 | N/A | 0.308 | -0.007 |
| Sugar | 0.162 | 0.075 | 0.134 | N/A | N/A | 0.002 | N/A | 0.025 | N/A | 0.106 | N/A | 0.235 | N/A | -0.118 |
| Wheat | 0.133 | 0.061 | 0.079 | 0.609 | N/A | 0.082 | 0.187 | 0.009 | 0.064 | 0.092 | 0.412 | N/A | 0.876 | N/A |
| ZAR | N/A | -0.017 | N/A | N/A | -0.019 | N/A | N/A | -0.013 | N/A | -0.085 | -0.012 | N/A | N/A | 0.778 |
| VECM After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | 0.999 | 0.216 | 0.598 | 0.129 | 0.130 | 0.424 | 0.318 | 0.037 | N/A | 0.408 | 0.218 | 0.090 | 0.105 | -0.381 |
| Brentoil | N/A | 0.752 | 0.489 | 0.130 | N/A | 0.671 | 0.290 | N/A | N/A | 0.473 | 0.208 | N/A | 0.098 | -0.510 |
| Copper | 0.776 | 0.267 | 0.962 | 0.134 | 0.162 | 0.573 | 0.418 | 0.020 | N/A | 0.509 | 0.264 | 0.119 | 0.125 | -0.500 |
| Corn | N/A | 0.160 | 0.221 | 0.872 | N/A | 0.145 | 0.227 | N/A | N/A | 0.221 | 0.626 | 0.107 | 0.586 | -0.239 |
| Cotton | 0.251 | 0.169 | 0.250 | 0.177 | 0.760 | 0.260 | N/A | 0.005 | N/A | 0.234 | N/A | 0.110 | 0.179 | -0.348 |
| FTSE/JSE40 | 0.289 | 0.176 | 0.297 | 0.043 | 0.083 | 0.960 | 0.095 | N/A | N/A | 0.241 | 0.113 | 0.060 | 0.041 | -0.217 |
| Gold | 0.219 | 0.076 | 0.224 | 0.036 | 0.067 | 0.125 | 0.837 | 0.001 | N/A | 0.515 | 0.081 | 0.021 | 0.042 | -0.236 |
| Jet Kerosene | N/A | 0.571 | 0.385 | 0.100 | N/A | N/A | 0.232 | N/A | N/A | 0.367 | 0.171 | N/A | 0.075 | -0.372 |
| Naphtha | 0.471 | 0.678 | 0.474 | 0.120 | N/A | 0.630 | 0.270 | 0.038 | N/A | 0.407 | 0.206 | N/A | 0.082 | -0.454 |
| Natural Gas | 0.098 | 0.040 | 0.015 | 0.078 | 0.011 | 0.093 | 0.027 | 0.307 | 0.028 | 0.064 | 0.077 | 0.043 | 0.130 | -0.011 |
| Palladium | 0.464 | 0.206 | 0.462 | 0.065 | 0.168 | 0.630 | 0.489 | 0.006 | 0.582 | 0.652 | 0.168 | 0.071 | 0.056 | -0.432 |
| Platinum | 0.323 | 0.119 | 0.282 | N/A | N/A | 0.335 | N/A | N/A | N/A | 0.621 | N/A | N/A | 0.053 | -0.275 |
| Soyabean | N/A | 0.154 | 0.233 | 0.373 | 0.119 | 0.207 | 0.190 | 0.037 | N/A | 0.235 | 0.779 | 0.061 | 0.304 | -0.255 |
| Sugar | 0.223 | 0.135 | 0.208 | 0.157 | 0.147 | 0.204 | 0.160 | 0.032 | 0.162 | 0.192 | 0.179 | 0.692 | 0.146 | -0.283 |
| Wheat | 0.258 | 0.164 | 0.233 | 0.685 | 0.202 | 0.231 | 0.275 | 0.074 | 0.169 | 0.268 | 0.639 | 0.108 | 0.941 | -0.359 |
| ZAR | -0.253 | N/A | -0.252 | -0.068 | -0.096 | -0.265 | N/A | N/A | N/A | -0.316 | N/A | N/A | -0.071 | 0.821 |

Source: Thomson Reuters DataStream and EViews.

7.5.3.4. ECM-GARCH

For the VECM analysis, the same cointegration analysis applies. In addition, the Lagrange Multiplier Test, also known as the ARCH-LM test, is run to determine if volatility clustering is present in order to apply the GARCH model. The hedge ratios based on the ECM-GARCH methodology are only performed for the combination of variables that are cointegrated according to the Engle and Granger cointegration methodology. In Table 7.8 the hedge ratios based on the ECM-GARCH are shown. The aspects highlighted in ECM and VECM apply to ECM-GARCH as well.



Table 7.8: ECM-GARCH hedge ratio

| ECM-GARCH Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|-------------------------|-------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|-----------------------|----------------------|----------------------|----------------------|-----------------------|
| Aluminium | 1.008 | 0.039 | 0.590 | N/A | N/A | 0.183 | 0.212 ARCH 0.0943 | N/A | N/A | 0.107 | N/A | 0.007 | 0.047 | N/A |
| Brentoil | 0.149 | 0.892 | 0.152 | N/A | N/A | 0.154 | 0.380 | 0.154 | N/A | 0.204 | N/A | 0.078 | 0.076 | N/A |
| Copper | 0.858 | 0.036 | 1.005 | N/A | N/A | 0.234 | 0.269 | N/A | N/A | 0.119 | N/A | N/A | 0.063 | N/A |
| Corn | 0.097 | N/A | 0.076 | 0.891 | N/A | 0.064 | 0.133 | N/A | N/A | 0.069 | 0.538 | N/A | 0.466 | N/A |
| Cotton | 0.090 | 0.066 arch 0.0688 | 0.065 | 0.116 | 0.910 | 0.037 ARCH 0.0534 | 0.111 ARCH 0.0639 | 0.002 ARCH 0.0667 | 0.013 ARCH 0.0618 | -0.028 ARCH 0.0503 | 0.205 | 0.022 ARCH 0.0679 | 0.122 ARCH 0.063 | -0.071 ARCH 0.0762 |
| FTSE/JSE40 | 0.178 | 0.040 | 0.164 | N/A | N/A | 0.918 | 0.106 | N/A | N/A | N/A | N/A | N/A | 0.036 | N/A |
| Gold | 0.183 | 0.036 | 0.165 | N/A | N/A | 0.041 | 0.691 | N/A | N/A | 0.169 | N/A | NEAR SINGULAR MATRIX | 0.036 | N/A |
| Jet Kerosene | 0.135 | 0.465 | 0.122 | N/A | N/A | 0.091 | 0.267 | 0.088 | N/A | 0.114 | N/A | 0.039 | N/A | N/A |
| Naphtha | 0.187 | 0.411 | 0.129 | N/A | N/A | 0.092 | 0.264 | 0.059 | N/A | 0.171 | N/A | N/A | 0.085 | 0.011 |
| Natural Gas | 0.096 | 0.246 | 0.033 | 0.070 | 0.044 | 0.082 | 0.180 | 0.390 | 0.043 | 0.031 | 0.074 | 0.062 | 0.007 | -0.039 |
| Palladium | N/A | N/A | N/A | N/A | N/A | N/A | N/A | N/A | 0.653 | N/A | N/A | N/A | N/A | N/A |
| Platinum | 0.161 | 0.054 | 0.114 | N/A | N/A | 0.078 | 0.290 | 0.011 | N/A | 0.662 | N/A | N/A | 0.020 | -0.110 |
| Soyabean | N/A | 0.038 arch 0.3815 | 0.069 ARCH 0.2816 | 0.461 ARCH 0.4864 | 0.113 ARCH 0.5331 | N/A | 0.131 ARCH 0.3266 | N/A | N/A | 0.056 ARCH 0.328 | 0.910 | N/A | 0.288 ARCH 0.3152 | -0.020 ARCH 0.3279 |
| Sugar | 0.151 | 0.064 | 0.116 | N/A | N/A | 0.002 | N/A | 0.013 | N/A | 0.112 | N/A | 0.493 | N/A | -0.110 |
| Wheat | 0.106 | 0.048 | 0.073 | 0.615 | N/A | 0.073 | 0.159 | 0.013 | 0.055 | 0.078 | 0.431 | N/A | 0.911 | N/A |
| ZAR | N/A | -0.003 | N/A | N/A | -0.006 | N/A | N/A | -0.009 | N/A | -0.043 | -0.012 | N/A | N/A | 0.789 |
| ECM-GARCH After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | 0.999 | 0.189 | 0.598 | 0.106 ARCH 0.1794 | 0.121 | 0.423 | 0.298 | 0.035 Arch 0.056 | N/A | 0.374 | 0.186 Arch 0.0546 | 0.073 Arch 0.1462 | 0.093 Arch 0.0679 | -0.326 |
| Brentoil | N/A | 0.751 | 0.421 | 0.088 | N/A | 0.572 | 0.305 | N/A | N/A | 0.416 | 0.138 | N/A | 0.084 | -0.384 |
| Copper | 0.712 | 0.235 | 1.012 ARCH 0.4714 | 0.105 | 0.141 | 0.511 | 0.389 | 0.015 | N/A | 0.466 | 0.192 | 0.090 | 0.096 | -0.407 |
| Corn | N/A | 0.160 ARCH 0.0743 | 0.184 ARCH 0.0631 | 0.980 | N/A | 0.094 | 0.228 | N/A | N/A | 0.161 | 0.618 | 0.085 | 0.581 | -0.179 |
| Cotton | 0.193 | 0.124 | 0.196 | 0.135 | 0.878 | 0.193 | N/A | 0.009 | N/A | 0.163 | N/A | 0.082 | 0.136 | -0.254 |
| FTSE/JSE40 | 0.260 | 0.160 | 0.284 | 0.044 | 0.078 | 0.964 | 0.136 | N/A | N/A | 0.223 | 0.088 | 0.053 | 0.041 | -0.182 |
| Gold | 0.218 | 0.086 | 0.240 | 0.039 | 0.064 | 0.121 | 0.856 | 0.001 | N/A | 0.517 | 0.066 | 0.018 | 0.035 | -0.255 |
| Jet Kerosene | N/A | 0.567 | 0.341 | 0.077 | N/A | N/A | 0.241 | N/A | N/A | 0.311 | 0.115 | N/A | 0.062 | -0.286 |
| Naphtha | 0.384 | 0.677 | 0.406 | 0.100 | N/A | 0.528 | 0.291 | 0.005 | N/A | 0.377 | 0.151 | N/A | 0.081 | -0.362 |
| Natural Gas | 0.049 | -0.017 | -0.137 | 0.053 | -0.007 | 0.083 | -0.038 | 0.330 | 0.023 | 0.039 | 0.036 | 0.040 | 0.051 | -0.030 |
| Palladium | 0.407 | 0.157 | 0.438 | 0.038 | 0.134 | 0.513 | 0.448 | -0.007 | 0.576 | 0.613 | 0.119 | 0.071 | 0.041 | -0.341 |
| Platinum | 0.309 | 0.123 | 0.286 | N/A | N/A | 0.342 | N/A | N/A | N/A | 0.620 | N/A | N/A | 0.049 | -0.281 |
| Soyabean | N/A | 0.121 | 0.200 | 0.343 | 0.113 | 0.171 | 0.129 | 0.026 | N/A | 0.185 | 0.919 | 0.071 | 0.277 | -0.233 |
| Sugar | 0.175 | 0.112 | 0.168 | 0.083 | 0.122 | 0.171 | 0.124 | 0.014 | 0.122 | 0.135 | 0.114 | 0.821 | 0.124 | -0.238 |
| Wheat | 0.137 | 0.092 | 0.161 | 0.663 | 0.167 | 0.113 | 0.182 | 0.054 | 0.123 | 0.178 | 0.562 | 0.067 | 0.926 | -0.238 |
| ZAR | -0.209 | N/A | -0.236 | -0.060 | -0.073 | -0.238 | N/A | N/A | N/A | -0.294 | N/A | N/A | -0.058 | 0.803 |

Source: Thomson Reuters DataStream and EViews.

7.5.4. Time-varying hedge ratio estimation

The time-varying hedge ratio analysis will be run based on asymmetric DCC-GARCH with GJR-GARCH specification to capture the time-varying effects. The results displayed in the preceding section will only include the final time-varying hedge ratio. The analysis prior to the hedge ratio analysis will not be included due to the substantial extent of analysis that had to be done in order to obtain the final hedge ratios graphs.

The time-varying hedge ratio figures as well as the conditional correlations based on the asymmetric DCC-GARCH model are displayed in the additional document provided. On average, the hedge ratios of the period after the crisis were more volatile and in certain instances more extreme values were reached. Certain of the time-varying hedge ratios could not be obtained because the time asymmetric DCC-GARCH method failed to achieve convergence.

The average time-varying hedge ratio is shown in Table 7.9. The values represent the mean of the time-varying hedge ratio values.

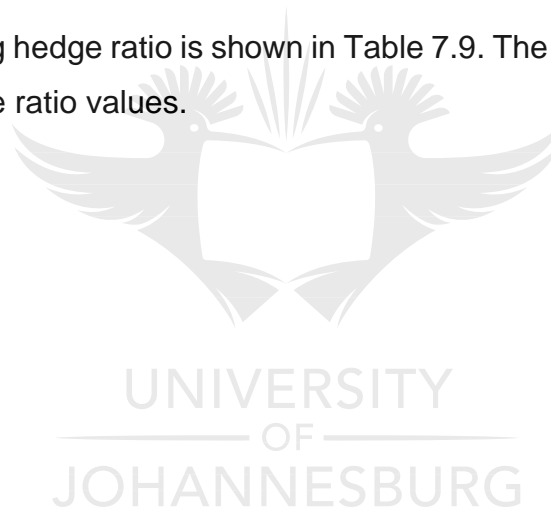


Table 7.9: Time-varying hedge ratio estimation summary

| TV Before crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|------------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|---------|---------|--------|
| Aluminium | 1.035 | 0.065 | 0.619 | 0.058 | 0.060 | 0.219 | 0.263 | 0.028 | 0.144 | 0.206 | 0.093 | 0.055 | 0.058 | -0.164 |
| Brentoil | 0.154 | 0.796 | 0.150 | 0.080 | 0.090 | 0.144 | 0.429 | 0.180 | 0.104 | 0.179 | 0.101 | 0.135 | 0.106 | -0.096 |
| Copper | 0.925 | 0.098 | 0.966 | 0.072 | 0.083 | 0.314 | 0.393 | 0.033 | 0.181 | 0.266 | 0.113 | 0.067 | 0.069 | -0.205 |
| Corn | 0.114 | 0.074 | 0.083 | 0.867 | 0.142 | 0.096 | 0.139 | 0.047 | 0.052 | 0.090 | 0.588 | 0.058 | 0.492 | 0.002 |
| Cotton | 0.137 | 0.076 | 0.121 | 0.138 | 0.837 | 0.038 | 0.155 | 0.011 | 0.028 | -0.003 | 0.222 | 0.063 | 0.138 | -0.065 |
| FTSE/JSE40 | 0.237 | 0.045 | 0.235 | 0.062 | 0.022 | 0.948 | 0.075 | 0.007 | 0.071 | 0.090 | 0.080 | 0.015 | 0.037 | 0.071 |
| Gold | 0.171 | 0.065 | 0.134 | 0.040 | 0.028 | 0.079 | 0.669 | 0.015 | 0.160 | 0.277 | 0.046 | 0.044 | 0.040 | -0.254 |
| Jet Kerosene | 0.114 | 0.484 | 0.108 | 0.070 | 0.089 | 0.068 | 0.294 | 0.111 | 0.069 | 0.141 | 0.079 | 0.083 | 0.080 | -0.084 |
| Naphtha | 0.183 | 0.432 | 0.134 | 0.067 | 0.078 | 0.062 | 0.273 | 0.070 | 0.128 | 0.193 | 0.082 | 0.104 | 0.076 | 0.001 |
| Natural Gas | 0.162 | 0.312 | 0.098 | 0.115 | 0.092 | 0.182 | 0.312 | 0.393 | 0.141 | 0.188 | 0.143 | 0.138 | 0.013 | -0.073 |
| Palladium | 0.220 | 0.037 | 0.141 | 0.068 | -0.010 | 0.197 | 0.388 | 0.006 | 0.651 | 0.551 | 0.093 | 0.089 | 0.025 | -0.101 |
| Platinum | 0.156 | 0.075 | 0.131 | 0.040 | -0.003 | 0.099 | 0.313 | 0.014 | 0.230 | 0.599 | 0.016 | 0.043 | 0.024 | -0.123 |
| Soyabean | 0.126 | 0.084 | 0.094 | 0.487 | 0.135 | 0.123 | 0.138 | 0.053 | 0.060 | 0.068 | 0.917 | 0.056 | 0.315 | -0.038 |
| Sugar | 0.156 | 0.083 | 0.141 | 0.110 | 0.088 | 0.009 | 0.171 | 0.024 | 0.074 | 0.147 | 0.086 | 0.458 | 0.050 | -0.127 |
| Wheat | 0.126 | 0.073 | 0.076 | 0.642 | 0.140 | 0.088 | 0.165 | 0.009 | 0.077 | 0.106 | 0.500 | 0.106 | 0.916 | -0.044 |
| ZAR | -0.119 | -0.022 | -0.071 | -0.018 | -0.014 | 0.147 | -0.294 | -0.008 | -0.059 | -0.113 | -0.014 | -0.014 | -0.012 | 0.757 |
| TV After crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | 1.003 | 0.260 | 0.635 | 0.117 | 0.143 | 0.486 | 0.310 | 0.039 | 0.289 | 0.422 | 0.229 | N/A | 0.089 | -0.383 |
| Brentoil | 0.474 | 0.754 | 0.488 | 0.123 | 0.197 | 0.666 | 0.328 | 0.054 | 0.328 | 0.463 | 0.232 | N/A | 0.075 | -0.463 |
| Copper | 0.733 | 0.317 | 1.010 | 0.123 | 0.173 | 0.592 | 0.381 | 0.024 | 0.363 | 0.501 | 0.278 | N/A | 0.099 | -0.480 |
| Corn | 0.274 | 0.195 | 0.221 | 0.884 | 0.187 | 0.154 | 0.217 | 0.062 | 0.157 | 0.218 | 0.653 | N/A | 0.593 | -0.232 |
| Cotton | 0.230 | 0.215 | 0.256 | 0.151 | 0.840 | 0.301 | 0.164 | 0.018 | 0.179 | 0.230 | 0.237 | N/A | 0.137 | -0.353 |
| FTSE/JSE40 | 0.278 | 0.186 | 0.297 | 0.044 | 0.102 | 1.029 | 0.086 | 0.014 | 0.202 | 0.237 | 0.122 | N/A | 0.031 | -0.185 |
| Gold | 0.211 | 0.123 | 0.234 | 0.037 | 0.083 | 0.185 | 0.836 | 0.004 | 0.245 | 0.525 | 0.094 | N/A | 0.045 | -0.276 |
| Jet Kerosene | 0.385 | 0.596 | 0.403 | 0.098 | 0.165 | 0.571 | 0.263 | 0.045 | 0.263 | 0.359 | 0.193 | N/A | 0.054 | -0.340 |
| Naphtha | 0.478 | 0.677 | 0.504 | 0.122 | 0.174 | 0.605 | 0.315 | 0.040 | 0.306 | 0.421 | 0.232 | N/A | 0.066 | -0.438 |
| Natural Gas | 0.063 | 0.045 | -0.058 | 0.098 | 0.031 | 0.103 | -0.013 | 0.346 | -0.012 | 0.054 | 0.126 | N/A | 0.118 | -0.014 |
| Palladium | 0.427 | 0.250 | 0.489 | 0.058 | 0.181 | 0.644 | 0.504 | 0.013 | 0.586 | 0.664 | 0.196 | N/A | 0.052 | -0.425 |
| Platinum | 0.325 | 0.158 | 0.322 | 0.052 | 0.111 | 0.403 | 0.510 | 0.006 | 0.315 | 0.607 | 0.137 | N/A | 0.057 | -0.288 |
| Soyabean | 0.253 | 0.191 | 0.242 | 0.367 | 0.137 | 0.249 | 0.179 | 0.038 | 0.154 | 0.238 | 0.844 | N/A | 0.304 | -0.265 |
| Sugar | 0.198 | 0.168 | 0.197 | 0.139 | 0.161 | 0.235 | 0.156 | 0.024 | 0.140 | 0.178 | 0.188 | N/A | 0.142 | -0.280 |
| Wheat | 0.216 | 0.187 | 0.200 | 0.672 | 0.188 | 0.233 | 0.280 | 0.088 | 0.148 | 0.251 | 0.664 | N/A | 0.963 | -0.321 |
| ZAR | -0.234 | -0.176 | -0.248 | -0.063 | -0.098 | -0.260 | -0.265 | -0.009 | -0.183 | -0.293 | -0.147 | N/A | -0.068 | 0.817 |

Source: Thomson Reuters DataStream and R.

7.5.5. Drawdown

The maximum drawdown for the spot variables before and after the crisis are displayed in Table 7.10. On average, the maximum drawdown was higher for the commodities after the crisis, but lower for the FTSE/JSE Top 40 Index and the ZAR. The only exceptions were natural gas, palladium, and soyabean.

Table 7.10: Maximum drawdown for spot variables before and after crisis

| | Before crisis | After crisis |
|-----------------|---------------|--------------|
| Aluminium | -29.182% | -48.824% |
| Brent Oil | -55.416% | -79.793% |
| Copper | -39.756% | -57.488% |
| Corn | -48.089% | -67.138% |
| Cotton | -60.000% | -73.460% |
| Gold | -21.897% | -44.582% |
| FTSE/JSE Top 40 | -40.254% | -15.848% |
| Jet Kerosene | -56.747% | -76.840% |
| Naphtha | -56.462% | -76.864% |
| Natural Gas | -83.889% | -81.187% |
| Palladium | -86.606% | -48.408% |
| Platinum | -35.106% | -56.863% |
| Soyabean | -53.846% | -53.073% |
| Sugar | -54.833% | -65.643% |
| Wheat | -42.227% | -64.333% |
| ZAR | -58.272% | -21.709% |

Source: Thomson Reuters DataStream and Excel.

The maximum drawdown for the future variables before and after are displayed in Table 7.11. On average, the maximum drawdown was higher for the commodities after the crisis, but lower for the FTSE/JSE Top 40 Index and the ZAR. The only exceptions were natural gas, palladium, soyabean, and sugar.

Table 7.11: Maximum drawdown for future variables before and after crisis

| | Before crisis | After crisis |
|-----------------|---------------|--------------|
| Aluminium | -28.966% | -48.456% |
| Brent Oil | -48.887% | -77.987% |
| Copper | -38.933% | -57.411% |
| Corn | -43.646% | -63.729% |
| Cotton | -57.966% | -73.882% |
| Gold | -21.816% | -44.431% |
| FTSE/JSE Top 40 | -39.961% | -16.267% |
| Natural Gas | -81.663% | -73.345% |
| Palladium | -86.286% | -48.187% |
| Platinum | -36.032% | -57.092% |
| Soyabean | -52.688% | -51.962% |
| Sugar | -78.051% | -70.575% |
| Wheat | -33.774% | -61.728% |
| ZAR | -57.973% | -21.866% |

Source: Thomson Reuters DataStream and Excel.

The drawdown figures for the spot and futures variables before and after the crisis are available in the additional document provided. On average, the drawdown has been higher for the commodities after the crisis, but lower for the FTSE/JSE Top 40 Index and the ZAR after the crisis. The drawdown figures on a portfolio level are not included in the thesis;

however, the results are included as part of the overall optimal cross relationships at the end of this chapter.

7.5.6. Hedging effectiveness

Hedging effectiveness results are included in conjunction with the hedge ratios in section 7.5.3 and 7.5.4 in order to determine which methods perform better. Hedging effectiveness results will be based on three methods – variance, Value at Risk, and Expected Shortfall – applied in the original hedging effectiveness formula from Ederington (1979).

7.5.6.1. Static hedge ratio hedging effectiveness

The hedging effectiveness between the static hedge ratio measures based on the original hedging effectiveness measure from Ederington (1979) are summarised in Table 7.12. The summary shows the measures by methods in order to identify which static measure performs the best in comparison.

By using the most effective hedge ratio, investment opportunities are refined and improved. Not all the cointegrated variables showed improved optimal hedge ratios due to the consideration of long run relationships. The number of combinations per method are:

- OLS
 - Before crisis: 209
 - After crisis: 204
- ECM:
 - Before crisis: 8
 - After crisis: 4
- VECM:
 - Before crisis: 7
 - After crisis: 12
- ECM-GARCH:
 - Before crisis: 0
 - After crisis: 4

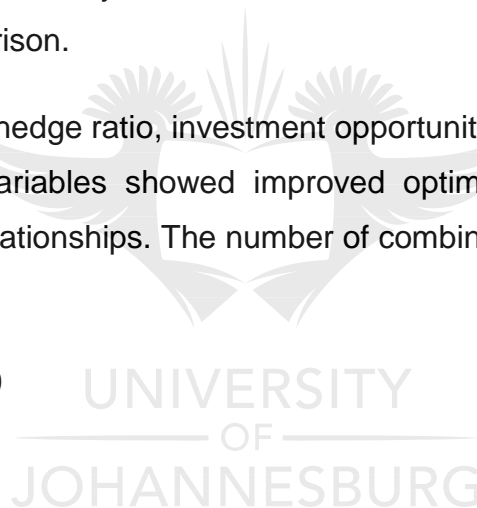


Table 7.12: Most reliable static hedge estimation method – variance measure

| Before Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
|---------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|---------|---------|-----------|
| Aluminium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Brentoil | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Copper | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| FTSE/JSE40 | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Gold | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Jet Kerosene | OLS | OLS | OLS | OLS | OLS | VECM | VECM | ECM | OLS | ECM | OLS | ECM | OLS | OLS |
| Naphtha | OLS | OLS | OLS | OLS | OLS | ECM | ECM | VECM | OLS | ECM | OLS | OLS | VECM | ECM |
| Natural Gas | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Soyabean | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Sugar | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Wheat | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| ZAR | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| After Crisis | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Brentoil | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| Copper | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| FTSE/JSE40 | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Gold | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Jet Kerosene | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Naphtha | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Natural Gas | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH |
| Soyabean | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| Sugar | OLS | VECM | VECM | OLS | VECM | ECM-GARCH | OLS | VECM | OLS | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH |
| Wheat | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| ZAR | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | VECM |

Source: Thomson Reuters DataStream and Excel.

The hedging effectiveness summary based on a VaR and ES measure by McNeil, Frey and Embrechts (2015) is shown in Table 7.13 and Table 7.14 respectively. The hedge variance and hedging effectiveness for each method are not shown in the Appendix, but are available on request.

Based on the original hedging effectiveness measure from Ederington (1979), the majority of the results indicated that OLS was the superior method after the crisis. In Table 7.13, the results are more mixed for before the crisis, considering the large number of combinations that did not show a cointegrating relationship, but overall OLS is still the superior method after the crisis.

The original hedging effectiveness measure from Ederington (1979) based on VaR and ES shows the following:

- OLS:
 - Before crisis 95%: 120, 122
 - Before crisis 99%: 124, 124
 - After crisis: 95%: 141, 146
 - After crisis: 99%: 150, 154
- ECM:
 - Before crisis 95%: 34, 34
 - Before crisis 99%: 35, 33
 - After crisis: 95%: 38, 38
 - After crisis: 99%: 38, 31
- VECM:
 - Before crisis 95%: 36, 37
 - Before crisis 99%: 34, 38
 - After crisis: 95%: 33, 29
 - After crisis: 99%: 28, 30
- ECM-GARCH:
 - Before crisis 95%: 34, 31
 - Before crisis 99%: 31, 29
 - After crisis: 95%: 12, 11
 - After crisis: 99%: 8, 9

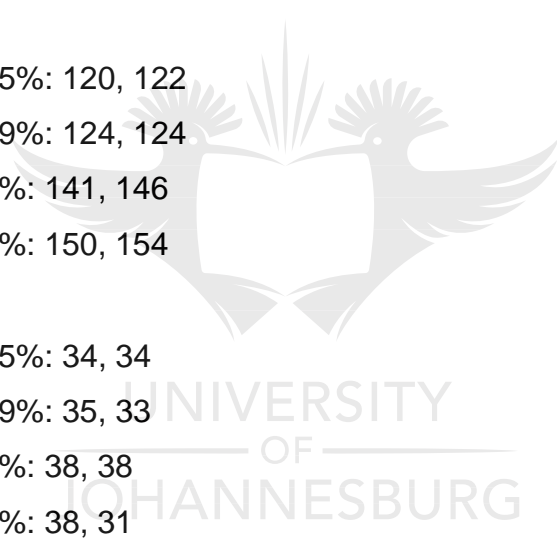


Table 7.13: Most reliable static hedge estimation method – VaR measure

| Maximum VaR Hedging effectiveness | | | | | | | | | | | | | | |
|-----------------------------------|-------------|------------|-----------|-----------|----------|--------------|-----------|---------------|-------------|------------|------------|-----------|-----------|-----------|
| Before Crisis 95% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | VECM | ECM-GARCH | OLS | OLS | ECM | ECM | OLS | OLS | VECM | OLS | VECM | OLS | OLS |
| Brentoil | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | VECM | OLS | ECM | ECM | OLS |
| Copper | ECM | VECM | OLS | OLS | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Corn | VECM | OLS | ECM-GARCH | ECM | OLS | OLS | VECM | OLS | OLS | VECM | ECM | OLS | ECM | OLS |
| Cotton | ECM | VECM | VECM | OLS | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | ECM | VECM | VECM | OLS |
| FTSE/JSE40 | ECM | ECM-GARCH | ECM | OLS | OLS | VECM | VECM | OLS | OLS | OLS | OLS | OLS | ECM | OLS |
| Gold | ECM | VECM | VECM | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | ECM | OLS | OLS | OLS | OLS |
| Jet Kerosene | ECM-GARCH | ECM | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | ECM-GARCH | OLS | ECM-GARCH | OLS | OLS |
| Naphtha | ECM-GARCH | ECM | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | ECM-GARCH | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM |
| Natural Gas | ECM | VECM | ECM | ECM-GARCH | ECM | ECM | ECM | OLS | VECM | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | VECM | OLS | VECM | OLS | OLS | ECM-GARCH | ECM | ECM | OLS | VECM | OLS | OLS | ECM | VECM |
| Soyabean | OLS | ECM | ECM-GARCH | VECM | OLS | OLS | VECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | OLS |
| Sugar | OLS | ECM-GARCH | VECM | OLS | OLS | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | ECM-GARCH |
| Wheat | ECM | VECM | VECM | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH | OLS | VECM | ECM-GARCH | OLS | VECM | OLS |
| ZAR | OLS | ECM-GARCH | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | ECM | OLS | OLS | OLS | ECM |
| Before Crisis 99% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | VECM | ECM-GARCH | OLS | OLS | ECM | ECM | OLS | OLS | VECM | OLS | ECM | OLS | OLS |
| Brentoil | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | VECM | OLS | ECM | ECM | OLS |
| Copper | ECM | VECM | OLS | OLS | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Corn | VECM | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | OLS | OLS | VECM | ECM | OLS | ECM | OLS |
| Cotton | ECM | VECM | VECM | OLS | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | ECM | VECM | VECM | OLS |
| FTSE/JSE40 | ECM | ECM-GARCH | ECM | OLS | OLS | VECM | VECM | OLS | OLS | OLS | OLS | OLS | ECM | OLS |
| Gold | ECM | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | OLS | OLS | OLS |
| Jet Kerosene | ECM | ECM | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | ECM-GARCH | OLS | ECM-GARCH | OLS | OLS |
| Naphtha | VECM | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | ECM | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM |
| Natural Gas | ECM | VECM | ECM | ECM-GARCH | ECM | ECM | ECM | OLS | VECM | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | ECM-GARCH | OLS | VECM | OLS | OLS | ECM-GARCH | ECM | ECM | OLS | OLS | OLS | OLS | ECM | VECM |
| Soyabean | OLS | ECM | ECM-GARCH | VECM | OLS | OLS | VECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | OLS |
| Sugar | OLS | ECM-GARCH | VECM | OLS | OLS | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | ECM-GARCH |
| Wheat | ECM | VECM | VECM | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH | OLS | VECM | ECM-GARCH | OLS | VECM | OLS |
| ZAR | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | ECM | OLS | OLS | OLS | ECM |
| After Crisis 95% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | OLS | OLS | VECM | ECM | OLS | VECM | OLS | OLS | OLS | OLS | ECM | ECM | OLS |
| Brentoil | OLS | OLS | OLS | VECM | OLS | ECM | VECM | OLS | OLS | VECM | ECM | OLS | OLS | OLS |
| Copper | ECM | OLS | VECM | OLS | VECM | VECM | ECM | OLS | OLS | OLS | VECM | ECM | OLS | OLS |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM | OLS | OLS | ECM-GARCH |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM | ECM |
| FTSE/JSE40 | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | VECM | VECM | OLS |
| Gold | ECM-GARCH | OLS | OLS | VECM | VECM | OLS | OLS | OLS | OLS | ECM | ECM | ECM-GARCH | OLS | ECM |
| Jet Kerosene | OLS | OLS | OLS | VECM | OLS | OLS | VECM | OLS | OLS | ECM | ECM | OLS | OLS | ECM |
| Naphtha | OLS | OLS | OLS | ECM | OLS | ECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Natural Gas | VECM | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | VECM | OLS | ECM |
| Palladium | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | ECM | OLS | ECM | OLS | VECM |
| Platinum | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM |
| Soyabean | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | OLS | ECM | ECM-GARCH |

| Maximum VaR Hedging effectiveness | | | | | | | | | | | | | | |
|-----------------------------------|-------------|------------|----------|--------|----------|--------------|--------|---------------|-------------|------------|------------|---------|---------|-----------|
| Sugar | OLS | VECM | VECM | OLS | VECM | ECM-GARCH | OLS | VECM | VECM | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH |
| Wheat | OLS | ECM | OLS | OLS | ECM | ECM | VECM | OLS | ECM | OLS | OLS | OLS | OLS | ECM |
| ZAR | OLS | OLS | ECM | OLS | ECM | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | OLS | VECM | ECM |
| After Crisis 99% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | OLS | OLS | VECM | ECM | OLS | VECM | OLS | OLS | OLS | OLS | ECM | VECM | OLS |
| Brentoil | OLS | OLS | OLS | VECM | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Copper | ECM | OLS | OLS | OLS | ECM | VECM | ECM | OLS | OLS | OLS | VECM | ECM | OLS | OLS |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | OLS | OLS | ECM | OLS | OLS | VECM |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM | ECM |
| FTSE/JSE40 | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | VECM | OLS | OLS |
| Gold | ECM-GARCH | OLS | OLS | OLS | ECM | OLS | OLS | OLS | OLS | VECM | ECM | OLS | OLS | ECM |
| Jet Kerosene | OLS | OLS | OLS | VECM | OLS | OLS | VECM | OLS | OLS | ECM | ECM | OLS | OLS | ECM |
| Naphtha | OLS | OLS | OLS | ECM | OLS | ECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Natural Gas | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | OLS | OLS | ECM |
| Palladium | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | ECM | OLS | VECM |
| Platinum | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM |
| Soyabean | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | OLS | ECM | ECM-GARCH |
| Sugar | OLS | VECM | VECM | OLS | VECM | ECM-GARCH | OLS | VECM | OLS | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH |
| Wheat | OLS | ECM | OLS | OLS | ECM | ECM | VECM | OLS | ECM | OLS | OLS | OLS | OLS | ECM |
| ZAR | OLS | OLS | ECM | OLS | ECM | ECM | OLS | OLS | OLS | VECM | OLS | OLS | VECM | ECM |

Source: Thomson Reuters DataStream and Excel.

Table 7.14: Most reliable static hedge estimation method – ES measure

| Maximum ES Hedging effectiveness | | | | | | | | | | | | | | |
|----------------------------------|-------------|------------|-----------|-----------|----------|--------------|-----------|---------------|-------------|------------|------------|-----------|-----------|-----------|
| Before Crisis 95% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | VECM | ECM-GARCH | OLS | OLS | ECM | ECM | OLS | OLS | VECM | OLS | VECM | OLS | OLS |
| Brentoil | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | VECM | OLS | ECM | ECM | OLS |
| Copper | ECM | VECM | OLS | OLS | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Corn | VECM | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | OLS | OLS | VECM | ECM | OLS | ECM | OLS |
| Cotton | ECM | VECM | VECM | OLS | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | ECM | VECM | VECM | OLS |
| FTSE/JSE40 | ECM | ECM-GARCH | ECM | OLS | OLS | VECM | VECM | OLS | OLS | OLS | OLS | OLS | ECM | OLS |
| Gold | ECM | VECM | VECM | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | ECM | OLS | OLS | OLS | OLS |
| Jet Kerosene | ECM | ECM | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | ECM-GARCH | OLS | ECM-GARCH | OLS | OLS |
| Naphtha | VECM | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | ECM | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM |
| Natural Gas | ECM | VECM | ECM | ECM-GARCH | ECM | ECM | ECM | OLS | VECM | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | VECM | OLS | VECM | OLS | OLS | ECM-GARCH | ECM | ECM | OLS | VECM | OLS | OLS | ECM | VECM |
| Soyabean | OLS | ECM | ECM-GARCH | VECM | OLS | OLS | VECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | OLS |
| Sugar | OLS | ECM-GARCH | VECM | OLS | OLS | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | ECM-GARCH |
| Wheat | ECM | VECM | VECM | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH | OLS | VECM | ECM-GARCH | OLS | VECM | OLS |
| ZAR | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | ECM | OLS | OLS | OLS | ECM |
| Before Crisis 99% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | VECM | ECM-GARCH | OLS | OLS | ECM | ECM | OLS | OLS | VECM | OLS | ECM | OLS | OLS |
| Brentoil | VECM | OLS | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | VECM | OLS | ECM | ECM | OLS |
| Copper | ECM | VECM | OLS | OLS | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Corn | VECM | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | OLS | OLS | VECM | ECM | OLS | ECM | OLS |
| Cotton | ECM | VECM | VECM | OLS | OLS | ECM-GARCH | ECM-GARCH | OLS | OLS | VECM | ECM | VECM | VECM | OLS |
| FTSE/JSE40 | VECM | ECM-GARCH | ECM | OLS | OLS | VECM | VECM | OLS | OLS | OLS | OLS | OLS | ECM | OLS |

| Maximum ES Hedging effectiveness | | | | | | | | | | | | | | |
|----------------------------------|-------------|------------|-----------|-----------|----------|--------------|-----------|---------------|-------------|------------|------------|-----------|-----------|-----------|
| Gold | ECM | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | OLS | OLS | OLS |
| Jet Kerosene | ECM | ECM | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | ECM-GARCH | OLS | ECM-GARCH | OLS | OLS |
| Naphtha | VECM | OLS | ECM-GARCH | OLS | OLS | ECM-GARCH | ECM-GARCH | VECM | OLS | ECM-GARCH | OLS | OLS | ECM | ECM |
| Natural Gas | ECM | VECM | ECM | ECM-GARCH | ECM | ECM | ECM | OLS | VECM | ECM | OLS | OLS | ECM-GARCH | ECM-GARCH |
| Palladium | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS |
| Platinum | ECM-GARCH | OLS | VECM | OLS | OLS | ECM-GARCH | ECM | ECM | OLS | OLS | OLS | OLS | ECM | VECM |
| Soyabean | OLS | ECM | ECM-GARCH | VECM | OLS | OLS | VECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | OLS |
| Sugar | OLS | ECM-GARCH | VECM | OLS | OLS | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | ECM-GARCH |
| Wheat | ECM | VECM | VECM | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH | OLS | VECM | VECM | OLS | VECM | OLS |
| ZAR | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | ECM | OLS | OLS | OLS | ECM |
| After Crisis 95% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | OLS | OLS | VECM | ECM | OLS | VECM | OLS | OLS | OLS | OLS | ECM | ECM | OLS |
| Brentoil | OLS | OLS | OLS | VECM | OLS | ECM | VECM | OLS | OLS | VECM | ECM | OLS | OLS | OLS |
| Copper | ECM | OLS | OLS | OLS | ECM | VECM | ECM | OLS | OLS | OLS | VECM | ECM | OLS | OLS |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM | OLS | OLS | VECM |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM | ECM |
| FTSE/JSE40 | ECM | OLS | ECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | VECM | OLS | OLS |
| Gold | ECM-GARCH | OLS | OLS | OLS | ECM | OLS | OLS | OLS | OLS | VECM | ECM | ECM-GARCH | OLS | ECM |
| Jet Kerosene | OLS | OLS | OLS | VECM | OLS | OLS | VECM | OLS | OLS | ECM | ECM | OLS | OLS | ECM |
| Naphtha | OLS | OLS | OLS | ECM | OLS | ECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Natural Gas | VECM | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | ECM | OLS | VECM | OLS | ECM |
| Palladium | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | ECM | OLS | VECM |
| Platinum | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM |
| Soyabean | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | OLS | ECM | ECM-GARCH |
| Sugar | OLS | VECM | VECM | OLS | VECM | ECM-GARCH | OLS | VECM | OLS | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH |
| Wheat | OLS | ECM | OLS | OLS | ECM | ECM | VECM | OLS | ECM | OLS | OLS | OLS | OLS | ECM |
| ZAR | OLS | OLS | ECM | OLS | ECM | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | OLS | VECM | ECM |
| After Crisis 99% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | OLS | OLS | OLS | ECM | ECM | OLS | VECM | OLS | OLS | OLS | OLS | VECM | VECM | OLS |
| Brentoil | OLS | OLS | OLS | VECM | OLS | ECM | VECM | OLS | OLS | VECM | OLS | OLS | OLS | OLS |
| Copper | ECM | OLS | OLS | OLS | ECM | VECM | ECM | OLS | OLS | OLS | ECM | ECM | OLS | OLS |
| Corn | OLS | OLS | OLS | OLS | OLS | OLS | VECM | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Cotton | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM | ECM |
| FTSE/JSE40 | VECM | OLS | ECM | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM | OLS | VECM | OLS | OLS |
| Gold | ECM-GARCH | OLS | OLS | OLS | ECM | OLS | OLS | OLS | OLS | ECM-GARCH | ECM | OLS | OLS | ECM |
| Jet Kerosene | OLS | OLS | OLS | VECM | OLS | OLS | VECM | OLS | OLS | ECM | OLS | OLS | OLS | ECM |
| Naphtha | OLS | OLS | OLS | ECM | OLS | ECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | VECM |
| Natural Gas | VECM | VECM | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | OLS | ECM |
| Palladium | OLS | OLS | OLS | OLS | OLS | ECM | ECM | OLS | OLS | OLS | OLS | ECM | OLS | VECM |
| Platinum | OLS | OLS | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | ECM-GARCH | OLS | OLS | OLS | VECM |
| Soyabean | OLS | OLS | OLS | OLS | OLS | ECM | VECM | OLS | OLS | OLS | OLS | OLS | ECM | ECM-GARCH |
| Sugar | OLS | VECM | VECM | OLS | VECM | ECM-GARCH | OLS | VECM | OLS | ECM-GARCH | OLS | OLS | VECM | ECM-GARCH |
| Wheat | OLS | ECM | OLS | OLS | ECM | ECM | VECM | OLS | ECM | OLS | OLS | OLS | OLS | ECM |
| ZAR | OLS | OLS | ECM | OLS | OLS | ECM | OLS | OLS | OLS | VECM | OLS | OLS | VECM | VECM |

Source: Thomson Reuters DataStream and Excel.

7.5.6.2. Time-varying hedge ratio hedging effectiveness

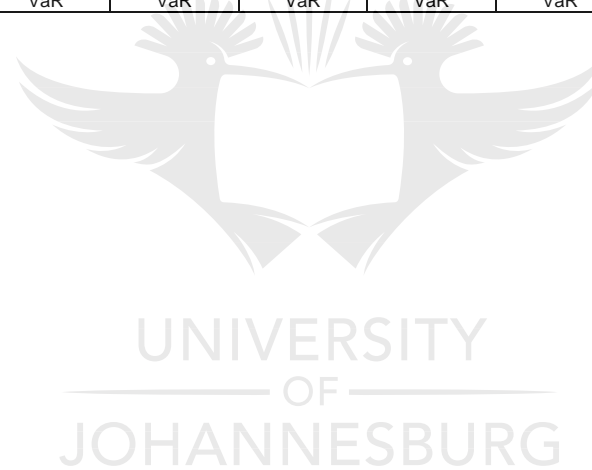
The time-varying hedge ratios are based on only one method, the ADCC-GARCH method, and therefore the comparison between the variance, Value at Risk and Expected Shortfall is shown to identify the measure that performs the best for this model. The summary is shown in Table 7.15 and the number of each measure is as follows:

- Before crisis 95%: variance (194), VaR (27), ES (3)
- Before crisis 99%: variance (204), VaR (17), ES (3)
- After crisis 95%: variance (139), VaR (36), ES (33)
- After crisis 99%: variance (139), VaR (36), ES (33)



| | | | | | | | | | | | | | | |
|-------------------------|-------------|------------|----------|----------|----------|--------------|----------|---------------|-------------|------------|------------|----------------|----------|----------|
| Wheat | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| ZAR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | N/A | VaR | VaR |
| After Crisis 99% | Aluminium_F | Brentoil_F | Copper_F | Corn_F | Cotton_F | FTSE/JSE40_F | Gold_F | Natural Gas_F | Palladium_F | Platinum_F | Soyabean_F | Sugar_F | Wheat_F | ZAR_F |
| Aluminium | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Brentoil | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Copper | ES | VaR | Variance | VaR | VaR | VaR | VaR | ES | VaR | ES | VaR | N/A | VaR | ES |
| Corn | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Cotton | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| FTSE/JSE40 | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Gold | ES | VaR | VaR | VaR | VaR | Variance | Variance | VaR | VaR | ES | VaR | N/A | VaR | ES |
| Jet Kerosene | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Naphtha | ES | ES | ES | ES | ES | VaR | ES | ES | VaR | ES | ES | N/A | ES | ES |
| Natural Gas | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Palladium | ES | VaR | ES | VaR | Variance | Variance | Variance | VaR | Variance | Variance | Variance | N/A | VaR | ES |
| Platinum | ES | ES | ES | ES | ES | ES | ES | ES | VaR | ES | ES | N/A | ES | ES |
| Soyabean | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Sugar | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| Wheat | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | Variance | N/A | Variance | Variance |
| ZAR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | VaR | N/A | VaR | VaR |

Source: Thomson Reuters DataStream and Excel.



7.5.7. Overall hedging effectiveness

Table 7.16 compares the static and the time-varying hedge ratios effectiveness based on the variance, VaR and ES methods. Overall the time-varying model of ADCC-GARCH returns the highest number of hedging effectiveness results, followed by OLS and then ECM-GARCH. ECM and VECM did return instances of the best performing model, but overall, the numbers were very low. Time-varying correlations are an important consideration in time series data, and the inclusion of this into the hedge ratio framework improves the reliability significantly.

Table 7.16: Overall hedging effectiveness

| | OLS | ECM | VECM | ECM-GARCH | Time-varying |
|------------------------|-----|-----|------|-----------|--------------|
| Variance before crisis | 58 | 3 | 3 | 2 | 158 |
| VaR before crisis 95% | 87 | 2 | 10 | 65 | 60 |
| ES before crisis 95% | 86 | 2 | 9 | 67 | 60 |
| VaR before crisis 99% | 2 | 0 | 0 | 1 | 221 |
| ES before crisis 99% | 2 | 0 | 0 | 1 | 221 |
| Variance after crisis | 103 | 0 | 4 | 1 | 116 |
| VaR after crisis 95% | 76 | 0 | 27 | 6 | 115 |
| ES after crisis 95% | 65 | 20 | 14 | 2 | 122 |
| VaR after crisis 99% | 40 | 10 | 6 | 3 | 165 |
| ES after crisis 99% | 47 | 9 | 9 | 4 | 155 |

Source: Thomson Reuters DataStream, R and Excel.

7.5.8. Overall optimal cross hedging relationships

The comparison of four methods to identify the optimal cross hedging relationships for each spot variable is shown in Table 7.17. The methods used are mean-variance, maximum drawdown, Value at Risk and Expected Shortfall. The mean variance analysis and the maximum drawdown for the portfolios before and after the crisis are shown in Table 7.17, based on OLS and ECM-GARCH for all spot variables against the included future variables. The portfolios consist of a combination of the spot and future variables in order to view the combined mean variance level. The graphs based on OLS, ECM, VECM and ECM-GARCH for the mean-variance analysis are shown in the additional document provided.

The time-varying Value at Risk and Expected Shortfall (also known as Conditional Value at Risk (CVaR)) for the spot and future variables as well as the portfolios before and after the crisis are shown in the additional document provided. The Value at Risk and Expected Shortfall are shown for a 95% and 99% confidence level. Only the last 500 data points of the full data period before and after the crisis are displayed in order to identify the breakthrough points of the two measures. Because of an error in the process, certain of the

relationships could not be estimated due to failure to achieve convergence when the model was estimated.

Table 7.17: Optimal relationships

| Before crisis | OLS Lowest Risk / Highest Return Mean-Variance portfolio | Time-varying Lowest Risk / Highest Return Mean-Variance portfolio | OLS Smallest maximum drawdown portfolio | Time-varying Smallest maximum drawdown portfolio |
|-----------------------|--|---|---|--|
| Aluminium | Aluminium / Palladium | Aluminium / ZAR | ZAR | Palladium |
| Brent oil | Brent oil / Palladium | Brent oil / ZAR | Aluminium | ZAR |
| Copper | Copper / Palladium | Copper / ZAR | ZAR | Brent oil |
| Corn | Corn / Palladium | Corn / Cotton | Soyabean | Wheat |
| Cotton | Cotton / Platinum | Cotton / Palladium | Soyabean | Copper |
| FTSE/JSE Top 40 Index | FTSE/JSE Top 40 Index / Palladium | FTSE/JSE Top 40 Index / ZAR | Palladium | Gold |
| Gold | Gold / ZAR | Gold / ZAR | FTSE/JSE Top 40 Index | Sugar |
| Jet kerosene | Brent oil / Palladium | Brent oil / Palladium | FTSE/JSE Top 40 Index | ZAR |
| Naphtha | Brent oil / Palladium | Brent oil / ZAR | FTSE/JSE Top 40 Index | Cotton |
| Natural gas | Natural gas / Wheat | Natural gas / Corn | Soyabean | Copper |
| Palladium | Palladium / Palladium | Palladium / Palladium | FTSE/JSE Top 40 Index | Cotton |
| Platinum | Platinum / Palladium | Platinum / Palladium | Palladium | ZAR |
| Soyabean | Soyabean / Palladium | Soyabean / Cotton | Soyabean | Corn |
| Sugar | Brent oil / Aluminium | Sugar / Palladium | Brent oil | Corn |
| Wheat | Wheat / Palladium | Wheat / ZAR | Soyabean | Copper |
| ZAR | ZAR / Gold | ZAR / Gold | FTSE/JSE Top 40 Index | Sugar |
| After crisis | | | | |
| Aluminium | Aluminium / ZAR | Aluminium / ZAR | FTSE/JSE Top 40 Index | Palladium |
| Brent oil | Brent oil / ZAR | Brent oil / ZAR | Palladium | ZAR |
| Copper | Copper / ZAR | Copper / ZAR | FTSE/JSE Top 40 Index | Platinum |
| Corn | Corn / ZAR | Corn / ZAR | Palladium | Wheat |
| Cotton | Cotton / ZAR | Palladium / ZAR | Palladium | FTSE/JSE Top 40 Index |
| FTSE/JSE Top 40 Index | FTSE/JSE Top 40 Index / ZAR | Cotton / Copper | Cotton | Gold |
| Gold | Gold / Platinum | FTSE/JSE Top 40 Index / Platinum | FTSE/JSE Top 40 Index | Corn |
| Jet kerosene | Brent oil / ZAR | Gold / ZAR | FTSE/JSE Top 40 Index | FTSE/JSE Top 40 Index |
| Naphtha | Brent oil / ZAR | ZAR / ZAR | FTSE/JSE Top 40 Index | ZAR |
| Natural gas | Natural gas / Natural gas | Palladium / ZAR | Gold | Soyabean |
| Palladium | Palladium / ZAR | Palladium / ZAR | FTSE/JSE Top 40 Index | FTSE/JSE Top 40 Index |
| Platinum | Platinum / Platinum | Platinum / ZAR | FTSE/JSE Top 40 Index | FTSE/JSE Top 40 Index |
| Soyabean | Soyabean / ZAR | Soyabean / ZAR | Palladium | Aluminium |
| Sugar | Brent oil / Brent oil | Wheat / ZAR | Soyabean | Wheat |
| Wheat | Wheat / ZAR | ZAR / ZAR | Palladium | Gold |
| ZAR | ZAR / FTSE/JSE Top 40 Index | Brent oil / Palladium | FTSE/JSE Top 40 Index | Natural gas |

Source: Thomson Reuters DataStream, R and Excel.

The results in Table 7.17 are mixed, but the majority of the results show that a variable other than the direct future provides the highest return mean-variance position, smallest maximum drawdown position and smallest maximum Value at Risk and Expected Shortfall position. In addition, the FTSE/JSE Top 40 Index as well as the ZAR provided the best opportunity for many of the commodities after the crisis. Lastly, cross commodity class combinations also featured in Table 7.17. Kumar and Pandey (2011) found that agricultural commodities provided a higher hedging effectiveness as compared to metal and energy commodities. In certain occurrences in Table 7.17, agricultural commodities do appear, but consensus is not reached.

The analysis of the smallest 95% and 99% Value at Risk and Expected shortfall shows that the majority of the combinations reflect that the direct future is the optimal variable of the spot under consideration. The deviations from that are:

- Brent future for sugar spot: before and after crisis 95% VaR and ES static, before and after crisis 99% VaR and ES static,
- Palladium future for cotton spot: after crisis 95% and 99% VaR and ES time-varying,
- ZAR future for naphtha spot: after crisis 95% and 99% VaR and ES time-varying
- Palladium future for natural gas spot: after crisis 95% and 99% VaR and ES time-varying
- ZAR future for wheat spot: after crisis 95% and 99% VaR and ES time-varying.

An example of the figures available in the additional supporting document is shown in Figure 7.1.

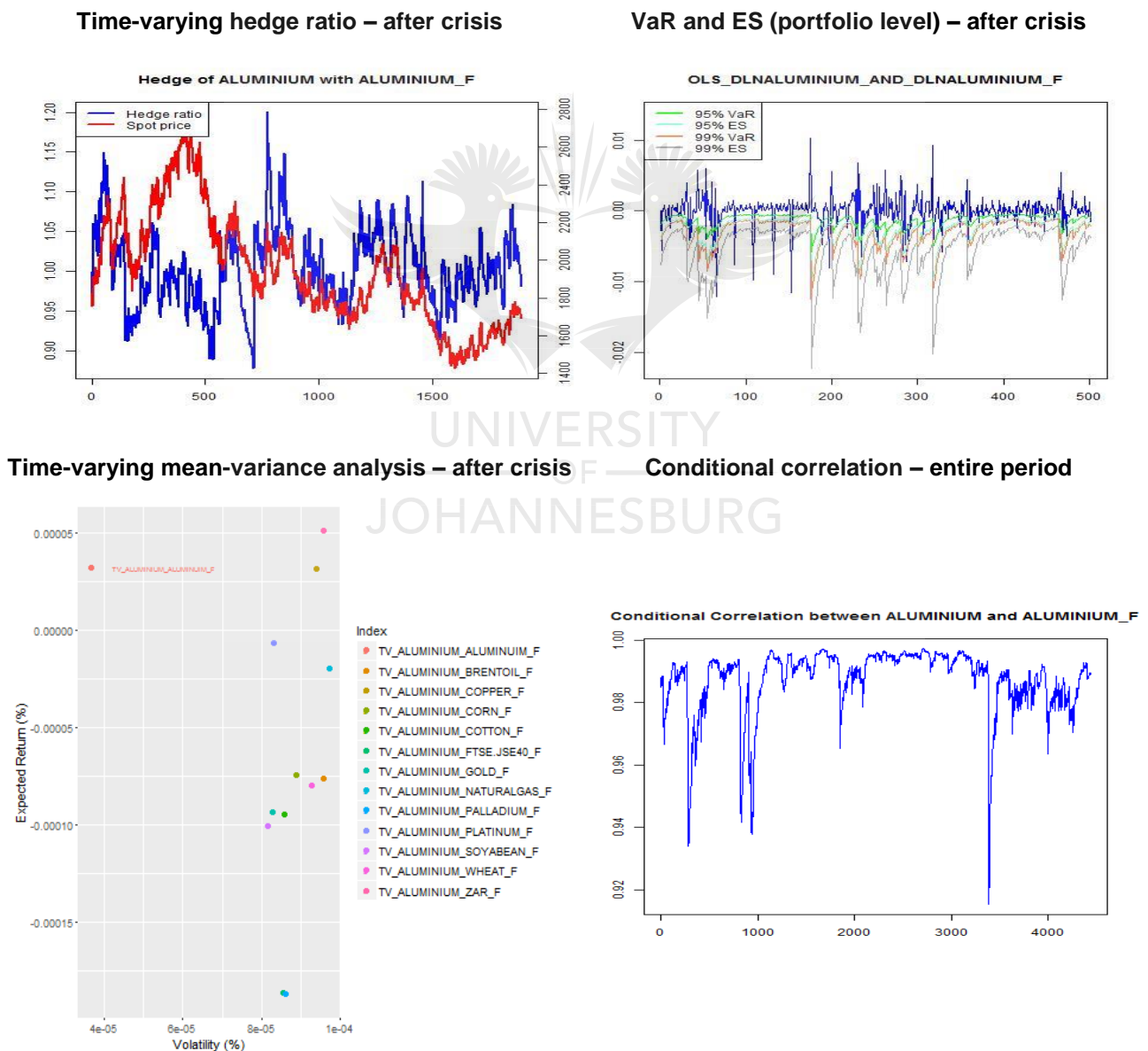


Figure 7.1: Examples of the figures included in the additional supporting document

Source: Thomson Reuters DataStream and R.

The objective of the study was to determine the optimal cross hedging relationships between commodities that have a tendency to move together for no known reason. As discussed previously, commodity prices show a tendency to move together, even if they have no reason to be related (Abdullah *et al.*, 2016; Baffes, 2007; Pindyck & Rotemberg, 1993; Pindyck & Rotemberg, 1990). The possible reasons are as a result of the financialisation of commodities since the early 2000s as well as the fundamental shifts that have occurred in commodity classes over time. The increase in correlations after the crisis as well as the number of Granger causality relationships support this finding.

The actual values for hedge ratios based on static and time-varying methods showed that in most cases the highest value was between the same spot and future variable. Going further into hedging effectiveness and optimal cross hedging relationships based on mean-variance analysis, maximum drawdown showed that future variables other than the direct match to the spot variable were optimal. For Value at Risk and Expected Shortfall the results showed that the direct future for each spot was the optimal choice, except in a few instances when a variable from a different commodity class or the ZAR showed the most optimal results. The results show that the optimal hedge ratio is not the only determinant when choosing optimal cross hedging opportunities for commodities.

7.6. CONCLUSION

The main research question of this study was to determine the optimal cross hedging relationships that are present within the South African financial market context in relation to a selection of commodities. In order to answer the research question, the following objectives related to the interrelationships between the variables were explored in Chapters 4 to 6:

- The long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index;
- The long run and short run relationships between each commodity price and the ZAR;
- The long run and short run relationships between the FTSE/JSE Top 40 Index and the ZAR.

A number of long run and short run relationships were identified in Chapters 4, 5 and 6. The relationships identified in Chapters 4 to 6 gave an indication of the interrelationships among variables and how variables reacted after a shock was applied. By establishing that long

and short run dynamics existed among the variables, further analysis was required in order to determine what investment opportunities existed between the variables for investment decisions and risk management strategies.

The latter part of the research objectives was to:

- Determine the cross hedging opportunities between the variables.
- Determine the co-movement between the variables.

This created the need to determine the hedging opportunities available (1) between commodities in the same category of commodities, (2) between different categories of commodities, and (3) between a commodity and the ZAR or FTSE/JSE Top 40 Index. The initial analysis showed a number of strong correlated combinations of variables; however, the majority of the variables showed low correlation, although the correlations did increase from before the crisis to after the crisis.

The correlation relationships identified create the opportunity for diversification within the investment and risk management practices. Therefore the optimal hedge ratios were investigated in order to determine the best hedging options available from the included variables, as Baur and Lucey (2010) mentioned that low or negative correlation between variables allows for the variables to be used for hedging purposes. The causality results indicated that soft commodities to metal commodities were accountable for the highest number of Granger causations, followed by energy commodities to metal commodities.

The optimal hedge ratio analysis was based on the spot and future prices of the variables included in the study. Static and time-varying hedge ratios were investigated in order to determine the best performing methods. The static hedge ratios were estimated using the OLS, ECM, VECM and ECM-GARCH methods. The time-varying hedge ratios were determined by the asymmetric DCC-GARCH with GJR specification.

To determine the most effective hedge available, hedging effectiveness was undertaken based on the formula from Ederington (1979), which was applied to three different risk measures, namely variance, Value at Risk and Expected Shortfall. The static hedge ratio comparison showed that OLS and ECM-GARCH provided best results. Since only one time-varying hedge ratio method was used, a comparison of the three hedge effectiveness measures was shown, which resulted in the use of variance emerging as the best method. A final comparison between static and time-varying hedge ratio effectiveness was done,

comparing variance, 95% and 99% Value at Risk and Expected Shortfall before and after the crisis. The time-varying method was the best performing method, followed by OLS.

The final objective of determining which variables provided optimal cross hedging relationships was done using mean-variance analysis along with maximum drawdown, Value at Risk and Expected Shortfall to identify the variables that showed the best mean-variance portfolio as well as the portfolio with the overall smallest maximum drawdown, Value at Risk and Expected Shortfall. The results were mixed, but the FTSE/JSE Top 40 Index and the ZAR were identified in a number of combinations as well as instances where commodities from a different commodity class was the best option. This shows that a number of methods needs to be considered in order to identify cross hedging relationships for the use of investment decisions and risk management purposes.

As the study was focused on selected commodities only to obtain the understanding of how the variables interacted, further analysis can be done based on the relationship between other commodities in order to determine whether similar relationships are identified. The optimal cross hedging relationships obtained in this chapter are used as a basis for making more informed investment decisions. The results can also be used to identify investment opportunities that would normally be overlooked due to the nature of the relationships being investigated which is linked to alternative investments and commodities.

CHAPTER 8

FINDINGS, CONCLUSION AND RECOMMENDATIONS

8.1. INTRODUCTION

In this research study, the relationships between the fourteen commodities, the FTSE/JSE Top 40 Index and the South African Rand were explored in order to answer the research question and achieve the objectives.

The main research question of this study was: What optimal cross hedging relationships are present within the South African financial market context in relation to a selection of commodities? To answer the research question regarding cross hedging opportunities, the following objectives were explored in Chapters 4, 5, 6 and 7. The main objective in this study was to:

Investigate optimal cross hedging relationships between the variables.

The sub-objectives to reach the main objective in order to answer the research question were:

- Determine the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index.
- Determine the long run and short run relationships between each commodity price and the ZAR.
- Determine the long run and short run relationships between the FTSE/JSE Top 40 Index and the ZAR.
- Determine the cross hedging opportunities between the variables.
- Determine the co-movement between the variables.

The research objectives were used as a starting point in order to obtain optimal cross hedging relationships and ratios using commodities in the South African financial market as well as between the commodities. These objectives were achieved by means of theoretical and empirical analyses that were conducted over eight chapters.

Chapters 4, 5, and 6 included subsets of selected commodities grouped according to categories of commodities, and Chapter 7 built on the results of Chapters 4, 5, and 6 in order to answer the research question stated above. Chapter 7 investigated the cross hedging relationships and optimal hedge ratios present between the sixteen variables included in the study. Secondary historical data was used to explore the relationships. The analysis was based on spot and future data as the overall objective of the study was to understand the long run and short run relationships as well as to obtain the cross hedging relationships between the variables.

In the previous four chapters, the findings of the study were discussed with the assistance of financial econometric and risk management tests. The tests used in the study related to Chapters 4 to 6 included unit root tests, correlation, the VAR model, Johansen cointegration test, Granger causality and Toda Yamamoto tests, VECM and innovation accounting methods. Chapter 7 used correlation, Granger causality test, OLS, ECM, VECM, ECM-GARCH, asymmetric DCC-GARCH with GJR specification, drawdown, VaR, CVaR, mean variance analysis, and the original hedging effectiveness combined with more advanced hedging effectiveness methods.

8.2. REASON FOR UNDERTAKING THE RESEARCH

The research was undertaken to determine the optimal cross hedging relationships between the variables for investment and risk management purposes. Commodities, being an asset within alternative assets, behave differently from traditional investments. The increasing popularity of commodities as investment tools within the last decade has sparked the interest in trying to understand commodities and the way they interact with other commodities and financial variables. Spot and future priced variables were included in the study to determine the fundamental relationships between the commodities, the FTSE/JSE Top 40 Index and the ZAR.

Co-movement both on a short and long-term basis between commodities is linked to the notion that commodities from different commodity classes move together without justification from fundamental economic principles. A similar concept within investment management is herd behaviour. Commodities have historically shown volatility of price movement associated with a trend, which is characterised by a stochastic trend. This means that prices follow a random walk with a trend. Commodity prices show time-varying volatility and volatility clustering, which could be seen by extreme volatility periods, followed by tranquil volatility periods.

The time-varying correlations that affect commodities assist in leveraging off commodities and the related hedging opportunities. When the current business cycle starts to change, the relationships between commodities will also change, which creates new investment opportunities.

Hedging allows risk within an investment portfolio to be reduced or transferred to another financial market participant. Hedging does not aim to eliminate all risk present within the investment portfolio. The use of commodities allows the investor to gain access to another asset class as well as investment strategy, which is a key characteristic of alternative investments.

The financialisation of commodities that has occurred within past ten to fifteen years has emphasised the market efficiency related to commodities. The market efficiency related to commodities has increased over the last decade as the speed of market reactions and the quantity of information to the market also increased. These two concepts have made investing within traditional investments more difficult. With fewer traditional investment opportunities, investors have started searching for alpha in other parts of the financial market, which has allowed alternative investments to develop as quickly as they have. Commodities have allowed for another avenue for diversification and hedging opportunities.

With the uncertainty currently facing the investment environment, the possibility of loss situations is managed and efforts are put in place in order to avoid or at least reduce the loss situation. Diversification and hedging practices are used in order to reduce the risk that is carried within an investment portfolio.

The information about the long run and short run relationships as well as optimal cross hedging relationships results obtained in the study create the possibility to use commodities as part of diversification and hedging practices within an investment portfolio. The use of these relationships and ratios ensure that investment practices utilised in investment portfolios keep up with the evolving nature of the investment environment. The aim of the research was to contribute to the field of commodities and alternative investments.

The hedging and market linkages discussed in Sections 2.8 and 2.9 suffered from the following problems, indicating that a gap exists in the literature. This thesis attempted to address the aspects related to limited commodities, limited time period as well as limited methodology.

This thesis aimed to address a gap in the South African market as well as between international commodity prices based on an extended methodology, lengthened time period as well as a larger selection of commodities.

8.3. SUMMARY AND SYNTHESIS OF THE FINDINGS

The findings in Chapters 4, 5, and 6 will be discussed together, followed by the findings of Chapter 7. Significant relationships were identified between each category of commodity, namely metal, soft and energy, and the FTSE/JSE Top 40 Index and the ZAR, which addresses the first two objectives of the three chapters. The last objective of the relationship between the ZAR and the FTSE/JSE Top 40 Index also returned significant results. The results indicated that both long run and short run relationships were present in the data.

Chapters 2 and 3 introduced the literature and discussed the methodologies that would be applied in this thesis. The literature review framed commodities, the South African Rand and the FTSE/JSE Top 40 Index, as those were the three main elements of the study. Within the commodities section, financialisation of commodities was discussed as an important element that has been gaining attention over the past ten to fifteen years. It was also shown in the analysis of the data that commodities have been moving closer together. The relationships of the variables were addressed next in three sections, the first being a historical account of the development of hedging techniques and the related inefficiencies. Thereafter the evidence of cross hedging relationships and cross market linkages was discussed to provide a background on the work that has been done in the two fields.

Chapter 3 explained methodology that was applied in Chapters 4 to 6 as well as Chapter 7. Chapters 4 to 6 focused on the relationships specific commodity classes have with the South African Rand and the FTSE/JSE Top 40 Index on a spot and future level. Chapters 4 to 6 included financial econometric tests comprised of Granger causality, Toda Yamamoto causality, VAR, Johansen Cointegration, VECM, as well as innovation accounting techniques to determine what long run and short run relationships existed. Chapter 4 focused on metal commodities, Chapter 5 on soft commodities and Chapter 6 on energy commodities.

The relationship analysis was taken further in Chapter 7 to include all the variables as part of the analysis. The overall correlation between all the variables was shown before and after the crisis to show the movement that has occurred. Thereafter, a summary was presented of Granger causality relationships to show which commodity class was Granger causing the

most movement to another commodity class. The remainder of Chapter 7 was focused on the hedging ratios, related hedging effectiveness of the methods included as well as the optimal cross hedging relationships between the variables. The hedging ratios were estimated using four static methods and one time-varying method. The static methods were OLS, ECM, VECM, and ECM-GARCH, and the time-varying method was the asymmetric DCC-GARCH with GJR specification using multivariate normal distribution. A short analysis of drawdown was shown to illustrate the value that was lost in the variables included in the study. In order to determine the most effective method and to contribute to the relationship analysis, hedging effectiveness was evaluated based on the hedging effectiveness measure from Ederington (1979) based on variance, as well as more recent hedging effectiveness tail risk measures of Value at Risk and Expected Shortfall. The optimal cross hedging relationships were identified using mean-variance analysis, smallest maximum drawdown, Value at Risk and Expected Shortfall of each spot variable compared to the future variables.

The overall research question of the study was to determine what optimal cross hedging relationships exist within the South African financial market context in relation to a selection of commodities. In order to answer the overall research question, the long run and short run relationships between each commodity price and the FTSE/JSE Top 40 Index, between each commodity price and the ZAR, and between the FTSE/JSE Top 40 Index and the ZAR needed to be determined so that the interrelationships between the variables were understood.

The research strategy utilised in this study was based on secondary data and the financial econometric analysis thereof. The secondary data required to answer the research question was historic time series data. The research instruments used in this study were EViews, R, Excel and the related financial econometric tests required to answer the research question and achieve the objectives.

The significance of the study is that research available on commodities as alternative assets is limited in scope and time as alternative assets are a continuously developing field. The financialisation of commodity markets has only been gaining momentum in the last ten to fifteen years. Therefore, commodities have emerged as an investable asset class that investors are looking at as they are looking for diversification opportunities outside traditional investment strategies and assets. The aim of the entire study was to contribute to the field of commodities as an alternative asset.

The main findings of Chapters 4, 5 and 6 are that after the crisis, a number of unidirectional relationships related to the FTSE/JSE Top 40 Index and the ZAR existed, most of which were with metal commodities. The VECM results also indicated that metal and energy commodities were significant in the analysis.

The main findings of Chapter 7 started with the initial analysis showing the correlation and Granger causality results between the variables. The majority of the variables showed low correlation; however, the correlations did increase from before the crisis to after the crisis. From the Granger causality results soft commodities to metal commodities were accountable for the highest number of Granger causations, followed by energy commodities to metal commodities.

Overall, the time-varying method of ADCC-GARCH was the best performing method based on hedging effectiveness, followed by the static measure of OLS. The final cross-hedging relationship analysis showed limited combinations based on the same spot and future variable, but rather more between a commodity and the FTSE/JSE Top 40 Index as well as commodities from other commodity classes and different commodities in the same commodity class. This identifies that cross hedging opportunities exist between the selected variables included in this study and can also be applied to other assets and asset classes.

The cross hedging analysis based on hedge ratios alone is therefore not sufficient to determine the cross hedging opportunities and relationships. Further analysis using the expanded hedging effectiveness analysis as well as the mean-variance analysis, drawdown, Value at Risk and Expected Shortfall needs to be considered for more informed decisions to be made.

The relationships identified throughout the study were used for an exploratory investigation for the final analysis in Chapter 7 to determine the hedge ratios, hedging effectiveness and optimal cross hedging relationships. The cross hedging relationships identified create an additional opportunity for further research which can be used to broaden investment opportunities and risk management strategies. The financialisation of commodities has created the channel for commodities to be used as investment tools within investment portfolios. The fundamental shift in the co-movement of commodities is also an important consideration when evaluating commodities as investment and risk management options as the relationship that existed at a specific point in time may not exist anymore.

The optimal cross hedging relationships are important to understand as inefficient combination of variables results in unnecessary financial losses. By optimising the choice of commodities, improved portfolio choices are obtained that ensure that investment and risk management decisions are more efficient with regard to the financial implications.

Within the South African market, South Africa is one of the largest producers of platinum and palladium in the world and the largest exporter. Even though South Africa produces about 75 000 KGs of platinum and palladium, the quantity only makes up a small portion of the import value of South Africa. South Africa currently produces corn and crude oil, but is currently a larger importer of corn and crude oil than an exporter, which also results in a different relationship in the commodity to the ZAR and FTSE/JSE Top 40 Index compared to a commodity that is exported in larger quantities. South Africa is ranked much higher in the export of sugar and platinum, but the value of currency associated with the export is different between the two.

The previous literature discussed in this thesis showed studies comparing commodities to exchange rates, equity prices and monetary policy instruments. The results of the studies are mixed as different aspects of the relationships were investigated. Groenewold and Paterson (2013) compared equity prices and exchange rates in Australia with commodity prices. The results obtained showed that the exchange rate had a short run effect, but not a long effect on commodity prices. The results also showed that commodity prices influenced equity prices in the short run. The directional relationship found in the study was that the exchange rate had a strong effect on commodity prices, but commodity prices did not have a strong effect on the exchange rate.

The exchange rate, equity price and commodity price relationship was investigated by Kurihara and Fukushima (2014) related to Japan and the Euro area. The results showed mostly weak relationships, with only the commodity prices and the exchange rate in Japan showing significant results. The results indicated that there was a significant effect of the commodity results from the exchange rate in Japan. The results obtained by Groenewold and Paterson (2013) and Kurihara and Fukushima (2014) indicate that further research should be done using commodities, as the results are currently mixed. The results of this study indicated that within the metal commodities group, certain metal commodities were affected by equity prices and the exchange rate, and certain metal commodities were affecting the equity prices and the exchange rate.

Metal commodities are an important commodity category for the South African market, but soft commodities can be evaluated in other financial markets as well. The literature discussed in this chapter, similar to the literature on metal commodities, also showed mixed results when comparing soft commodities to other commodities and to financial variables (Hameed & Arshad, 2009; Harri *et al.*, 2009; Bhar & Hamori, 2006; Booth & Ciner, 2001). The selection of commodities and related financial variables is vital to consider when investigating the relationship of commodities to other variables.

Similar to the literature related to metal commodities and soft commodities, the literature related to energy commodities also showed mixed results (Bhunia, 2013; Samanta & Zadeh, 2012; Ziegelbäck & Kastner, 2011; Panagiotidis & Rutledge, 2004). The selection of commodities as well as the comparative financial variables or other comparative commodities need to be explored further as conclusive results as well as non-conclusive results are found when comparing certain commodities to other variables. The time period selected for the study is also an important consideration as differing results have been found when using different time periods with the same variables.

Previous literature related to hedging indicated that the OLS method performed as well and in certain instances better than other methods that were observed in this study (Alexander & Barbosa, 2007; Moosa, 2003; Bystrom, 2003; Lien *et al.*, 2002). In this study, the time-varying method provided the most occurrences of the best hedging effectiveness, which is similar to the findings of Basher and Sadorsky (2016), Chang *et al.* (2011), Lien and Yang (2008), Kumar, Singh and Pandey (2008), Floros and Vougas (2006) and Yang (2005).

Degiannakis and Floros (2010) also compared static and time-varying hedge ratio methods in the South African market and found ECM-GARCH and the time-varying methods of CCC-ARCH and Diag-BEKK ARCH to provide superior results. They concluded that no unique model exists, but rather that the best performing model needs to be identified for each market. Similar findings were obtained in this study; however, this study expanded on the results to include additional tests and measures.

Exploratory research should be undertaken to identify the initial relationships of commodities on other financial variables. Once the initial relationships are identified, focused research can be done to look for more meaningful results between commodities and other financial variables. The empirical results indicate that there is opportunity for further study in metal, soft and energy commodities and related markets. Further research can be done related to the forecasting ability of the commodities. Further research can also be done to identify the

presence of speculative bubbles, which can create the prospect for short term profit opportunities.

8.4. CONTRIBUTION OF THE STUDY

The contribution of the study is threefold. Firstly, this kind of research has not been done before in this manner, and therefore this is an original contribution mainly in the field of commodities, linking into alternative investments and risk management. Available literature that includes the financial econometric methodology and hedging methodology is limited to a few commodities, normally focusing on the effect of one or possibly only a very small group of commodities on other variables. The studies focused on the relationships between commodities, or otherwise the relationships between commodities and monetary policy variables. No literature was found that applied the full methodology used in this study and this is significant, as it is an adapted application of traditional financial econometric and risk management methods.

The second contribution is the identification of relevant relationships between commodities, the FTSE/JSE Top 40 Index and the ZAR. The relevant relationships are related to the long run relationships and short run dynamics as well as the optimal cross hedging relationships that were identified in Chapter 7. This creates an understanding of how the variables move when compared together. The asymmetries identified in the optimal cross hedging relationships create a new diversification opportunity with commodities. The asymmetries identified showed that the hedge ratios differed between the variables related to when a variable was an independent variable compared to when the variable was a dependent variable. The asymmetry finding is consistent with the findings of Groenewold and Paterson (2013) and Kurihara and Fukushima (2014).

The third contribution relates to the adaptation and application of a known financial econometric and risk management methodology of calculating the optimal cross hedging relationships to the context of commodities in the South African market. The cross hedging relationships and optimal hedge ratios were focused on relationships between different commodity classes. This results in a contribution to academic literature, as the full methodology process in its entirety applied in this study and the combination of variables studied have not been done so before.

Elements from different studies were taken related to static and time-varying hedge ratios, the hedging effectiveness using variance, Value at Risk and Expected Shortfall. Lastly the

cross hedging relationship analysis employed mean-variance analysis, drawdown, Value at Risk and Expected Shortfall to identify the best variable to use to improve the risk-return opportunity as well as to limit loss. This thesis has created an empirical framework that can be applied to commodities as well as other assets and asset classes.

Another important concept is the development of the financialisation of commodity markets which only started gaining momentum in the last ten to fifteen years. Commodities have emerged as an investable asset class with institutional investors holding larger quantities as diversification benefits are sought outside traditional assets (Büyükoşahin & Robe, 2014; Singleton, 2014; Basak & Pavlova, 2013). The financialisation of commodities has created access to the commodities to be used as investment tools both for investment opportunities outside of traditional investment opportunities as well as for risk management strategies that have not previously been exploited.

The financialisation of commodities accompanied with the fundamental shift in the co-movement and interrelationships of commodities and related markets requires the use of more advanced methods to analyse the relationships. The use of only hedge ratios provides a skewed result for the purposes of investment decisions. The comparison of three hedging effectiveness measures of variance, Value at Risk and Expected Shortfall provides a more accurate comparison of the hedging methods. The ADCC-GARCH method and OLS method outperform the other static methods; however, certain combinations still showed that ECM, VECM and ECM-GARCH was the best performing model. No single method has been shown to provide the best performing result, which links to the findings of Ederington (1979) and Moosa (2003) that the underlying relationship between the variables is still the most important consideration.

The cross hedging relationship analysis using mean-variance analysis, drawdown, Value at Risk and Expected Shortfall provides a more accurate analysis of the interrelationships and provides stakeholders with more information in order to make more effective decisions. The combination of all the methods applied in Chapter 7 allows for various aspects of the relationships to be considered.

The significance of this study is important for fellow academics who conduct research in similar fields and for market participants who are interested in a better understanding of the relationships present between the variables. The findings of this study will add to the current body of literature available on this topic by expanding on the sample size with regard to the variables included, the time period selected as well as the methodology applied. Financial

markets as well as commodity price movement change over time, with market implications of commodity price movements affecting many aspects of the financial markets, such as the equity market, the foreign exchange market as well as alternative investments.

Both traditional assets and alternative assets are traded in the financial market, with traditional assets widely researched and understood. The research available on commodities and alternative investments is limited in scope and time as alternative assets are a continuously developing field, which adds to the significance of this study. The relationships identified in the study add to the understanding of commodities and alternative investments and the way that they can be used in investment and risk management decisions, by means of cross hedging opportunities as well as the optimal allocation of commodities.

8.5. LIMITATIONS

Limitations to the study are created by the variables used as well as the literature available on the specific research question and objectives. The first limitation is the data sets that were used in the study. Not all commodity data sets are included in the study and only selected commodity benchmarks were selected to represent each commodity class included in the study. The second limitation is based on the currency selected as well as the index selected. A final limitation is that the study ignores transaction costs, taxation as well as investments in other securities.

The knowledge and understanding available on commodity markets is limited to the analysis that has been done based on the types of commodities chosen for the study, the time frame included in the study as well as the method of analysis. This study is limited to a time frame, namely before and after the financial crisis of 2007, but the commodities included in the study, metal, soft and energy commodities, were chosen with the aim of being broad. The methodology applied to the data was formal analysis procedures based on the financial econometrics and risk management aimed to identify both long and short run relationships present between the variables. The relationships were further analysed to determine investable opportunities that market participants and academics could apply.

South Africa was the country of focus and therefore the ZAR was the selected currency. A number of indices are available in the South African financial market and only one index was selected to represent the market. The FTSE/JSE Top 40 Index was chosen as it was the most representative of the South African financial market.

The analysis of the data is based on accepted econometric and risk management standards as well as on other peer-reviewed research conducted. A limitation on this concept exists if other methods of analysis were to be applied to the same data sets. This difference could result in different research findings and conclusions.

8.6. RECOMMENDATIONS FOR FURTHER RESEARCH

Further research can be done in various forms. The first main derivation of this study can be based on a selection of commodities in other geographical locations. Further research can also be done based on a different combination of commodities, replacing commodities with commodity based equities as well as different time periods, since this study was limited to 2000–2007 and 2009–2016.

Another research option can be to create factors for different commodity classes. The financial econometric and risk management methodology applied can also be changed to evaluate the same variables and time period or a different selection of variables and time period. The research in this study can be taken further by investigating the volatility effects of the cross hedging relationships to further test the results obtained in this study.

8.7. FINAL REMARKS

The field of alternative investments, specifically the contribution of commodities, has been broadened. Alternative investments are still limited in use due to the risks that are associated with them. This study has taken an in-depth look at how commodities interact with themselves, as well as with the FTSE/JSE Top 40 Index and the ZAR. By understanding how the variables react with each other, the use of alternatives investments can be increased, especially since commodities have been financialised. Financial market participants are continuously looking for investment opportunities, and the use of commodities by means of cross hedging relationships is important to understand in order to leverage the use of commodities in investment and risk management strategies. Commodities can be used for investment and risk management needs, which creates an avenue for individuals and institutions. The field of investment and risk management is an ever changing field as the world is constantly evolving.

The results of this study related to all the relationships identified in Chapters 4 to 6 as well as the cross hedging relationships that create new opportunities needed in the evolving fields of investment management and risk management. This study indicates that there is an opportunity to use commodities as instruments within investment portfolios that consist

of equities, exchange rates and other commodities. It is possible to use commodities as a risk management tool as well, by using them more efficiently and effectively.



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APPENDIX A.1: Pairwise Granger causality test and Toda Yamamoto test

| Spot before crisis Null Hypothesis: | Pairwise Granger causality test | | | Toda Yamamoto test | | |
|---|---------------------------------|-------------|----------|--------------------|----|----------|
| | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOPPER does not Granger Cause DLALUMINIUM | 1952 | 0.870 | 0.419 | 1.942 | 3 | 0.584 |
| DLALUMINIUM does not Granger Cause DLCOPPER | | 2.292 | 0.101 | 5.186 | 3 | 0.159 |
| DLFTSE_JSE40 does not Granger Cause DLALUMINIUM | 1952 | 1.502 | 0.223 | 4.244 | 3 | 0.236 |
| DLALUMINIUM does not Granger Cause DLFTSE_JSE40 | | 8.304 | 0.000*** | 17.487 | 3 | 0.001*** |
| DLGOLD does not Granger Cause DLALUMINIUM | 1952 | 1.322 | 0.267 | 40.718 | 3 | 0.000*** |
| DLALUMINIUM does not Granger Cause DLGOLD | | 10.551 | 0.000*** | 18.418 | 3 | 0.000*** |
| DLPALLADIUM does not Granger Cause DLALUMINIUM | 1952 | 1.124 | 0.325 | 11.204 | 8 | 0.190 |
| DLALUMINIUM does not Granger Cause DLPALLADIUM | | 13.129 | 0.000*** | 32.242 | 8 | 0.000*** |
| DLPLATINUM does not Granger Cause DLALUMINIUM | 1952 | 1.930 | 0.146 | 5.313 | 4 | 0.257 |
| DLALUMINIUM does not Granger Cause DLPLATINUM | | 8.858 | 0.000*** | 34.245 | 4 | 0.000*** |
| DLZAR does not Granger Cause DLALUMINIUM | 1952 | 0.223 | 0.800 | 2.698 | 3 | 0.441 |
| DLALUMINIUM does not Granger Cause DLZAR | | 0.393 | 0.675 | 0.870 | 3 | 0.833 |
| DLFTSE_JSE40 does not Granger Cause DLCOPPER | 1952 | 0.692 | 0.501 | 1.814 | 3 | 0.612 |
| DLCOPPER does not Granger Cause DLFTSE_JSE40 | | 5.750 | 0.003*** | 12.067 | 3 | 0.007*** |
| DLGOLD does not Granger Cause DLCOPPER | 1952 | 1.593 | 0.204 | 2.941 | 3 | 0.401 |
| DLCOPPER does not Granger Cause DLGOLD | | 11.198 | 0.000*** | 25.523 | 3 | 0.000*** |
| DLPALLADIUM does not Granger Cause DLCOPPER | 1952 | 0.301 | 0.740 | 4.755 | 8 | 0.783 |
| DLCOPPER does not Granger Cause DLPALLADIUM | | 14.279 | 0.000*** | 43.887 | 8 | 0.000*** |
| DLPLATINUM does not Granger Cause DLCOPPER | 1952 | 0.375 | 0.687 | 4.380 | 4 | 0.357 |
| DLCOPPER does not Granger Cause DLPLATINUM | | 12.579 | 0.000*** | 42.468 | 4 | 0.000*** |
| DLZAR does not Granger Cause DLCOPPER | 1952 | 1.319 | 0.268 | 4.285 | 3 | 0.232 |
| DLCOPPER does not Granger Cause DLZAR | | 0.106 | 0.899 | 0.384 | 3 | 0.943 |
| DLGOLD does not Granger Cause DLFTSE_JSE40 | 1952 | 1.009 | 0.365 | 1.872 | 2 | 0.392 |
| DLFTSE_JSE40 does not Granger Cause DLGOLD | | 4.548 | 0.011** | 9.424 | 2 | 0.009*** |
| DLPALLADIUM does not Granger Cause DLFTSE_JSE40 | 1952 | 1.205 | 0.300 | 6.906 | 6 | 0.330 |
| DLFTSE_JSE40 does not Granger Cause DLPALLADIUM | | 1.673 | 0.188 | 12.171 | 6 | 0.058* |
| DLPLATINUM does not Granger Cause DLFTSE_JSE40 | 1952 | 0.117 | 0.890 | 1.233 | 3 | 0.745 |
| DLFTSE_JSE40 does not Granger Cause DLPLATINUM | | 0.468 | 0.626 | 3.023 | 3 | 0.388 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1952 | 0.278 | 0.758 | 0.490 | 1 | 0.484 |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 0.206 | 0.814 | 0.010 | 1 | 0.921 |
| DLPALLADIUM does not Granger Cause DLGOLD | 1952 | 3.448 | 0.032 | 12.596 | 8 | 0.127 |
| DLGOLD does not Granger Cause DLPALLADIUM | | 14.094 | 0.000*** | 37.285 | 8 | 0.000*** |
| DLPLATINUM does not Granger Cause DLGOLD | 1952 | 0.328 | 0.721 | 2.080 | 3 | 0.556 |
| DLGOLD does not Granger Cause DLPLATINUM | | 6.669 | 0.001*** | 15.063 | 3 | 0.002*** |
| DLZAR does not Granger Cause DLGOLD | 1952 | 4.307 | 0.014** | 8.551 | 2 | 0.014** |
| DLGOLD does not Granger Cause DLZAR | | 1.079 | 0.340 | 2.123 | 2 | 0.346 |
| DLPLATINUM does not Granger Cause DLPALLADIUM | 1952 | 3.489 | 0.031** | 11.607 | 6 | 0.071* |
| DLPALLADIUM does not Granger Cause DLPLATINUM | | 8.664 | 0.000*** | 24.329 | 6 | 0.001*** |
| DLZAR does not Granger Cause DLPALLADIUM | 1952 | 3.807 | 0.022** | 10.134 | 6 | 0.119 |
| DLPALLADIUM does not Granger Cause DLZAR | | 1.299 | 0.273 | 5.692 | 6 | 0.459 |
| DLZAR does not Granger Cause DLPLATINUM | 1952 | 3.700 | 0.025** | 8.480 | 3 | 0.037** |
| DLPLATINUM does not Granger Cause DLZAR | | 1.930 | 0.145 | 4.612 | 3 | 0.203 |
| | | | | | | |
| Spot after crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOPPER does not Granger Cause DLALUMINIUM | 1892 | 0.829 | 0.437 | 1.366 | 2 | 0.505 |
| DLALUMINIUM does not Granger Cause DLCOPPER | | 9.889 | 0.000*** | 19.409 | 2 | 0.000*** |
| DLGOLD does not Granger Cause DLALUMINIUM | 1892 | 0.182 | 0.833 | 0.178 | 1 | 0.674 |
| DLALUMINIUM does not Granger Cause DLGOLD | | 0.379 | 0.685 | 0.103 | 1 | 0.748 |
| DLPALLADIUM does not Granger Cause DLALUMINIUM | 1892 | 2.358 | 0.095* | 5.365 | 2 | 0.068* |
| DLALUMINIUM does not Granger Cause DLPALLADIUM | | 24.845 | 0.000*** | 48.727 | 2 | 0.000*** |
| DLPLATINUM does not Granger Cause DLALUMINIUM | 1892 | 0.603 | 0.548 | 0.962 | 2 | 0.618 |
| DLALUMINIUM does not Granger Cause DLPLATINUM | | 22.873 | 0.000*** | 46.521 | 2 | 0.000*** |
| DLFTSE_JSE40 does not Granger Cause DLALUMINIUM | 1892 | 1.004 | 0.367 | 1.821 | 3 | 0.611 |

| | | | | | | |
|---|------------|--------------------|--------------|---------------|-----------|--------------|
| DLALUMINIUM does not Granger Cause DLFTSE_JSE40 | | 1.625 | 0.197 | 2.820 | 3 | 0.420 |
| DLZAR does not Granger Cause DLALUMINIUM | 1892 | 3.362 | 0.035** | 4.140 | 1 | 0.042** |
| DLALUMINIUM does not Granger Cause DLZAR | | 0.548 | 0.578 | 1.136 | 1 | 0.287 |
| DLGOLD does not Granger Cause DLCOPPER | 1892 | 1.296 | 0.274 | 2.290 | 1 | 0.130 |
| DLCOPPER does not Granger Cause DLGOLD | | 1.624 | 0.197 | 1.790 | 1 | 0.181 |
| DLPALLADIUM does not Granger Cause DLCOPPER | 1892 | 1.148 | 0.317 | 2.984 | 2 | 0.225 |
| DLCOPPER does not Granger Cause DLPALLADIUM | | 34.125 | 0.000*** | 66.531 | 2 | 0.000*** |
| DLPLATINUM does not Granger Cause DLCOPPER | 1892 | 1.270 | 0.281 | 1.993 | 2 | 0.369 |
| DLCOPPER does not Granger Cause DLPLATINUM | | 26.997 | 0.000*** | 56.345 | 2 | 0.000*** |
| DLFTSE_JSE40 does not Granger Cause DLCOPPER | 1892 | 0.262 | 0.769 | 0.610 | 3 | 0.894 |
| DLCOPPER does not Granger Cause DLFTSE_JSE40 | | 7.775 | 0.000*** | 15.265 | 3 | 0.002*** |
| DLZAR does not Granger Cause DLCOPPER | 1892 | 3.044 | 0.048** | 1.454 | 1 | 0.228 |
| DLCOPPER does not Granger Cause DLZAR | | 0.291 | 0.747 | 0.417 | 1 | 0.518 |
| DLPALLADIUM does not Granger Cause DLGOLD | 1892 | 1.145 | 0.318 | 2.252 | 2 | 0.324 |
| DLGOLD does not Granger Cause DLPALLADIUM | | 8.124 | 0.000*** | 15.416 | 2 | 0.000*** |
| DLPLATINUM does not Granger Cause DLGOLD | 1892 | 0.140 | 0.870 | 0.313 | 3 | 0.958 |
| DLGOLD does not Granger Cause DLPLATINUM | | 37.525 | 0.000*** | 74.395 | 3 | 0.000*** |
| DLFTSE_JSE40 does not Granger Cause DLGOLD | 1892 | 2.582 | 0.076* | 5.583 | 3 | 0.134 |
| DLGOLD does not Granger Cause DLFTSE_JSE40 | | 0.573 | 0.564 | 2.086 | 3 | 0.555 |
| DLZAR does not Granger Cause DLGOLD | 1892 | 2.082 | 0.125 | 3.517 | 1 | 0.061* |
| DLGOLD does not Granger Cause DLZAR | | 0.264 | 0.768 | 0.510 | 1 | 0.475 |
| DLPLATINUM does not Granger Cause DLPALLADIUM | 1892 | 0.489 | 0.613 | 0.062 | 1 | 0.803 |
| DLPALLADIUM does not Granger Cause DLPLATINUM | | 0.251 | 0.778 | 0.567 | 1 | 0.451 |
| DLFTSE_JSE40 does not Granger Cause DLPALLADIUM | 1892 | 11.134 | 0.000*** | 23.650 | 3 | 0.000*** |
| DLPALLADIUM does not Granger Cause DLFTSE_JSE40 | | 1.149 | 0.317 | 4.985 | 3 | 0.173 |
| DLZAR does not Granger Cause DLPALLADIUM | 1892 | 16.769 | 0.000*** | 33.578 | 3 | 0.000*** |
| DLPALLADIUM does not Granger Cause DLZAR | | 1.714 | 0.181 | 5.710 | 3 | 0.127 |
| DLFTSE_JSE40 does not Granger Cause DLPLATINUM | 1892 | 6.444 | 0.002*** | 12.314 | 3 | 0.006*** |
| DLPLATINUM does not Granger Cause DLFTSE_JSE40 | | 0.274 | 0.761 | 2.069 | 3 | 0.558 |
| DLZAR does not Granger Cause DLPLATINUM | 1892 | 28.813 | 0.000*** | 59.891 | 3 | 0.000*** |
| DLPLATINUM does not Granger Cause DLZAR | | 2.823 | 0.060* | 5.681 | 3 | 0.128 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1892 | 6.842 | 0.001*** | 12.491 | 3 | 0.006*** |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 1.024 | 0.359 | 2.989 | 3 | 0.393 |
| | | | | | | |
| Future before Crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOPPER_F does not Granger Cause DLALUMINIUM_F | 1952 | 1.556 | 0.211 | 3.168 | 3 | 0.367 |
| DLALUMINIUM_F does not Granger Cause DLCOPPER_F | | 0.540 | 0.583 | 2.292 | 3 | 0.514 |
| DLGOLD_F does not Granger Cause DLALUMINIUM_F | 1952 | 1.516 | 0.220 | 9.864 | 5 | 0.079* |
| DLALUMINIUM_F does not Granger Cause DLGOLD_F | | 1.429 | 0.240 | 15.731 | 5 | 0.008*** |
| DLPALLADIUM_F does not Granger Cause DLALUMINIUM_F | 1952 | 0.026 | 0.974 | 2.950 | 6 | 0.815 |
| DLALUMINIUM_F does not Granger Cause DLPALLADIUM_F | | 0.211 | 0.809 | 16.049 | 6 | 0.014** |
| DLPLATINUM_F does not Granger Cause DLALUMINIUM_F | 1952 | 1.134 | 0.322 | 4.046 | 4 | 0.400 |
| DLALUMINIUM_F does not Granger Cause DLPLATINUM_F | | 3.264 | 0.038** | 18.601 | 4 | 0.001*** |
| DLFTSE_JSE40_F does not Granger Cause DLALUMINIUM_F | 1952 | 1.375 | 0.253 | 4.367 | 3 | 0.225 |
| DLALUMINIUM_F does not Granger Cause DLFTSE_JSE40_F | | 5.569 | 0.004*** | 12.675 | 3 | 0.005*** |
| DLZAR_F does not Granger Cause DLALUMINIUM_F | 1952 | 1.511 | 0.221 | 3.189 | 3 | 0.363 |
| DLALUMINIUM_F does not Granger Cause DLZAR_F | | 0.101 | 0.904 | 0.175 | 3 | 0.982 |
| DLGOLD_F does not Granger Cause DLCOPPER_F | 1952 | 0.665 | 0.515 | 8.369 | 4 | 0.079* |
| DLCOPPER_F does not Granger Cause DLGOLD_F | | 1.008 | 0.365 | 13.743 | 4 | 0.008*** |
| DLPALLADIUM_F does not Granger Cause DLCOPPER_F | 1952 | 0.502 | 0.605 | 1.114 | 3 | 0.774 |
| DLCOPPER_F does not Granger Cause DLPALLADIUM_F | | 0.379 | 0.684 | 4.391 | 3 | 0.222 |
| DLPLATINUM_F does not Granger Cause DLCOPPER_F | 1952 | 2.811 | 0.060* | 15.008 | 4 | 0.005*** |
| DLCOPPER_F does not Granger Cause DLPLATINUM_F | | 3.621 | 0.027** | 22.860 | 4 | 0.000*** |
| DLFTSE_JSE40_F does not Granger Cause DLCOPPER_F | 1952 | 0.643 | 0.526 | 1.352 | 2 | 0.509 |
| DLCOPPER_F does not Granger Cause DLFTSE_JSE40_F | | 3.869 | 0.021** | 7.800 | 2 | 0.020** |
| DLZAR_F does not Granger Cause DLCOPPER_F | 1952 | 0.256 | 0.774 | 0.008 | 1 | 0.927 |
| DLCOPPER_F does not Granger Cause DLZAR_F | | 0.238 | 0.788 | 0.384 | 1 | 0.536 |
| DLPALLADIUM_F does not Granger Cause DLGOLD_F | 1952 | 0.639 | 0.528 | 1.259 | 3 | 0.739 |
| DLGOLD_F does not Granger Cause DLPALLADIUM_F | | 0.215 | 0.807 | 0.604 | 3 | 0.895 |
| DLPLATINUM_F does not Granger Cause DLGOLD_F | 1952 | 2.847 | 0.058* | 14.038 | 5 | 0.015** |
| DLGOLD_F does not Granger Cause DLPLATINUM_F | | 1.313 | 0.269 | 23.456 | 5 | 0.000*** |
| DLFTSE_JSE40_F does not Granger Cause DLGOLD_F | 1952 | 4.632 | 0.010*** | 9.632 | 2 | 0.008*** |
| DLGOLD_F does not Granger Cause DLFTSE_JSE40_F | | 3.758 | 0.024** | 7.617 | 2 | 0.022** |
| DLZAR_F does not Granger Cause DLGOLD_F | 1952 | 0.950 | 0.387 | 1.596 | 1 | 0.207 |

| | | | | | | |
|--|------|-------------|----------|--------|----|----------|
| DLGOLD_F does not Granger Cause DLZAR_F | | 0.668 | 0.513 | 0.167 | 1 | 0.683 |
| DLPLATINUM_F does not Granger Cause DLPALLADIUM_F | 1952 | 0.023 | 0.977 | 4.397 | 5 | 0.494 |
| DLPALLADIUM_F does not Granger Cause DLPLATINUM_F | | 3.809 | 0.022** | 11.797 | 5 | 0.038** |
| DLTSE_JSE40_F does not Granger Cause DLPALLADIUM_F | 1952 | 1.124 | 0.325 | 12.406 | 6 | 0.054* |
| DLPALLADIUM_F does not Granger Cause DLTSE_JSE40_F | | 3.859 | 0.021** | 10.833 | 6 | 0.094* |
| DLZAR_F does not Granger Cause DLPALLADIUM_F | 1952 | 2.333 | 0.097* | 5.280 | 3 | 0.152 |
| DLPALLADIUM_F does not Granger Cause DLZAR_F | | 0.918 | 0.399 | 2.307 | 3 | 0.511 |
| DLTSE_JSE40_F does not Granger Cause DLPLATINUM_F | 1952 | 2.554 | 0.078* | 5.342 | 2 | 0.069* |
| DLPLATINUM_F does not Granger Cause DLTSE_JSE40_F | | 0.133 | 0.875 | 0.355 | 2 | 0.837 |
| DLZAR_F does not Granger Cause DLPLATINUM_F | 1952 | 2.104 | 0.122 | 4.561 | 2 | 0.102 |
| DLPLATINUM_F does not Granger Cause DLZAR_F | | 0.285 | 0.752 | 0.430 | 2 | 0.806 |
| DLZAR_F does not Granger Cause DLTSE_JSE40_F | 1952 | 0.420 | 0.657 | 0.692 | 1 | 0.406 |
| DLTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.522 | 0.594 | 0.534 | 1 | 0.465 |
| | | | | | | |
| Future after crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOPPER_F does not Granger Cause DLALUMINIUM_F | 1892 | 0.364 | 0.695 | 0.606 | 2 | 0.739 |
| DLALUMINIUM_F does not Granger Cause DLCOPPER_F | | 11.233 | 0.000*** | 22.187 | 2 | 0.000*** |
| DLGOLD_F does not Granger Cause DLALUMINIUM_F | 1892 | 1.100 | 0.333 | 2.267 | 2 | 0.322 |
| DLALUMINIUM_F does not Granger Cause DLGOLD_F | | 1.778 | 0.169 | 3.504 | 2 | 0.173 |
| DLPALLADIUM_F does not Granger Cause DLALUMINIUM_F | 1892 | 2.956 | 0.052* | 5.848 | 2 | 0.054* |
| DLALUMINIUM_F does not Granger Cause DLPALLADIUM_F | | 0.478 | 0.620 | 0.908 | 2 | 0.635 |
| DLPLATINUM_F does not Granger Cause DLALUMINIUM_F | 1892 | 2.860 | 0.058* | 6.285 | 2 | 0.043** |
| DLALUMINIUM_F does not Granger Cause DLPLATINUM_F | | 0.145 | 0.865 | 0.313 | 2 | 0.855 |
| DLTSE_JSE40_F does not Granger Cause DLALUMINIUM_F | 1892 | 0.938 | 0.392 | 1.662 | 3 | 0.645 |
| DLALUMINIUM_F does not Granger Cause DLTSE_JSE40_F | | 1.194 | 0.303 | 1.984 | 3 | 0.576 |
| DLZAR_F does not Granger Cause DLALUMINIUM_F | 1892 | 9.529 | 0.000*** | 20.804 | 2 | 0.000*** |
| DLALUMINIUM_F does not Granger Cause DLZAR_F | | 1.248 | 0.287 | 2.177 | 2 | 0.337 |
| DLGOLD_F does not Granger Cause DLCOPPER_F | 1892 | 2.442 | 0.087* | 1.330 | 1 | 0.249 |
| DLCOPPER_F does not Granger Cause DLGOLD_F | | 0.251 | 0.778 | 0.222 | 1 | 0.638 |
| DLPALLADIUM_F does not Granger Cause DLCOPPER_F | 1892 | 0.403 | 0.668 | 0.928 | 2 | 0.629 |
| DLCOPPER_F does not Granger Cause DLPALLADIUM_F | | 1.991 | 0.137 | 3.668 | 2 | 0.160 |
| DLPLATINUM_F does not Granger Cause DLCOPPER_F | 1892 | 0.419 | 0.658 | 0.938 | 2 | 0.626 |
| DLCOPPER_F does not Granger Cause DLPLATINUM_F | | 1.138 | 0.321 | 2.732 | 2 | 0.255 |
| DLTSE_JSE40_F does not Granger Cause DLCOPPER_F | 1892 | 0.199 | 0.820 | 0.478 | 3 | 0.924 |
| DLCOPPER_F does not Granger Cause DLTSE_JSE40_F | | 7.697 | 0.001*** | 14.841 | 3 | 0.002*** |
| DLZAR_F does not Granger Cause DLCOPPER_F | 1892 | 6.652 | 0.001*** | 14.206 | 2 | 0.001*** |
| DLCOPPER_F does not Granger Cause DLZAR_F | | 0.734 | 0.480 | 1.407 | 2 | 0.495 |
| DLPALLADIUM_F does not Granger Cause DLGOLD_F | 1892 | 0.478 | 0.620 | 0.991 | 2 | 0.609 |
| DLGOLD_F does not Granger Cause DLPALLADIUM_F | | 5.361 | 0.005*** | 10.996 | 2 | 0.004*** |
| DLPLATINUM_F does not Granger Cause DLGOLD_F | 1892 | 1.587 | 0.205 | 3.143 | 2 | 0.208 |
| DLGOLD_F does not Granger Cause DLPLATINUM_F | | 3.981 | 0.019** | 7.893 | 2 | 0.019** |
| DLTSE_JSE40_F does not Granger Cause DLGOLD_F | 1892 | 0.007 | 0.993 | 0.000 | 1 | 0.985 |
| DLGOLD_F does not Granger Cause DLTSE_JSE40_F | | 2.230 | 0.108 | 0.452 | 1 | 0.502 |
| DLZAR_F does not Granger Cause DLGOLD_F | 1892 | 4.476 | 0.012** | 8.946 | 2 | 0.011** |
| DLGOLD_F does not Granger Cause DLZAR_F | | 0.755 | 0.470 | 1.541 | 2 | 0.463 |
| DLPLATINUM_F does not Granger Cause DLPALLADIUM_F | 1892 | 1.345 | 0.261 | 2.909 | 2 | 0.234 |
| DLPALLADIUM_F does not Granger Cause DLPLATINUM_F | | 2.238 | 0.107 | 4.550 | 2 | 0.103 |
| DLTSE_JSE40_F does not Granger Cause DLPALLADIUM_F | 1892 | 1.499 | 0.224 | 6.421 | 3 | 0.093* |
| DLPALLADIUM_F does not Granger Cause DLTSE_JSE40_F | | 6.171 | 0.002*** | 11.744 | 3 | 0.008*** |
| DLZAR_F does not Granger Cause DLPALLADIUM_F | 1892 | 9.416 | 0.000*** | 18.282 | 2 | 0.000*** |
| DLPALLADIUM_F does not Granger Cause DLZAR_F | | 1.392 | 0.249 | 3.344 | 2 | 0.188 |
| DLTSE_JSE40_F does not Granger Cause DLPLATINUM_F | 1892 | 1.743 | 0.175 | 3.218 | 3 | 0.359 |
| DLPLATINUM_F does not Granger Cause DLTSE_JSE40_F | | 2.406 | 0.090* | 5.217 | 3 | 0.157 |
| DLZAR_F does not Granger Cause DLPLATINUM_F | 1892 | 14.601 | 0.000*** | 29.874 | 2 | 0.000*** |
| DLPLATINUM_F does not Granger Cause DLZAR_F | | 1.865 | 0.155 | 3.725 | 2 | 0.155 |
| DLZAR_F does not Granger Cause DLTSE_JSE40_F | 1892 | 14.844 | 0.000*** | 28.011 | 3 | 0.000*** |
| DLTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.457 | 0.633 | 1.345 | 3 | 0.719 |

, **, * indicate significance at a 10%, 5% and 1% level of significance respectively*

Source: Thomson Reuters DataStream and EViews.

APPENDIX A.2: VAR FTSE/JSE Top 40 Index and five metal commodities

| Spot before crisis | LFTSE_JSE40 | LALUMINIUM | LCOPPER | LGOLD | LPALLADIUM | LPLATINUM |
|--------------------|--------------------------------|--------------------------------|--------------------------------|---------------------------------|---------------------------------|--------------------------------|
| LFTSE_JSE40(-1) | 1.030 (0.023) [43.881] | 0.035 (0.024) [1.471] | 0.024 (0.029) [0.807] | 0.020 (0.018) [1.085] | -0.002 (0.042) [-0.037] | -0.025 (0.026) [-0.956] |
| LFTSE_JSE40(-2) | -0.031 (0.024) [-1.314] | -0.033 (0.024) [-1.388] | -0.021 (0.029) [-0.711] | -0.014 (0.018) [-0.763] | 0.000 (0.042) [0.008] | 0.023 (0.026) [0.872] |
| LALUMINIUM(-1) | 0.054 (0.033) [1.670] | 0.926 (0.033) [28.000] | -0.081 (0.041) [-1.986] | 0.032 (0.025) [1.261] | 0.104 (0.058) [1.798] | 0.035 (0.036) [0.951] |
| LALUMINIUM(-2) | -0.051 (0.033) [-1.569] | 0.056 (0.033) [1.703] | 0.076 (0.041) [1.865] | -0.021 (0.025) [-0.829] | -0.077 (0.058) [-1.338] | -0.020 (0.036) [-0.563] |
| LCOPPER(-1) | 0.040 (0.027) [1.466] | 0.001 (0.027) [0.043] | 1.008 (0.034) [29.902] | 0.050 (0.021) [2.378] | 0.100 (0.048) [2.083] | 0.077 (0.03) [2.551] |
| LCOPPER(-2) | -0.036 (0.027) [-1.328] | 0.002 (0.027) [0.088] | -0.014 (0.034) [-0.411] | -0.051 (0.021) [-2.426] | -0.097 (0.048) [-2.027] | -0.076 (0.03) [-2.509] |
| LGOLD(-1) | -0.079 (0.032) [-2.461] | -0.014 (0.033) [-0.417] | -0.085 (0.04) [-2.105] | 0.906 (0.025) [36.261] | 0.182 (0.057) [3.174] | 0.065 (0.036) [1.795] |
| LGOLD(-2) | 0.072 (0.032) [2.235] | 0.020 (0.033) [0.608] | 0.093 (0.04) [2.316] | 0.077 (0.025) [3.112] | -0.197 (0.057) [-3.442] | -0.062 (0.036) [-1.719] |
| LPALLADIUM(-1) | 0.017 (0.015) [1.155] | -0.010 (0.015) [-0.679] | 0.005 (0.018) [0.276] | 0.022 (0.011) [1.967] | 1.038 (0.026) [40.139] | 0.056 (0.016) [3.423] |
| LPALLADIUM(-2) | -0.019 (0.015) [-1.301] | 0.011 (0.015) [0.763] | -0.004 (0.018) [-0.246] | -0.026 (0.011) [-2.329] | -0.045 (0.026) [-1.724] | -0.059 (0.016) [-3.615] |
| LPLATINUM(-1) | 0.000 (0.024) [-0.017] | -0.019 (0.024) [-0.795] | 0.024 (0.029) [0.830] | -0.010 (0.018) [-0.531] | -0.145 (0.042) [-3.470] | 0.869 (0.026) [33.035] |
| LPLATINUM(-2) | -0.001 (0.024) [-0.032] | 0.019 (0.024) [0.806] | -0.020 (0.029) [-0.679] | 0.010 (0.018) [0.575] | 0.134 (0.042) [3.207] | 0.115 (0.026) [4.393] |
| C | 0.02121 (0.024) [0.882] | 0.04205 (0.024) [1.720] | -0.02613 (0.03) [-0.871] | -0.00822 (0.019) [-0.442] | -0.01128 (0.043) [-0.264] | 0.00822 (0.027) [0.306] |
| R-squared | 0.999 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 |
| Adj. R-squared | 0.999 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 |
| Spot after crisis | LFTSE_JSE40 | LALUMINIUM | LCOPPER | LGOLD | LPALLADIUM | LPLATINUM |
| LFTSE_JSE40(-1) | 0.940 (0.026) [35.724] | 0.047 (0.032) [1.456] | 0.000 (0.036) [0.006] | 0.026 (0.027) [0.963] | 0.095 (0.046) [2.076] | 0.063 (0.030) [2.112] |
| LFTSE_JSE40(-2) | -0.028 (0.036) [-0.787] | -0.056 (0.044) [-1.262] | -0.012 (0.049) [-0.246] | -0.081 (0.037) [-2.207] | 0.024 (0.062) [0.384] | -0.050 (0.041) [-1.233] |
| LFTSE_JSE40(-3) | 0.080 (0.026) [3.041] | 0.001 (0.032) [0.024] | 0.002 (0.036) [0.057] | 0.053 (0.027) [1.969] | -0.093 (0.046) [-2.040] | -0.006 (0.030) [-0.185] |
| LALUMINIUM(-1) | -0.021 (0.026) [-0.814] | 0.964 (0.032) [29.868] | -0.141 (0.036) [-3.938] | -0.024 (0.027) [-0.913] | 0.100 (0.046) [2.201] | 0.074 (0.030) [2.495] |
| LALUMINIUM(-2) | 0.017 (0.038) [0.456] | 0.091 (0.047) [1.949] | 0.212 (0.052) [4.093] | 0.095 (0.039) [2.468] | -0.056 (0.066) [-0.855] | -0.055 (0.043) [-1.268] |
| LALUMINIUM(-3) | -0.006 (0.026) [-0.236] | -0.069 (0.033) [-2.131] | -0.075 (0.036) [-2.076] | -0.071 (0.027) [-2.632] | -0.032 (0.046) [-0.697] | -0.020 (0.030) [-0.667] |
| LCOPPER(-1) | 0.092 (0.025) [3.698] | -0.032 (0.031) [-1.034] | 1.064 (0.034) [31.339] | 0.040 (0.025) [1.569] | 0.180 (0.043) [4.181] | 0.085 (0.028) [3.015] |
| LCOPPER(-2) | -0.085 (0.036) [-2.368] | 0.014 (0.044) [0.317] | -0.098 (0.049) [-2.000] | -0.095 (0.036) [-2.609] | -0.169 (0.062) [-2.725] | -0.065 (0.041) [-1.599] |
| LCOPPER(-3) | -0.006 (0.025) [-0.252] | 0.019 (0.031) [0.618] | 0.025 (0.034) [0.745] | 0.064 (0.025) [2.510] | 0.011 (0.043) [0.255] | 0.000 (0.028) [-0.002] |

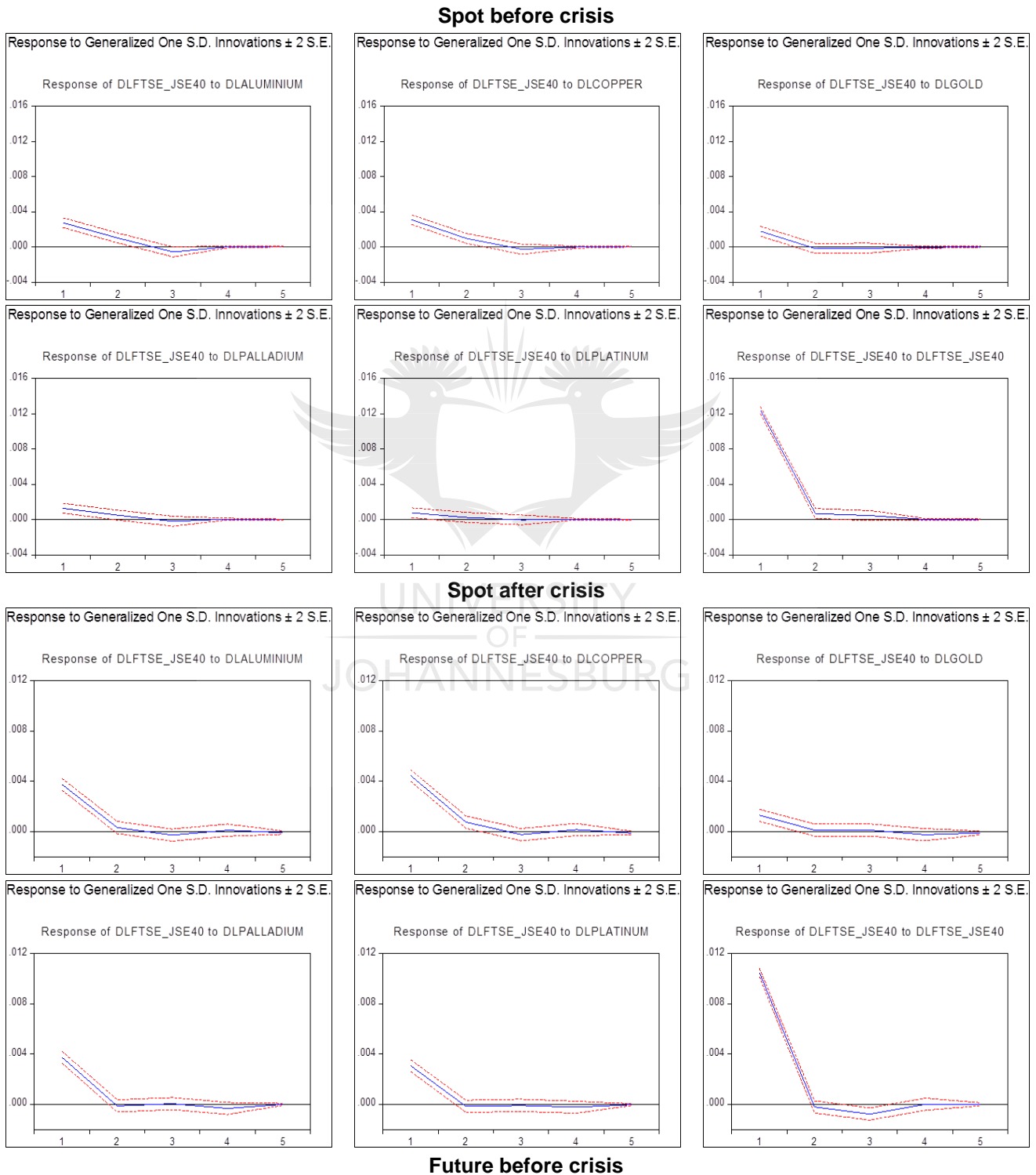
| | | | | | | |
|----------------------|---------------|--------------|-----------|-----------|--------------|-------------|
| LGOLD(-1) | 0.003 | 0.015 | -0.031 | 0.976 | 0.165 | 0.244 |
| | (0.027) | (0.034) | (0.037) | (0.028) | (0.047) | (0.031) |
| | [0.128] | [-0.457] | [-0.821] | [35.060] | [3.475] | [7.879] |
| LGOLD(-2) | 0.025 | -0.017 | 0.063 | 0.004 | -0.097 | -0.188 |
| | (0.036) | (0.045) | (0.050) | (0.037) | (0.063) | (0.041) |
| | [0.696] | [-0.380] | [1.260] | [0.104] | [-1.532] | [-4.558] |
| LGOLD(-3) | -0.029 | -0.001 | -0.033 | 0.017 | -0.065 | -0.055 |
| | (0.028) | (0.034) | (0.038) | (0.028) | (0.048) | (0.032) |
| | [-1.031] | [-0.037] | [-0.870] | [0.592] | [-1.340] | [-1.745] |
| LPALLADIUM(-1) | -0.007 | -0.026 | -0.012 | -0.037 | 0.932 | -0.053 |
| | (0.019) | (0.023) | (0.026) | (0.019) | (0.032) | (0.021) |
| | [-0.357] | [-1.124] | [-0.469] | [-1.955] | [28.750] | [-2.498] |
| LPALLADIUM(-2) | 0.035 | -0.005 | 0.001 | 0.080 | 0.043 | 0.056 |
| | (0.026) | (0.032) | (0.036) | (0.027) | (0.045) | (0.030) |
| | [1.339] | [-0.162] | [0.024] | [3.011] | [0.936] | [1.885] |
| LPALLADIUM(-3) | -0.025 | 0.033 | 0.014 | -0.045 | -0.002 | -0.014 |
| | (0.019) | (0.023) | (0.025) | (0.019) | (0.032) | (0.021) |
| | [-1.365] | [1.464] | [0.573] | [-2.403] | [-0.062] | [-0.677] |
| LPLATINUM(-1) | -0.027 | 0.020 | -0.014 | 0.034 | -0.145 | 0.871 |
| | (0.031) | (0.038) | (0.042) | (0.031) | (0.054) | (0.035) |
| | [-0.865] | [0.525] | [-0.334] | [1.075] | [-2.701] | [24.882] |
| LPLATINUM(-2) | 0.003 | -0.010 | 0.003 | -0.080 | 0.049 | 0.102 |
| | (0.041) | (0.051) | (0.056) | (0.042) | (0.072) | (0.047) |
| | [0.063] | [-0.205] | [0.054] | [-1.895] | [0.679] | [2.170] |
| LPLATINUM(-3) | 0.023 | -0.008 | 0.012 | 0.038 | 0.092 | 0.016 |
| | (0.030) | (0.037) | (0.041) | (0.031) | (0.052) | (0.034) |
| | [0.751] | [-0.226] | [0.300] | [1.244] | [1.756] | [0.457] |
| C | 0.143 | 0.178 | 0.185 | 0.043 | -0.367 | -0.100 |
| | (0.063) | (0.078) | (0.086) | (0.065) | (0.110) | (0.072) |
| | [2.260] | [2.285] | [2.139] | [0.673] | [-3.339] | [-1.399] |
| R-squared | 0.998 | 0.993 | 0.995 | 0.995 | 0.992 | 0.997 |
| Adj. R-squared | 0.998 | 0.992 | 0.995 | 0.995 | 0.992 | 0.997 |
| Future before crisis | LFTSE/JSE40_F | LALUMINIUM_F | LCOPPER_F | LGOLD_F | LPALLADIUM_F | LPLATINUM_F |
| LFTSE_JSE40_F(-1) | 1.039 | 0.032 | 0.016 | 0.038 | -0.001 | -0.031 |
| | (0.023) | (0.023) | (0.028) | (0.019) | (0.040) | (0.027) |
| | [44.306] | [1.423] | [0.564] | [2.048] | [-0.015] | [-1.161] |
| LFTSE_JSE40_F(-2) | -0.041 | -0.031 | -0.014 | -0.033 | 0.001 | 0.030 |
| | (0.024) | (0.023) | (0.028) | (0.019) | (0.040) | (0.027) |
| | [-1.751] | [-1.355] | [-0.511] | [-1.737] | [0.026] | [1.101] |
| LALUMINIUM_F(-1) | 0.039 | 0.912 | 0.035 | -0.008 | -0.018 | 0.026 |
| | (0.033) | (0.032) | (0.040) | (0.026) | (0.056) | (0.038) |
| | [1.177] | [28.501] | [0.885] | [-0.312] | [-0.322] | [0.676] |
| LALUMINIUM_F(-2) | -0.038 | 0.068 | -0.040 | 0.019 | 0.042 | -0.018 |
| | (0.033) | (0.032) | (0.040) | (0.026) | (0.056) | (0.038) |
| | [-1.149] | [2.126] | [-1.003] | [0.704] | [0.743] | [-0.469] |
| LCOPPER_F(-1) | 0.016 | -0.003 | 0.909 | 0.021 | 0.041 | 0.045 |
| | (0.027) | (0.026) | (0.033) | (0.022) | (0.046) | (0.031) |
| | [0.584] | [-0.098] | [27.975] | [0.961] | [0.896] | [1.454] |
| LCOPPER_F(-2) | -0.012 | 0.007 | 0.085 | -0.021 | -0.039 | -0.043 |
| | (0.027) | (0.026) | (0.032) | (0.022) | (0.046) | (0.031) |
| | [-0.430] | [0.255] | [2.617] | [-0.977] | [-0.846] | [-1.386] |
| LGOLD_F(-1) | 0.047 | 0.041 | 0.027 | 0.924 | 0.007 | 0.007 |
| | (0.032) | (0.031) | (0.038) | (0.026) | (0.054) | (0.037) |
| | [1.476] | [1.335] | [0.697] | [36.207] | [1.132] | [0.196] |
| LGOLD_F(-2) | -0.053 | -0.033 | -0.016 | 0.060 | -0.023 | -0.002 |
| | (0.032) | (0.031) | (0.038) | (0.025) | (0.054) | (0.037) |
| | [-1.661] | [-1.082] | [-0.407] | [2.344] | [-0.428] | [-0.066] |
| LPALLADIUM_F(-1) | 0.029 | -0.005 | 0.001 | -0.005 | 1.071 | 0.039 |
| | (0.015) | (0.014) | (0.018) | (0.012) | (0.025) | (0.017) |
| | [1.931] | [-0.381] | [0.048] | [-0.441] | [42.17] | [2.258] |
| LPALLADIUM_F(-2) | -0.030 | 0.007 | 0.000 | 0.001 | -0.077 | -0.041 |
| | (0.015) | (0.014) | (0.018) | (0.012) | (0.025) | (0.017) |
| | [-2.038] | [0.499] | [0.007] | [0.086] | [-3.049] | [-2.397] |
| LPLATINUM_F(-1) | -0.028 | -0.005 | 0.023 | 0.028 | -0.018 | 0.902 |
| | (0.022) | (0.022) | (0.027) | (0.018) | (0.038) | (0.026) |
| | [-1.247] | [-0.217] | [0.849] | [1.584] | [-0.463] | [35.259] |
| LPLATINUM_F(-2) | 0.027 | 0.005 | -0.019 | -0.028 | 0.009 | 0.084 |
| | (0.022) | (0.021) | (0.027) | (0.018) | (0.038) | (0.026) |
| | [1.228] | [0.223] | [-0.723] | [-1.574] | [0.236] | [3.270] |
| C | 0.025 | 0.047 | -0.027 | -0.004 | -0.012 | 0.016 |
| | (0.026) | (0.025) | (0.031) | (0.021) | (0.044) | (0.030) |
| | [0.974] | [1.864] | [-0.884] | [-0.210] | [-0.264] | [0.549] |
| R-squared | 0.999 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 |
| Adj. R-squared | 0.999 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 |
| Future after crisis | LFTSE/JSE40_F | LALUMINIUM_F | LCOPPER_F | LGOLD_F | LPALLADIUM_F | LPLATINUM_F |
| LFTSE_JSE40_F(-1) | 0.912 | 0.020 | -0.026 | 0.004 | 0.012 | 0.031 |
| | (0.026) | (0.031) | (0.035) | (0.027) | (0.045) | (0.031) |
| | [34.626] | [0.646] | [-0.727] | [0.155] | [0.273] | [0.992] |
| LFTSE_JSE40_F(-2) | 0.077 | -0.027 | 0.014 | -0.007 | 0.006 | -0.028 |
| | (0.026) | (0.031) | (0.035) | (0.027) | (0.045) | (0.031) |

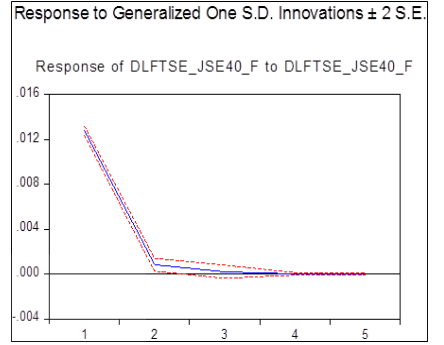
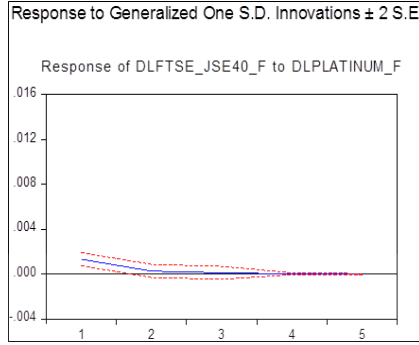
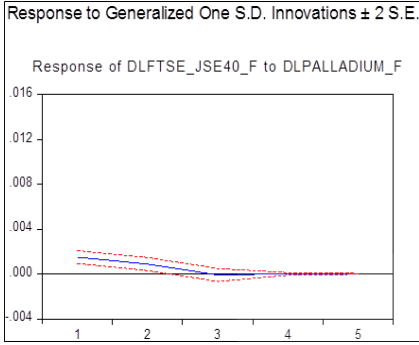
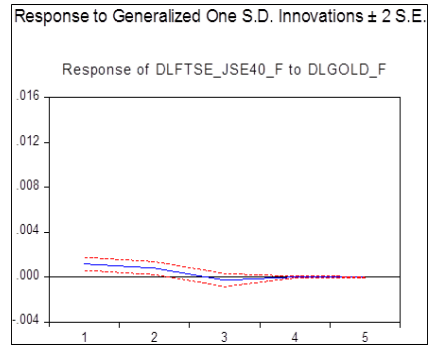
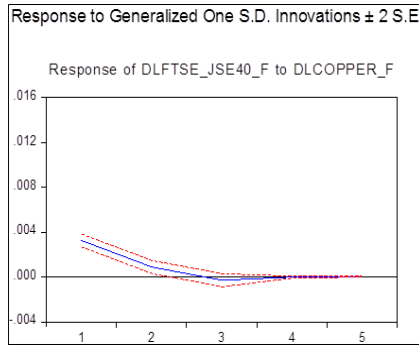
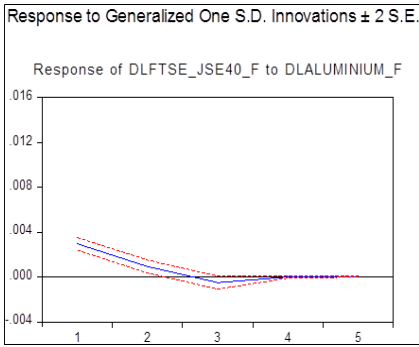
| | | | | | | |
|------------------|----------|-----------|-----------|-----------|-----------|----------|
| | [2.938] | [-0.860] | [0.382] | [-0.261] | [0.130] | [-0.897] |
| LALUMINIUM_F(-1) | -0.041 | 0.935 | -0.153 | -0.054 | -0.052 | -0.025 |
| | (0.027) | (0.032) | (0.036) | (0.027) | (0.046) | (0.032) |
| | [-1.515] | [29.324] | [-4.218] | [-1.977] | [-1.126] | [-0.784] |
| LALUMINIUM_F(-2) | 0.028 | 0.050 | 0.147 | 0.054 | 0.060 | 0.023 |
| | (0.027) | (0.032) | (0.036) | (0.027) | (0.046) | (0.032) |
| | [1.050] | [1.576] | [4.037] | [1.972] | [1.288] | [0.707] |
| LCOPPER_F(-1) | 0.077 | -0.030 | 1.042 | 0.010 | 0.077 | 0.040 |
| | (0.025) | (0.029) | (0.034) | (0.025) | (0.043) | (0.029) |
| | [3.113] | [-1.003] | [31.066] | [0.384] | [1.791] | [1.353] |
| LCOPPER_F(-2) | -0.077 | 0.032 | -0.052 | -0.002 | -0.057 | -0.022 |
| | (0.025) | (0.030) | (0.034) | (0.025) | (0.043) | (0.029) |
| | [-3.105] | [1.093] | [-1.539] | [-0.068] | [-1.340] | [-0.731] |
| LGOLD_F(-1) | -0.039 | -0.030 | -0.061 | -0.040 | -0.129 | -0.059 |
| | (0.032) | (0.038) | (0.044) | (0.033) | (0.056) | (0.038) |
| | [-1.201] | [-0.773] | [-1.397] | [28.845] | [-2.322] | [-1.554] |
| LGOLD_F(-2) | 0.039 | 0.027 | 0.060 | 0.056 | 0.131 | 0.059 |
| | (0.032) | (0.038) | (0.043) | (0.033) | (0.056) | (0.038) |
| | [1.198] | [0.701] | [1.372] | [1.721] | [2.361] | [1.537] |
| LPALLADIUM_F(-1) | 0.045 | 0.009 | 0.037 | 0.006 | 1.073 | 0.011 |
| | (0.020) | (0.024) | (0.027) | (0.020) | (0.034) | (0.024) |
| | [2.262] | [0.389] | [1.383] | [0.316] | [31.380] | [0.488] |
| LPALLADIUM_F(-2) | -0.040 | -0.008 | -0.032 | -0.008 | -0.097 | -0.020 |
| | (0.020) | (0.023) | (0.027) | (0.020) | (0.034) | (0.023) |
| | [-1.999] | [-0.333] | [-1.193] | [-0.398] | [-2.837] | [-0.857] |
| LPLATINUM_F(-1) | 0.004 | 0.074 | 0.014 | 0.033 | -0.008 | 1.027 |
| | (0.034) | (0.040) | (0.046) | (0.034) | (0.059) | (0.040) |
| | [0.121] | [1.823] | [0.308] | [0.945] | [-0.135] | [25.46] |
| LPLATINUM_F(-2) | -0.006 | -0.073 | -0.013 | -0.041 | 0.003 | -0.039 |
| | (0.034) | (0.040) | (0.046) | (0.034) | (0.059) | (0.040) |
| | [-0.181] | [-1.798] | [-0.282] | [-1.184] | [0.045] | [-0.973] |
| C | 0.188 | 0.163 | 0.226 | 0.058 | -0.245 | -0.025 |
| | (0.064) | (0.076) | (0.087) | (0.065) | (0.111) | (0.076) |
| | [2.920] | [2.138] | [2.609] | [0.885] | [-2.215] | [-0.329] |
| R-squared | 0.998 | 0.993 | 0.995 | 0.995 | 0.992 | 0.996 |
| Adj. R-squared | 0.998 | 0.993 | 0.995 | 0.995 | 0.992 | 0.996 |

Note: Standard errors in () and t-statistics in []

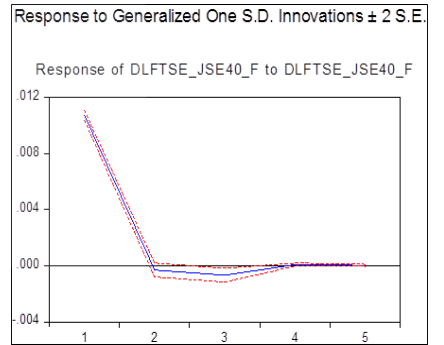
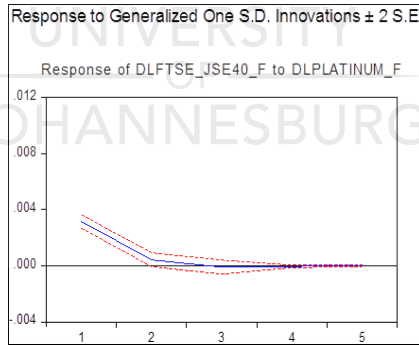
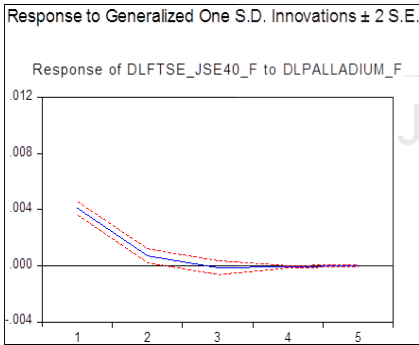
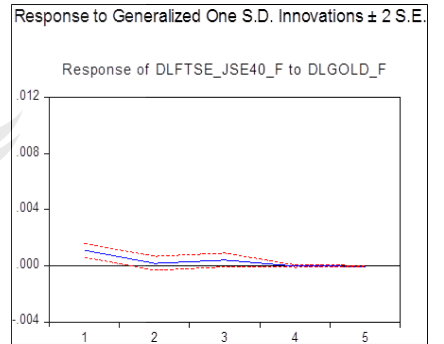
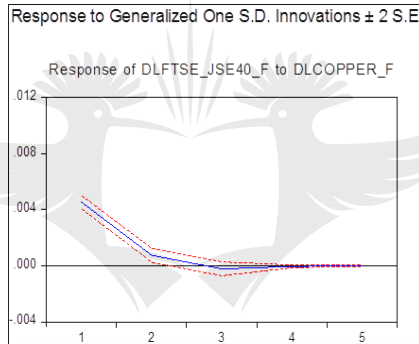
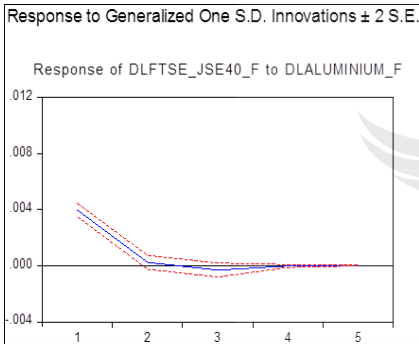
Source: Thomson Reuters DataStream and EViews.

APPENDIX A.3: Impulse response functions and variance decompositions for FTSE/JSE Top 40 Index and five metal commodities





Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLFTSE/JSE40 | DLALUMINIUM | DLCOPPER | DLGOLD | DLPALLADIUM | DLPLATINUM |
|----------------------|--------|-------|----------------|---------------|------------|----------|---------------|--------------|
| DLFTSE/JSE40 | 1 | 0.012 | 93.461 | 0.353 | 6.186 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.013 | 92.240 | 0.673 | 6.713 | 0.217 | 0.125 | 0.032 |
| DLFTSE/JSE40 | 10 | 0.013 | 92.240 | 0.673 | 6.713 | 0.217 | 0.125 | 0.032 |
| DLFTSE/JSE40 | 20 | 0.013 | 92.240 | 0.673 | 6.713 | 0.217 | 0.125 | 0.032 |
| Spot after crisis | | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.010 | 87.195 | 12.805 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.011 | 86.107 | 12.740 | 0.708 | 0.128 | 0.257 | 0.060 |
| DLFTSE/JSE40 | 10 | 0.011 | 86.105 | 12.740 | 0.709 | 0.129 | 0.258 | 0.060 |
| DLFTSE/JSE40 | 20 | 0.011 | 86.105 | 12.740 | 0.709 | 0.129 | 0.258 | 0.060 |
| Future before crisis | Period | S.E. | DLFTSE_JSE40_F | DLALUMINIUM_F | DLCOPPER_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F |
| DLFTSE/JSE40 | 1 | 0.013 | 92.666 | 0.463 | 5.502 | 0.000 | 1.370 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.013 | 91.577 | 0.637 | 5.783 | 0.085 | 1.822 | 0.096 |
| DLFTSE/JSE40 | 10 | 0.013 | 91.577 | 0.637 | 5.783 | 0.085 | 1.822 | 0.096 |
| DLFTSE/JSE40 | 20 | 0.013 | 91.577 | 0.637 | 5.783 | 0.085 | 1.822 | 0.096 |
| Future after crisis | | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.011 | 78.607 | 12.604 | 0.000 | 1.054 | 3.448 | 4.287 |
| DLFTSE/JSE40 | 5 | 0.011 | 77.635 | 12.545 | 0.496 | 1.200 | 3.658 | 4.466 |
| DLFTSE/JSE40 | 10 | 0.011 | 77.635 | 12.545 | 0.496 | 1.200 | 3.658 | 4.466 |
| DLFTSE/JSE40 | 20 | 0.011 | 77.635 | 12.545 | 0.496 | 1.200 | 3.658 | 4.466 |

Cholesky Ordering spot before crisis: DLCOPPER DLALUMINIUM DLFTSE_JSE40 DLGOLD DLPLATINUM DLPALLADIUM

Cholesky Ordering spot after crisis: DLALUMINIUM DLFTSE_JSE40 DLGOLD DLCOPPER DLPALLADIUM DLPLATINUM

Cholesky Ordering future before crisis: Cholesky Ordering: DLPALLADIUM_F DLCOPPER_F DLALUMINIUM_F DLFTSE_JSE40_F DLGOLD_F DLPLATINUM_F

Cholesky Ordering future after crisis: DLGOLD_F DLALUMINIUM_F DLPLATINUM_F DLPALLADIUM_F DLFTSE_JSE40_F DLCOPPER_F

Source: Thomson Reuters DataStream and EViews.



APPENDIX A.4: VAR ZAR, FTSE/JSE Top 40 Index and five metal commodities

| Spot before crisis | LZAR | LALUMINIUM | LCOPPER | LGOLD | LPALLADIUM | LPLATINUM | LFTSE/JSE40 |
|--------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| LZAR(-1) | 1.021 (0.025) [41.151] | -0.029 (0.031) [-0.953] | 0.027 (0.037) [0.727] | -0.063 (0.023) [-2.722] | -0.007 (0.054) [-0.136] | -0.042 (0.034) [-1.255] | 0.034 (0.030) [1.114] |
| LZAR(-2) | -0.027 (0.025) [-1.081] | 0.012 (0.031) [0.389] | -0.047 (0.037) [-1.263] | 0.064 (0.023) [2.735] | 0.004 (0.054) [0.081] | 0.042 (0.034) [1.235] | -0.028 (0.030) [-0.926] |
| LALUMINIUM(-1) | -0.017 (0.027) [-0.637] | 0.915 (0.033) [27.648] | -0.087 (0.041) [-2.151] | 0.026 (0.025) [1.031] | 0.102 (0.058) [1.753] | 0.030 (0.037) [0.830] | 0.060 (0.033) [1.837] |
| LALUMINIUM(-2) | 0.011 (0.027) [0.417] | 0.045 (0.033) [1.354] | 0.057 (0.041) [1.393] | -0.015 (0.025) [-0.582] | -0.079 (0.058) [-1.356] | -0.017 (0.037) [-0.467] | -0.050 (0.033) [-1.510] |
| LCOPPER(-1) | 0.000 (0.022) [-0.017] | -0.005 (0.027) [-0.171] | 1.003 (0.034) [29.832] | 0.048 (0.021) [2.287] | 0.099 (0.048) [2.056] | 0.075 (0.030) [2.496] | 0.042 (0.027) [1.564] |
| LCOPPER(-2) | 0.003 (0.022) [0.131] | 0.005 (0.027) [0.172] | -0.013 (0.034) [-0.394] | -0.048 (0.021) [-2.325] | -0.097 (0.048) [-2.015] | -0.074 (0.030) [-2.457] | -0.037 (0.027) [-1.386] |
| LGOLD(-1) | 0.029 (0.028) [1.039] | -0.018 (0.034) [-0.522] | -0.070 (0.042) [-1.687] | 0.886 (0.026) [34.104] | 0.181 (0.060) [3.022] | 0.052 (0.038) [1.378] | -0.071 (0.034) [-2.101] |
| LGOLD(-2) | -0.023 (0.028) [-0.823] | 0.033 (0.034) [0.962] | 0.089 (0.042) [2.129] | 0.097 (0.026) [3.749] | -0.194 (0.060) [-3.251] | -0.048 (0.037) [-1.292] | 0.060 (0.034) [1.795] |
| LPALLADIUM(-1) | -0.003 (0.012) [-0.289] | -0.011 (0.015) [-0.739] | 0.005 (0.018) [0.257] | 0.022 (0.011) [1.913] | 1.038 (0.026) [40.103] | 0.055 (0.016) [3.394] | 0.017 (0.015) [1.191] |
| LPALLADIUM(-2) | 0.005 (0.012) [0.436] | 0.015 (0.015) [1.039] | 0.000 (0.018) [-0.022] | -0.026 (0.011) [-2.275] | -0.044 (0.026) [-1.693] | -0.058 (0.016) [-3.572] | -0.021 (0.015) [-1.407] |
| LPLATINUM(-1) | 0.004 (0.019) [0.191] | -0.019 (0.024) [-0.776] | 0.024 (0.029) [0.835] | -0.009 (0.018) [-0.499] | -0.145 (0.042) [-3.465] | 0.869 (0.026) [33.044] | -0.001 (0.024) [-0.034] |
| LPLATINUM(-2) | -0.011 (0.019) [-0.564] | 0.015 (0.024) [0.621] | -0.024 (0.029) [-0.829] | 0.010 (0.018) [0.529] | 0.133 (0.042) [3.183] | 0.115 (0.026) [4.359] | 0.001 (0.024) [0.045] |
| LFTSE/JSE40(-1) | 0.001 (0.020) [0.028] | 0.048 (0.025) [1.944] | 0.026 (0.030) [0.857] | 0.003 (0.019) [1.739] | 0.001 (0.043) [0.025] | -0.016 (0.027) [-0.589] | 0.021 (0.024) [41.903] |
| LFTSE/JSE40(-2) | 0.000 (0.020) [-0.006] | -0.033 (0.025) [-1.323] | -0.007 (0.030) [-0.247] | -0.027 (0.019) [-1.445] | 0.000 (0.043) [-0.001] | 0.014 (0.027) [0.528] | -0.026 (0.024) [-1.071] |
| C | 0.032 (0.023) [1.439] | 0.100 (0.028) [3.616] | 0.041 (0.034) [1.208] | -0.008 (0.021) [-0.398] | -0.001 (0.049) [-0.028] | 0.011 (0.031) [0.360] | 0.002 (0.027) [0.060] |
| R-squared | 0.997 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 | 0.999 |
| Adj. R-squared | 0.997 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 | 0.999 |
| Spot after crisis | LZAR | LALUMINIUM | LCOPPER | LGOLD | LPALLADIUM | LPLATINUM | LFTSE/JSE40 |
| LZAR(-1) | 1.018 (0.026) [39.069] | -0.076 (0.034) [-2.229] | -0.082 (0.038) [-2.165] | -0.040 (0.028) [-1.432] | -0.138 (0.048) [-2.876] | -0.145 (0.031) [-4.658] | -0.073 (0.028) [-2.641] |
| LZAR(-2) | -0.052 (0.036) [-1.424] | -0.014 (0.048) [-0.304] | -0.021 (0.053) [-0.399] | 0.006 (0.040) [0.160] | 0.044 (0.067) [0.659] | 0.075 (0.044) [1.722] | 0.039 (0.039) [1.014] |
| LZAR(-3) | 0.010 (0.026) [0.380] | 0.077 (0.034) [2.245] | 0.086 (0.038) [2.271] | 0.040 (0.028) [1.408] | 0.093 (0.048) [1.932] | 0.067 (0.031) [2.129] | 0.042 (0.028) [1.495] |
| LALUMINIUM(-1) | 0.014 (0.025) [0.548] | 0.958 (0.032) [29.679] | -0.148 (0.036) [-4.135] | -0.027 (0.027) [-0.996] | 0.091 (0.046) [2.000] | 0.065 (0.030) [2.178] | -0.026 (0.026) [-0.971] |
| LALUMINIUM(-2) | -0.015 (0.036) [-0.432] | 0.091 (0.047) [1.950] | 0.212 (0.052) [4.090] | 0.097 (0.039) [2.497] | -0.052 (0.066) [-0.788] | -0.049 (0.043) [-1.134] | 0.021 (0.038) [0.548] |
| LALUMINIUM(-3) | 0.000 (0.025) [0.008] | -0.065 (0.032) [-1.998] | -0.070 (0.036) [-1.938] | -0.069 (0.027) [-2.561] | -0.027 (0.046) [-0.597] | -0.017 (0.030) [-0.562] | -0.005 (0.026) [-0.171] |
| LCOPPER(-1) | -0.014 (0.024) [-0.612] | -0.042 (0.031) [-1.372] | 1.052 (0.034) [30.775] | 0.036 (0.026) [1.424] | 0.165 (0.043) [3.798] | 0.068 (0.028) [2.409] | 0.085 (0.025) [3.402] |

| | | | | | | | |
|----------------------|-----------|--------------|-----------|-----------|--------------|-------------|---------------|
| LCOPPER(-2) | 0.000 | 0.013 | -0.099 | -0.094 | -0.162 | -0.054 | -0.079 |
| | (0.034) | (0.044) | (0.049) | (0.037) | (0.062) | (0.041) | (0.036) |
| | [-0.012] | [0.304] | [-2.011] | [-2.549] | [-2.588] | [-1.320] | [-2.191] |
| LCOPPER(-3) | 0.004 | 0.025 | 0.032 | 0.068 | 0.019 | 0.005 | -0.002 |
| | (0.024) | (0.031) | (0.034) | (0.026) | (0.043) | (0.028) | (0.025) |
| | [0.187] | [0.807] | [0.932] | [2.667] | [0.443] | [0.165] | [-0.074] |
| LGOLD(-1) | -0.009 | 0.011 | -0.035 | 0.971 | 0.150 | 0.229 | -0.006 |
| | (0.026) | (0.034) | (0.037) | (0.028) | (0.048) | (0.031) | (0.028) |
| | [-0.365] | [0.316] | [-0.938] | [34.62] | [3.154] | [7.375] | [-0.217] |
| LGOLD(-2) | -0.024 | -0.018 | 0.061 | 0.005 | -0.091 | -0.178 | 0.030 |
| | (0.035) | (0.045) | (0.050) | (0.037) | (0.064) | (0.041) | (0.037) |
| | [-0.701] | [-0.400] | [1.220] | [0.122] | [-1.431] | [-4.315] | [0.820] |
| LGOLD(-3) | 0.036 | 0.006 | -0.025 | 0.021 | -0.056 | -0.049 | -0.025 |
| | (0.026) | (0.034) | (0.038) | (0.028) | (0.048) | (0.031) | (0.028) |
| | [1.384] | [0.166] | [-0.664] | [0.727] | [-1.160] | [-1.561] | [-0.887] |
| LPALLADIUM(-1) | -0.004 | -0.029 | -0.015 | -0.039 | 0.926 | -0.059 | -0.010 |
| | (0.018) | (0.023) | (0.026) | (0.019) | (0.032) | (0.021) | (0.019) |
| | [-0.235] | [-1.244] | [-0.583] | [-2.039] | [28.560] | [-2.812] | [-0.533] |
| LPALLADIUM(-2) | 0.028 | -0.008 | -0.003 | 0.079 | 0.041 | 0.056 | 0.035 |
| | (0.025) | (0.032) | (0.036) | (0.027) | (0.045) | (0.030) | (0.026) |
| | [1.114] | [-0.264] | [-0.084] | [2.970] | [0.897] | [1.888] | [1.339] |
| LPALLADIUM(-3) | -0.023 | 0.039 | 0.021 | -0.043 | 0.005 | -0.008 | -0.022 |
| | (0.017) | (0.023) | (0.025) | (0.019) | (0.032) | (0.021) | (0.019) |
| | [-1.342] | [1.712] | [0.824] | [-2.266] | [0.160] | [-0.386] | [-1.197] |
| LPLATINUM(-1) | 0.056 | 0.005 | -0.030 | 0.028 | -0.163 | 0.854 | -0.034 |
| | (0.029) | (0.038) | (0.042) | (0.032) | (0.054) | (0.035) | (0.031) |
| | [1.917] | [0.142] | [-0.718] | [0.896] | [-3.033] | [24.406] | [-1.110] |
| LPLATINUM(-2) | -0.033 | -0.002 | 0.012 | -0.075 | 0.065 | 0.118 | 0.012 |
| | (0.039) | (0.051) | (0.056) | (0.042) | (0.072) | (0.047) | (0.041) |
| | [-0.855] | [-0.045] | [0.207] | [-1.764] | [0.905] | [2.532] | [0.284] |
| LPLATINUM(-3) | -0.027 | -0.006 | 0.015 | 0.040 | 0.094 | 0.015 | 0.023 |
| | (0.028) | (0.037) | (0.041) | (0.031) | (0.052) | (0.034) | (0.030) |
| | [-0.937] | [-0.156] | [0.373] | [1.299] | [1.794] | [0.449] | [0.777] |
| LFTSE_JSE40(-1) | 0.013 | 0.040 | -0.007 | 0.019 | 0.077 | 0.046 | 0.929 |
| | (0.025) | (0.032) | (0.036) | (0.027) | (0.046) | (0.030) | (0.026) |
| | [0.514] | [1.226] | [-0.199] | [0.698] | [1.686] | [1.554] | [35.113] |
| LFTSE_JSE40(-2) | -0.048 | -0.052 | -0.009 | -0.078 | 0.034 | -0.037 | -0.022 |
| | (0.034) | (0.044) | (0.049) | (0.037) | (0.062) | (0.041) | (0.036) |
| | [-1.431] | [-1.185] | [-0.181] | [-2.128] | [0.548] | [-0.922] | [-0.607] |
| LFTSE_JSE40(-3) | 0.051 | 0.012 | 0.016 | 0.054 | -0.085 | 0.001 | 0.081 |
| | (0.025) | (0.033) | (0.036) | (0.027) | (0.046) | (0.030) | (0.026) |
| | [2.055] | [0.378] | [0.431] | [2.012] | [-1.854] | [0.022] | [3.049] |
| C | 0.006 | 0.210 | 0.226 | 0.024 | -0.373 | -0.098 | 0.117 |
| | (0.062) | (0.081) | (0.090) | (0.067) | (0.114) | (0.074) | (0.066) |
| | [0.095] | [2.604] | [2.517] | [0.358] | [-3.277] | [-1.325] | [1.784] |
| R-squared | 0.999 | 0.993 | 0.995 | 0.995 | 0.993 | 0.997 | 0.998 |
| Adj. R-squared | 0.999 | 0.992 | 0.995 | 0.995 | 0.992 | 0.997 | 0.998 |
| Future before crisis | LZAR_F | LALUMINIUM_F | LCOPPER_F | LGOLD_F | LPALLADIUM_F | LPLATINUM_F | LFTSE_JSE40_F |
| LZAR_F(-1) | 0.992 | -0.010 | 0.009 | -0.038 | 0.046 | -0.037 | 0.059 |
| | (0.024) | (0.027) | (0.033) | (0.022) | (0.048) | (0.032) | (0.028) |
| | [41.028] | [-0.380] | [0.282] | [-1.706] | [0.973] | [-1.163] | [2.113] |
| LZAR_F(-2) | 0.002 | -0.008 | -0.028 | -0.037 | -0.051 | 0.034 | -0.053 |
| | (0.024) | (0.027) | (0.033) | (0.022) | (0.048) | (0.032) | (0.028) |
| | [0.078] | [-0.281] | [-0.835] | [1.656] | [-1.072] | [1.064] | [-1.885] |
| LALUMINIUM_F(-1) | -0.008 | 0.899 | 0.024 | -0.012 | -0.018 | 0.021 | 0.048 |
| | (0.029) | (0.032) | (0.040) | (0.027) | (0.057) | (0.038) | (0.033) |
| | [-0.273] | [28.108] | [0.596] | [-0.444] | [-0.314] | [0.545] | [1.429] |
| LALUMINIUM_F(-2) | 0.002 | 0.055 | -0.055 | 0.021 | 0.035 | -0.017 | -0.038 |
| | (0.029) | (0.032) | (0.040) | (0.027) | (0.057) | (0.038) | (0.033) |
| | [0.059] | [1.721] | [-1.377] | [0.780] | [0.611] | [-0.454] | [-1.135] |
| LCOPPER_F(-1) | 0.010 | -0.006 | 0.906 | 0.020 | 0.042 | 0.044 | 0.019 |
| | (0.023) | (0.026) | (0.032) | (0.022) | (0.046) | (0.031) | (0.027) |
| | [0.421] | [-0.232] | [27.957] | [0.906] | [0.903] | [1.404] | [0.683] |
| LCOPPER_F(-2) | -0.008 | -0.008 | 0.085 | -0.020 | -0.040 | -0.042 | -0.014 |
| | (0.023) | (0.026) | (0.032) | (0.022) | (0.046) | (0.031) | (0.027) |
| | [-0.329] | [0.290] | [2.635] | [-0.925] | [-0.870] | [-1.347] | [-0.500] |
| LGOLD_F(-1) | 0.003 | 0.043 | 0.034 | 0.913 | 0.021 | -0.002 | 0.062 |
| | (0.028) | (0.032) | (0.039) | (0.026) | (0.056) | (0.038) | (0.033) |
| | [0.114] | [1.350] | [0.861] | [34.790] | [0.380] | [-0.065] | [1.890] |
| LGOLD_F(-2) | 0.001 | -0.026 | -0.013 | 0.070 | -0.035 | 0.009 | -0.071 |
| | (0.028) | (0.032) | (0.039) | (0.026) | (0.056) | (0.038) | (0.033) |
| | [0.046] | [-0.822] | [-0.342] | [2.690] | [-0.624] | [0.232] | [-2.163] |
| LPALLADIUM_F(-1) | 0.006 | -0.006 | 0.001 | -0.006 | 1.072 | 0.038 | 0.030 |
| | (0.013) | (0.014) | (0.018) | (0.012) | (0.025) | (0.017) | (0.015) |
| | [0.449] | [-0.400] | [0.047] | [-0.477] | [42.178] | [2.231] | [1.980] |
| LPALLADIUM_F(-2) | -0.004 | 0.011 | 0.004 | 0.002 | -0.077 | -0.040 | -0.032 |
| | (0.013) | (0.014) | (0.018) | (0.012) | (0.025) | (0.017) | (0.015) |
| | [-0.323] | [0.748] | [0.201] | [0.139] | [-3.027] | [-2.334] | [-2.162] |
| LPLATINUM_F(-1) | 0.000 | -0.005 | 0.022 | 0.028 | -0.018 | 0.902 | -0.028 |
| | (0.019) | (0.021) | (0.027) | (0.018) | (0.038) | (0.026) | (0.022) |

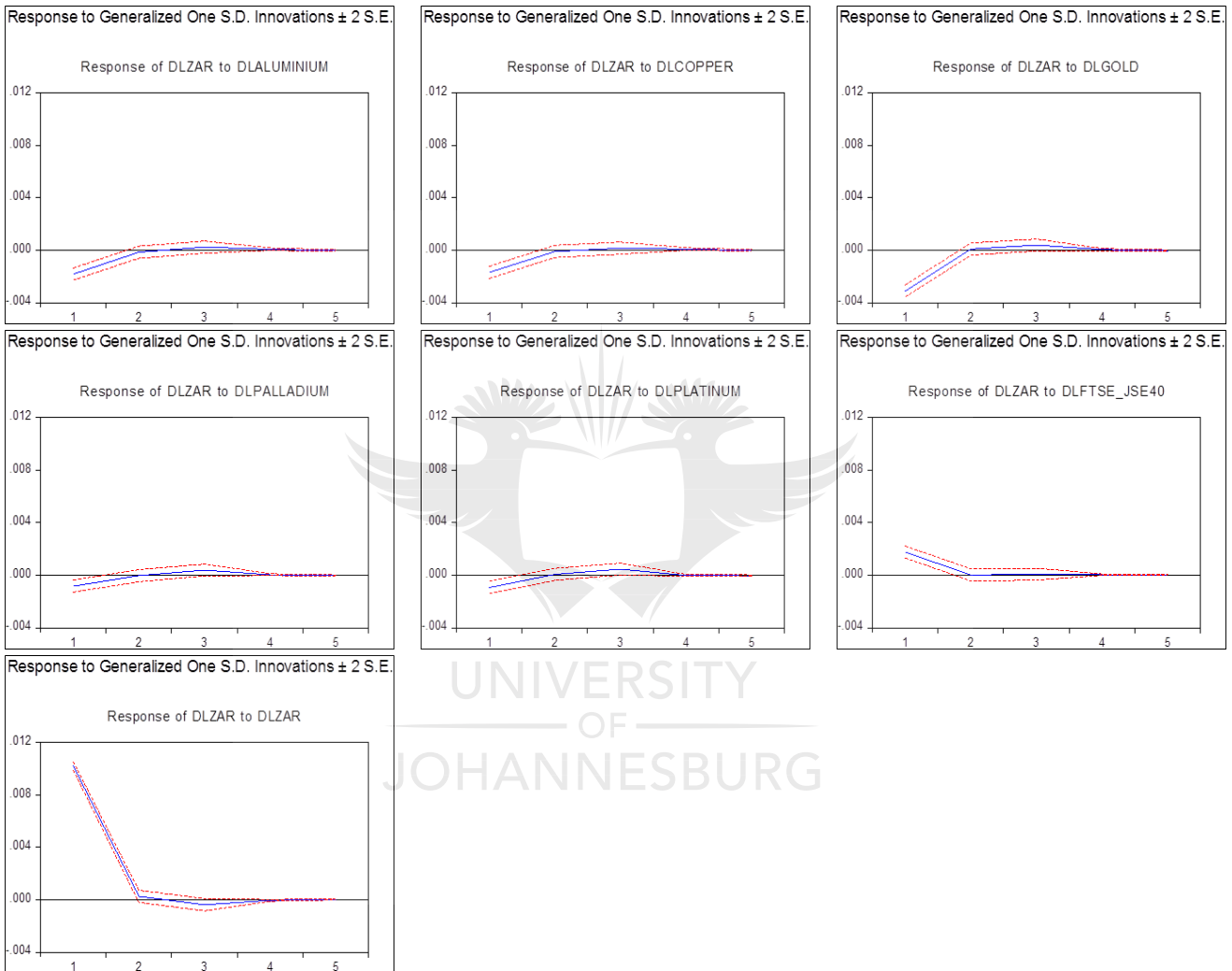
| | | | | | | | |
|---------------------|-----------|--------------|-----------|-----------|--------------|-------------|---------------|
| | [-0.009] | [-0.254] | [0.822] | [1.582] | [-0.469] | [35.251] | [-1.237] |
| LPLATINUM_F(-2) | -0.006 | 0.001 | -0.023 | -0.028 | 0.008 | 0.083 | 0.029 |
| | (0.019) | (0.021) | (0.027) | (0.018) | (0.038) | (0.026) | (0.022) |
| | [-0.317] | [0.057] | [-0.861] | [-1.595] | [0.216] | [3.237] | [1.297] |
| LFTSE_JSE40_F(-1) | 0.013 | 0.041 | 0.022 | 0.045 | -0.006 | -0.024 | 1.027 |
| | (0.021) | (0.023) | (0.029) | (0.019) | (0.041) | (0.028) | (0.024) |
| | [0.646] | [1.781] | [0.762] | [2.343] | [-0.147] | [-0.878] | [42.977] |
| LFTSE_JSE40_F(-2) | -0.012 | -0.025 | -0.005 | -0.038 | 0.010 | 0.025 | -0.034 |
| | (0.021) | (0.023) | (0.029) | (0.019) | (0.041) | (0.028) | (0.024) |
| | [-0.570] | [-1.096] | [-0.190] | [-1.997] | [0.252] | [0.912] | [-1.437] |
| C | 0.032 | 0.116 | 0.044 | 0.000 | 0.006 | 0.029 | 0.000 |
| | (0.026) | (0.029) | (0.036) | (0.024) | (0.051) | (0.035) | (0.030) |
| | [1.214] | [4.004] | [1.234] | [0.004] | [0.125] | [0.835] | [0.010] |
| R-squared | 0.996 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 | 0.999 |
| Adj. R-squared | 0.996 | 0.997 | 0.999 | 0.999 | 0.998 | 0.998 | 0.999 |
| Future after crisis | LZAR_F | LALUMINIUM_F | LCOPPER_F | LGOLD_F | LPALLADIUM_F | LPLATINUM_F | LFTSE_JSE40_F |
| LZAR_F(-1) | 1.040 | -0.133 | -0.138 | -0.085 | -0.220 | -0.171 | -0.111 |
| | (0.025) | (0.033) | (0.037) | (0.028) | (0.048) | (0.033) | (0.028) |
| | [40.844] | [-4.053] | [-3.677] | [-3.021] | [-4.604] | [-5.215] | [-3.977] |
| LZAR_F(-2) | -0.062 | 0.118 | 0.116 | 0.088 | 0.214 | 0.166 | 0.118 |
| | (0.025) | (0.033) | (0.038) | (0.028) | (0.048) | (0.033) | (0.028) |
| | [-2.444] | [3.569] | [3.094] | [3.108] | [4.477] | [5.058] | [4.242] |
| LALUMINIUM_F(-1) | 0.023 | 0.931 | -0.158 | -0.055 | -0.058 | -0.029 | -0.042 |
| | (0.025) | (0.032) | (0.036) | (0.027) | (0.046) | (0.032) | (0.027) |
| | [0.952] | [29.363] | [-4.370] | [-2.043] | [-1.262] | [-0.926] | [-1.579] |
| LALUMINIUM_F(-2) | -0.025 | 0.052 | 0.148 | 0.056 | 0.065 | 0.026 | 0.031 |
| | (0.025) | (0.032) | (0.036) | (0.027) | (0.046) | (0.032) | (0.027) |
| | [-1.031] | [1.624] | [4.089] | [2.053] | [1.405] | [0.823] | [1.156] |
| LCOPPER_F(-1) | 0.006 | -0.051 | 1.021 | 0.001 | 0.052 | 0.018 | 0.065 |
| | (0.023) | (0.030) | (0.034) | (0.025) | (0.043) | (0.030) | (0.025) |
| | [0.271] | [-1.711] | [30.250] | [0.020] | [1.205] | [0.624] | [2.584] |
| LCOPPER_F(-2) | -0.016 | 0.048 | -0.039 | 0.009 | -0.034 | -0.002 | -0.061 |
| | (0.023) | (0.030) | (0.034) | (0.025) | (0.043) | (0.030) | (0.025) |
| | [-0.696] | [1.605] | [-1.164] | [0.345] | [-0.799] | [-0.055] | [-2.436] |
| LGOLD_F(-1) | 0.007 | -0.029 | -0.059 | 0.938 | -0.131 | -0.061 | -0.042 |
| | (0.029) | (0.038) | (0.043) | (0.033) | (0.055) | (0.038) | (0.032) |
| | [0.244] | [-0.762] | [-1.357] | [28.821] | [-2.366] | [-1.607] | [-1.306] |
| LGOLD_F(-2) | -0.005 | 0.028 | 0.060 | 0.057 | 0.133 | 0.061 | 0.041 |
| | (0.029) | (0.038) | (0.043) | (0.033) | (0.055) | (0.038) | (0.032) |
| | [-0.159] | [0.725] | [1.377] | [1.766] | [2.415] | [1.601] | [1.277] |
| LPALLADIUM_F(-1) | -0.010 | 0.002 | 0.030 | 0.002 | 1.063 | 0.003 | 0.039 |
| | (0.018) | (0.023) | (0.027) | (0.020) | (0.034) | (0.023) | (0.020) |
| | [-0.572] | [0.091] | [1.135] | [0.111] | [31.163] | [0.128] | [1.977] |
| LPALLADIUM_F(-2) | 0.011 | -0.001 | -0.026 | -0.004 | -0.087 | -0.012 | -0.034 |
| | (0.018) | (0.023) | (0.027) | (0.020) | (0.034) | (0.023) | (0.020) |
| | [0.596] | [-0.062] | [-0.970] | [-0.205] | [-2.555] | [-0.519] | [-1.736] |
| LPLATINUM_F(-1) | 0.026 | 0.053 | -0.008 | 0.021 | -0.040 | 1.002 | -0.011 |
| | (0.031) | (0.040) | (0.046) | (0.035) | (0.059) | (0.040) | (0.034) |
| | [0.835] | [1.300] | [-0.184] | [0.597] | [-0.688] | [24.812] | [-0.310] |
| LPLATINUM_F(-2) | -0.030 | -0.056 | 0.004 | -0.028 | 0.034 | -0.015 | 0.011 |
| | (0.031) | (0.040) | (0.046) | (0.035) | (0.059) | (0.040) | (0.034) |
| | [-0.964] | [-1.386] | [0.076] | [-0.812] | [0.573] | [-0.380] | [0.315] |
| LFTSE_JSE40_F(-1) | -0.023 | 0.022 | -0.023 | 0.002 | 0.009 | 0.029 | 0.908 |
| | (0.024) | (0.031) | (0.035) | (0.027) | (0.045) | (0.031) | (0.026) |
| | [-0.946] | [0.722] | [-0.660] | [0.069] | [0.202] | [0.945] | [34.581] |
| LFTSE_JSE40_F(-2) | 0.037 | -0.021 | 0.023 | -0.006 | 0.013 | -0.023 | 0.077 |
| | (0.024) | (0.031) | (0.035) | (0.027) | (0.045) | (0.031) | (0.026) |
| | [1.548] | [-0.663] | [0.641] | [-0.215] | [0.282] | [-0.750] | [2.935] |
| C | 0.009 | 0.208 | 0.290 | 0.046 | -0.237 | -0.016 | 0.161 |
| | (0.061) | (0.079) | (0.090) | (0.068) | (0.115) | (0.079) | (0.067) |
| | [0.151] | [2.622] | [3.207] | [0.681] | [-2.053] | [-0.207] | [2.396] |
| R-squared | 0.999 | 0.993 | 0.995 | 0.995 | 0.992 | 0.996 | 0.998 |
| Adj. R-squared | 0.999 | 0.993 | 0.995 | 0.995 | 0.992 | 0.996 | 0.998 |

Note: Standard errors in () and t-statistics in []

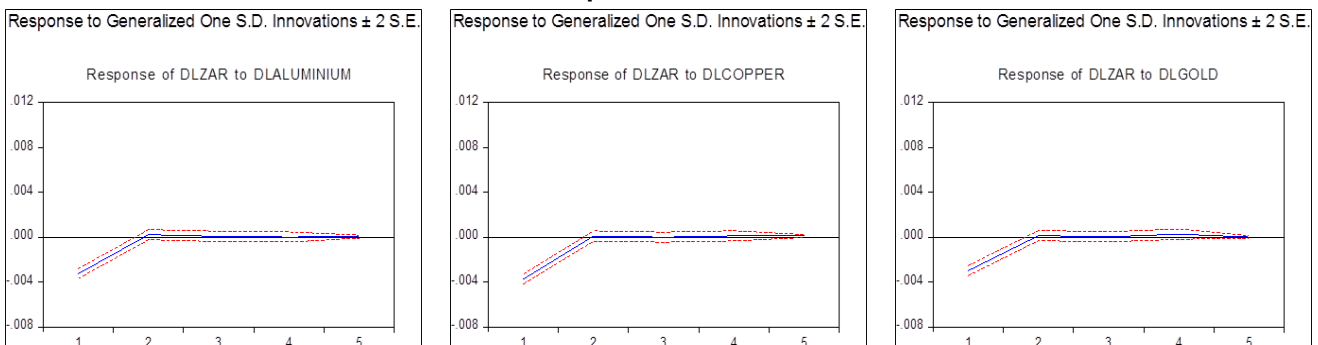
Source: Thomson Reuters DataStream and EViews.

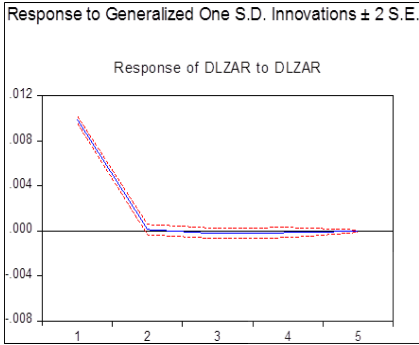
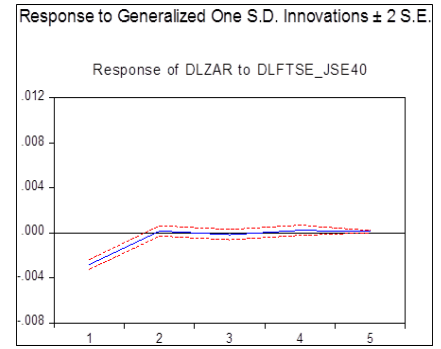
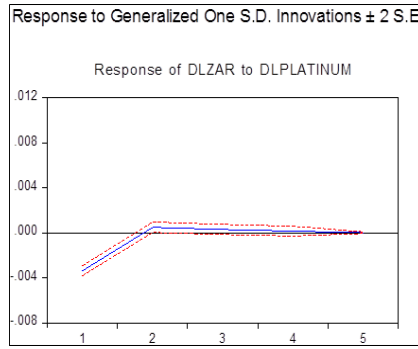
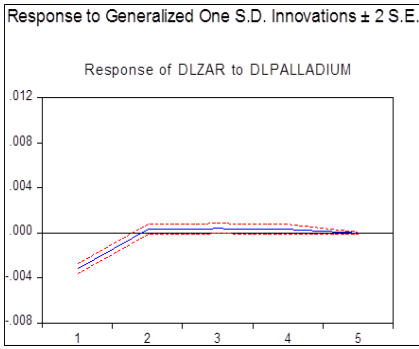
APPENDIX A.5: Impulse response functions and variance decompositions for ZAR, FTSE/JSE Top 40 Index and five metal commodities

Spot before crisis

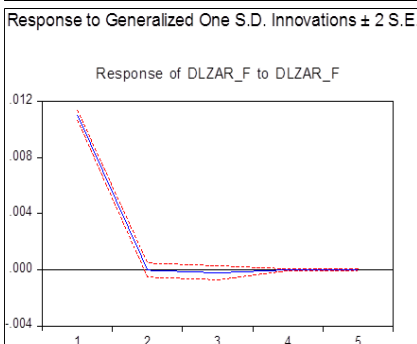
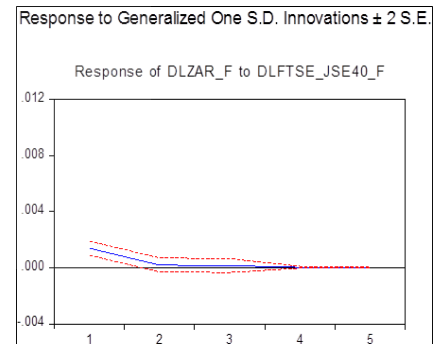
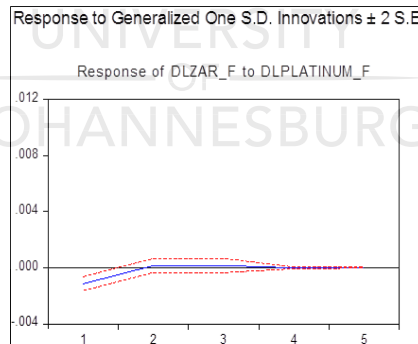
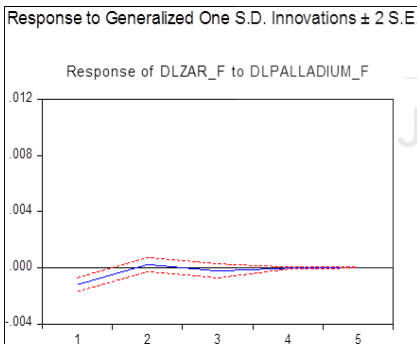
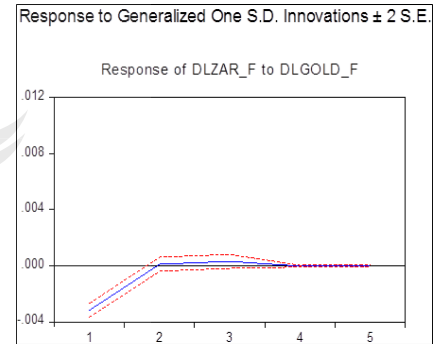
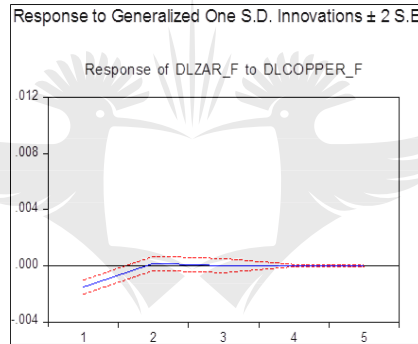
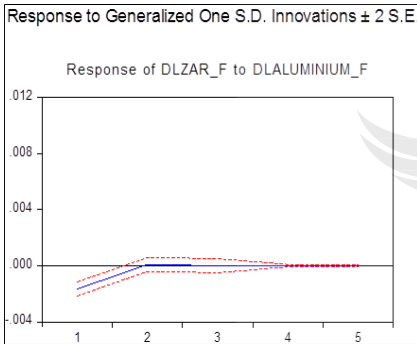


Spot after crisis





Future before crisis



Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLZAR | DLALUMINIUM | DLCOPPER | DLGOLD | DLPALLADIUM | DLPLATINUM | DLFTSE/JSE40 |
|-----------------------------|---------------|-------------|----------------|----------------------|-------------------|-----------------|----------------------|---------------------|-----------------------|
| DLZAR | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR | 5 | 0.010 | 99.685 | 0.029 | 0.017 | 0.050 | 0.027 | 0.179 | 0.012 |
| DLZAR | 10 | 0.010 | 99.685 | 0.029 | 0.017 | 0.050 | 0.027 | 0.179 | 0.012 |
| DLZAR | 20 | 0.010 | 99.685 | 0.029 | 0.017 | 0.050 | 0.027 | 0.179 | 0.012 |
| DLFTSE/JSE40 | 1 | 0.013 | 2.968 | 0.613 | 7.976 | 0.000 | 0.000 | 0.000 | 88.442 |
| DLFTSE/JSE40 | 5 | 0.013 | 2.978 | 0.948 | 8.573 | 0.181 | 0.125 | 0.008 | 87.187 |
| DLFTSE/JSE40 | 10 | 0.013 | 2.978 | 0.948 | 8.573 | 0.181 | 0.125 | 0.008 | 87.187 |
| DLFTSE/JSE40 | 20 | 0.013 | 2.978 | 0.948 | 8.573 | 0.181 | 0.125 | 0.008 | 87.187 |
| Spot after crisis | | | | | | | | | |
| DLZAR | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR | 5 | 0.010 | 99.158 | 0.079 | 0.019 | 0.079 | 0.294 | 0.233 | 0.139 |
| DLZAR | 10 | 0.010 | 99.155 | 0.079 | 0.020 | 0.079 | 0.294 | 0.234 | 0.139 |
| DLZAR | 20 | 0.010 | 99.155 | 0.079 | 0.020 | 0.079 | 0.294 | 0.234 | 0.139 |
| DLFTSE/JSE40 | 1 | 0.013 | 8.091 | 7.668 | 0.000 | 0.014 | 0.000 | 0.000 | 84.226 |
| DLFTSE/JSE40 | 5 | 0.013 | 8.331 | 7.617 | 0.572 | 0.119 | 0.285 | 0.094 | 82.982 |
| DLFTSE/JSE40 | 10 | 0.013 | 8.331 | 7.617 | 0.572 | 0.120 | 0.285 | 0.095 | 82.980 |
| DLFTSE/JSE40 | 20 | 0.013 | 8.331 | 7.617 | 0.572 | 0.120 | 0.285 | 0.095 | 82.980 |
| Future before crisis | Period | S.E. | DLZAR_F | DLALUMINIUM_F | DLCOPPER_F | DLGOLD_F | DLPALLADIUM_F | DLPLATINUM_F | DLFTSE_JSE40_F |
| DLZAR_F | 1 | 0.011 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR_F | 5 | 0.011 | 99.703 | 0.002 | 0.012 | 0.104 | 0.094 | 0.026 | 0.058 |
| DLZAR_F | 10 | 0.011 | 99.703 | 0.003 | 0.012 | 0.104 | 0.094 | 0.026 | 0.058 |
| DLZAR_F | 20 | 0.011 | 99.703 | 0.003 | 0.012 | 0.104 | 0.094 | 0.026 | 0.058 |
| DLFTSE/JSE40_F | 1 | 0.012 | 1.595 | 0.625 | 6.461 | 0.000 | 1.716 | 0.000 | 89.603 |
| DLFTSE/JSE40_F | 5 | 0.012 | 1.643 | 0.813 | 6.784 | 0.157 | 2.209 | 0.099 | 88.294 |

| | | | | | | | | | |
|---------------------|----|-------|---------|--------|-------|-------|-------|-------|--------|
| DLFTSE/JSE40_F | 10 | 0.012 | 1.643 | 0.813 | 6.784 | 0.157 | 2.209 | 0.099 | 88.294 |
| DLFTSE/JSE40_F | 20 | 0.012 | 1.643 | 0.813 | 6.784 | 0.157 | 2.209 | 0.099 | 88.294 |
| Future after crisis | | | | | | | | | |
| DLZAR_F | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR_F | 5 | 0.010 | 99.227 | 0.078 | 0.011 | 0.070 | 0.271 | 0.155 | 0.187 |
| DLZAR_F | 10 | 0.010 | 99.227 | 0.078 | 0.011 | 0.070 | 0.272 | 0.155 | 0.187 |
| DLZAR_F | 20 | 0.010 | 99.227 | 0.078 | 0.011 | 0.070 | 0.272 | 0.155 | 0.187 |
| DLFTSE/JSE40_F | 1 | 0.013 | 3.854 | 10.099 | 0.000 | 0.229 | 6.337 | 0.465 | 79.016 |
| DLFTSE/JSE40_F | 5 | 0.013 | 4.966 | 9.960 | 0.319 | 0.385 | 6.380 | 0.586 | 77.403 |
| DLFTSE/JSE40_F | 10 | 0.013 | 4.966 | 9.960 | 0.319 | 0.385 | 6.380 | 0.586 | 77.403 |
| DLFTSE/JSE40_F | 20 | 0.013 | 4.966 | 9.960 | 0.319 | 0.385 | 6.380 | 0.586 | 77.403 |

Cholesky ordering spot before crisis: DLLAHCASH DLGOLDBLN DLCOMRAN\$ DLJSEAL40 DLLCPCASH
DLPALLADM DLPLATFRE

Cholesky Ordering spot after crisis: DLZAR DLALUMINIUM DLGOLD DLFTSE_JSE40 DLCOPPER
DLPALLADIUM DLPLATINUM

Cholesky Ordering future before crisis: DLZAR_F DLPALLADIUM_F DLCOPPER_F DLALUMINIUM_F
DLFTSE_JSE40_F DLGOLD_F DLPLATINUM_F

Cholesky Ordering future after crisis: DLZAR_F DLGOLD_F DLALUMINIUM_F DLPALLADIUM_F
DLPLATINUM_F DLFTSE_JSE40_F DLCOPPER_F

Source: Thomson Reuters DataStream and EViews.



APPENDIX B.1: Pairwise Granger causality test and Toda Yamamoto test

| Spot before crisis Null Hypothesis: | Pairwise Granger causality test | | | Toda Yamamoto test | | |
|--|---------------------------------|-------------|----------|--------------------|----|----------|
| | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOTTON does not Granger Cause DLCORN | 1952 | 1.138 | 0.321 | 18.821 | 7 | 0.009*** |
| DLCORN does not Granger Cause DLCOTTON | | 1.057 | 0.348 | 12.453 | 7 | 0.087* |
| DLSOYABEAN does not Granger Cause DLCORN | 1952 | 3.037 | 0.048** | 6.051 | 2 | 0.049** |
| DLCORN does not Granger Cause DLSOYABEAN | | 1.010 | 0.365 | 2.152 | 2 | 0.341 |
| DLSUGAR does not Granger Cause DLCORN | 1952 | 2.396 | 0.091* | 4.758 | 2 | 0.093* |
| DLCORN does not Granger Cause DLSUGAR | | 0.735 | 0.480 | 1.454 | 2 | 0.483 |
| DLWHEAT does not Granger Cause DLCORN | 1952 | 0.286 | 0.751 | 0.420 | 1 | 0.517 |
| DLCORN does not Granger Cause DLWHEAT | | 1.969 | 0.140 | 1.672 | 1 | 0.196 |
| DLFTSE_JSE40 does not Granger Cause DLCORN | 1952 | 0.005 | 0.995 | 0.000 | 1 | 0.999 |
| DLCORN does not Granger Cause DLFTSE_JSE40 | | 0.155 | 0.856 | 0.158 | 1 | 0.691 |
| DLZAR does not Granger Cause DLCORN | 1952 | 0.881 | 0.414 | 1.555 | 1 | 0.213 |
| DLCORN does not Granger Cause DLZAR | | 2.132 | 0.119 | 4.294 | 1 | 0.038** |
| DLSOYABEAN does not Granger Cause DLCOTTON | 1952 | 0.008 | 0.992 | 8.943 | 5 | 0.111 |
| DLCOTTON does not Granger Cause DLSOYABEAN | | 2.706 | 0.067* | 9.972 | 5 | 0.076* |
| DLSUGAR does not Granger Cause DLCOTTON | 1952 | 0.568 | 0.567 | 1.162 | 4 | 0.884 |
| DLCOTTON does not Granger Cause DLSUGAR | | 0.019 | 0.981 | 1.605 | 4 | 0.808 |
| DLWHEAT does not Granger Cause DLCOTTON | 1952 | 0.132 | 0.876 | 1.878 | 4 | 0.758 |
| DLCOTTON does not Granger Cause DLWHEAT | | 1.234 | 0.291 | 4.848 | 4 | 0.303 |
| DLFTSE_JSE40 does not Granger Cause DLCOTTON | 1952 | 0.992 | 0.371 | 2.616 | 4 | 0.624 |
| DLCOTTON does not Granger Cause DLFTSE_JSE40 | | 0.838 | 0.433 | 2.453 | 4 | 0.653 |
| DLZAR does not Granger Cause DLCOTTON | 1952 | 0.688 | 0.503 | 7.127 | 4 | 0.129 |
| DLCOTTON does not Granger Cause DLZAR | | 5.147 | 0.006*** | 10.244 | 4 | 0.037** |
| DLSUGAR does not Granger Cause DLSOYABEAN | 1952 | 0.840 | 0.432 | 1.706 | 2 | 0.426 |
| DLSOYABEAN does not Granger Cause DLSUGAR | | 1.371 | 0.254 | 2.685 | 2 | 0.261 |
| DLWHEAT does not Granger Cause DLSOYABEAN | 1952 | 0.204 | 0.816 | 0.236 | 2 | 0.889 |
| DLSOYABEAN does not Granger Cause DLWHEAT | | 0.628 | 0.534 | 1.153 | 2 | 0.562 |
| DLFTSE_JSE40 does not Granger Cause DLSOYABEAN | 1952 | 0.080 | 0.923 | 0.177 | 2 | 0.916 |
| DLSOYABEAN does not Granger Cause DLFTSE_JSE40 | | 0.095 | 0.909 | 0.170 | 2 | 0.919 |
| DLZAR does not Granger Cause DLSOYABEAN | 1952 | 0.259 | 0.772 | 0.578 | 2 | 0.749 |
| DLSOYABEAN does not Granger Cause DLZAR | | 1.317 | 0.268 | 2.823 | 2 | 0.244 |
| DLWHEAT does not Granger Cause DLSUGAR | 1952 | 0.579 | 0.560 | 1.129 | 2 | 0.569 |
| DLSUGAR does not Granger Cause DLWHEAT | | 0.282 | 0.755 | 0.542 | 2 | 0.763 |
| DLFTSE_JSE40 does not Granger Cause DLSUGAR | 1952 | 1.478 | 0.229 | 3.209 | 2 | 0.201 |
| DLSUGAR does not Granger Cause DLFTSE_JSE40 | | 0.244 | 0.784 | 0.387 | 2 | 0.824 |
| DLZAR does not Granger Cause DLSUGAR | 1952 | 2.886 | 0.056* | 13.485 | 6 | 0.036** |
| DLSUGAR does not Granger Cause DLZAR | | 0.497 | 0.608 | 5.731 | 6 | 0.454 |
| DLFTSE_JSE40 does not Granger Cause DLWHEAT | 1952 | 0.501 | 0.606 | 0.949 | 2 | 0.622 |
| DLWHEAT does not Granger Cause DLFTSE_JSE40 | | 0.124 | 0.884 | 0.186 | 2 | 0.911 |
| DLZAR does not Granger Cause DLWHEAT | 1952 | 0.613 | 0.542 | 1.117 | 2 | 0.572 |
| DLWHEAT does not Granger Cause DLZAR | | 0.269 | 0.765 | 0.678 | 2 | 0.713 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1952 | 0.278 | 0.758 | 0.490 | 1 | 0.484 |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 0.206 | 0.814 | 0.010 | 1 | 0.921 |
| | | | | | | |
| Spot after crisis Null Hypothesis: | | | | | | |
| | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOTTON does not Granger Cause DLCORN | 1892 | 0.620 | 0.538 | 1.150 | 1 | 0.284 |
| DLCORN does not Granger Cause DLCOTTON | | 2.092 | 0.124 | 3.368 | 1 | 0.067* |
| DLSOYABEAN does not Granger Cause DLCORN | 1892 | 2.607 | 0.074* | 6.271 | 3 | 0.099* |
| DLCORN does not Granger Cause DLSOYABEAN | | 3.806 | 0.022** | 11.893 | 3 | 0.008*** |
| DLSUGAR does not Granger Cause DLCORN | 1892 | 0.978 | 0.376 | 2.226 | 2 | 0.329 |
| DLCORN does not Granger Cause DLSUGAR | | 8.013 | 0.000*** | 16.729 | 2 | 0.000*** |
| DLWHEAT does not Granger Cause DLCORN | 1892 | 0.214 | 0.807 | 0.526 | 2 | 0.769 |
| DLCORN does not Granger Cause DLWHEAT | | 2.688 | 0.068* | 6.676 | 2 | 0.036** |
| DLFTSE_JSE40 does not Granger Cause DLCORN | 1892 | 0.419 | 0.658 | 0.878 | 3 | 0.831 |

| | | | | | | |
|--|------------|--------------------|--------------|---------------|-----------|--------------|
| DLCORN does not Granger Cause DLFTSE_JSE40 | | 3.763 | 0.023** | 7.541 | 3 | 0.057* |
| DLZAR does not Granger Cause DLCORN | 1892 | 0.384 | 0.681 | 0.169 | 1 | 0.681 |
| DLCORN does not Granger Cause DLZAR | | 1.682 | 0.186 | 2.375 | 1 | 0.123 |
| DLSOYABEAN does not Granger Cause DLCOTTON | 1892 | 1.276 | 0.279 | 2.525 | 2 | 0.283 |
| DLCOTTON does not Granger Cause DLSOYABEAN | | 2.654 | 0.071* | 5.298 | 2 | 0.071* |
| DLSUGAR does not Granger Cause DLCOTTON | 1892 | 1.209 | 0.299 | 2.822 | 2 | 0.244 |
| DLCOTTON does not Granger Cause DLSUGAR | | 2.467 | 0.085* | 5.462 | 2 | 0.065* |
| DLWHEAT does not Granger Cause DLCOTTON | 1892 | 0.163 | 0.850 | 0.347 | 2 | 0.841 |
| DLCOTTON does not Granger Cause DLWHEAT | | 2.894 | 0.056* | 5.927 | 2 | 0.052* |
| DLFTSE_JSE40 does not Granger Cause DLCOTTON | 1892 | 0.436 | 0.647 | 0.485 | 1 | 0.486 |
| DLCOTTON does not Granger Cause DLFTSE_JSE40 | | 0.694 | 0.500 | 0.895 | 1 | 0.344 |
| DLZAR does not Granger Cause DLCOTTON | 1892 | 0.331 | 0.719 | 0.513 | 1 | 0.474 |
| DLCOTTON does not Granger Cause DLZAR | | 0.718 | 0.488 | 1.217 | 1 | 0.270 |
| DLSUGAR does not Granger Cause DLSOYABEAN | 1892 | 2.537 | 0.079* | 12.567 | 6 | 0.051* |
| DLSOYABEAN does not Granger Cause DLSUGAR | | 2.966 | 0.052* | 17.817 | 6 | 0.007*** |
| DLWHEAT does not Granger Cause DLSOYABEAN | 1892 | 2.536 | 0.080* | 18.200 | 5 | 0.003*** |
| DLSOYABEAN does not Granger Cause DLWHEAT | | 1.168 | 0.311 | 10.243 | 5 | 0.069* |
| DLFTSE_JSE40 does not Granger Cause DLSOYABEAN | 1892 | 1.139 | 0.320 | 3.250 | 3 | 0.355 |
| DLSOYABEAN does not Granger Cause DLFTSE_JSE40 | | 3.862 | 0.021** | 7.936 | 3 | 0.047** |
| DLZAR does not Granger Cause DLSOYABEAN | 1892 | 0.963 | 0.382 | 1.480 | 1 | 0.224 |
| DLSOYABEAN does not Granger Cause DLZAR | | 0.383 | 0.682 | 0.513 | 1 | 0.474 |
| DLWHEAT does not Granger Cause DLSUGAR | 1892 | 1.705 | 0.182 | 3.774 | 2 | 0.152 |
| DLSUGAR does not Granger Cause DLWHEAT | | 0.462 | 0.630 | 1.080 | 2 | 0.583 |
| DLFTSE_JSE40 does not Granger Cause DLSUGAR | 1892 | 0.004 | 0.996 | 7.088 | 4 | 0.131 |
| DLSUGAR does not Granger Cause DLFTSE_JSE40 | | 1.793 | 0.167 | 5.079 | 4 | 0.279 |
| DLZAR does not Granger Cause DLSUGAR | 1892 | 2.010 | 0.134 | 0.213 | 1 | 0.644 |
| DLSUGAR does not Granger Cause DLZAR | | 0.586 | 0.557 | 0.374 | 1 | 0.541 |
| DLFTSE_JSE40 does not Granger Cause DLWHEAT | 1892 | 0.045 | 0.956 | 0.626 | 3 | 0.890 |
| DLWHEAT does not Granger Cause DLFTSE_JSE40 | | 0.612 | 0.542 | 2.137 | 3 | 0.544 |
| DLZAR does not Granger Cause DLWHEAT | 1892 | 0.225 | 0.799 | 0.263 | 1 | 0.608 |
| DLWHEAT does not Granger Cause DLZAR | | 1.011 | 0.364 | 0.197 | 1 | 0.657 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1892 | 6.842 | 0.001*** | 12.491 | 3 | 0.006*** |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 1.024 | 0.359 | 2.989 | 3 | 0.393 |
| | | | | | | |
| Future before Crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOTTON_F does not Granger Cause DLCORN_F | 1952 | 0.976 | 0.377 | 0.004 | 1 | 0.947 |
| DLCORN_F does not Granger Cause DLCOTTON_F | | 0.808 | 0.446 | 0.010 | 1 | 0.920 |
| DLSOYABEAN_F does not Granger Cause DLCORN_F | 1952 | 3.916 | 0.020** | 7.783 | 2 | 0.020** |
| DLCORN_F does not Granger Cause DLSOYABEAN_F | | 2.162 | 0.115 | 4.231 | 2 | 0.121 |
| DLSUGAR_F does not Granger Cause DLCORN_F | 1952 | 0.026 | 0.974 | 0.057 | 2 | 0.972 |
| DLCORN_F does not Granger Cause DLSUGAR_F | | 2.846 | 0.058* | 5.663 | 2 | 0.059* |
| DLWHEAT_F does not Granger Cause DLCORN_F | 1952 | 2.348 | 0.096* | 4.072 | 2 | 0.131 |
| DLCORN_F does not Granger Cause DLWHEAT_F | | 1.169 | 0.311 | 2.585 | 2 | 0.275 |
| DLFTSE_JSE40_F does not Granger Cause DLCORN_F | 1952 | 0.417 | 0.659 | 0.739 | 2 | 0.691 |
| DLCORN_F does not Granger Cause DLFTSE_JSE40_F | | 0.244 | 0.784 | 0.367 | 2 | 0.832 |
| DLZAR_F does not Granger Cause DLCORN_F | 1952 | 0.184 | 0.832 | 0.152 | 1 | 0.697 |
| DLCORN_F does not Granger Cause DLZAR_F | | 0.503 | 0.605 | 0.932 | 1 | 0.334 |
| DLSOYABEAN_F does not Granger Cause DLCOTTON_F | 1952 | 1.184 | 0.306 | 1.511 | 1 | 0.219 |
| DLCOTTON_F does not Granger Cause DLSOYABEAN_F | | 4.056 | 0.018** | 2.895 | 1 | 0.089* |
| DLSUGAR_F does not Granger Cause DLCOTTON_F | 1952 | 2.430 | 0.088* | 2.155 | 1 | 0.142 |
| DLCOTTON_F does not Granger Cause DLSUGAR_F | | 0.480 | 0.619 | 0.076 | 1 | 0.783 |
| DLWHEAT_F does not Granger Cause DLCOTTON_F | 1952 | 2.025 | 0.132 | 2.268 | 1 | 0.132 |
| DLCOTTON_F does not Granger Cause DLWHEAT_F | | 0.607 | 0.545 | 0.540 | 1 | 0.463 |
| DLFTSE_JSE40_F does not Granger Cause DLCOTTON_F | 1952 | 0.339 | 0.713 | 0.029 | 1 | 0.864 |
| DLCOTTON_F does not Granger Cause DLFTSE_JSE40_F | | 0.662 | 0.516 | 0.900 | 1 | 0.343 |
| DLZAR_F does not Granger Cause DLCOTTON_F | 1952 | 1.754 | 0.173 | 3.306 | 1 | 0.069* |
| DLCOTTON_F does not Granger Cause DLZAR_F | | 1.593 | 0.204 | 3.547 | 1 | 0.060* |
| DLSUGAR_F does not Granger Cause DLSOYABEAN_F | 1952 | 0.653 | 0.521 | 1.402 | 2 | 0.496 |
| DLSOYABEAN_F does not Granger Cause DLSUGAR_F | | 0.270 | 0.764 | 0.456 | 2 | 0.796 |
| DLWHEAT_F does not Granger Cause DLSOYABEAN_F | 1952 | 3.704 | 0.025** | 6.893 | 2 | 0.032** |
| DLSOYABEAN_F does not Granger Cause DLWHEAT_F | | 2.462 | 0.086* | 4.786 | 2 | 0.091* |
| DLFTSE_JSE40_F does not Granger Cause DLSOYABEAN_F | 1952 | 0.254 | 0.775 | 0.584 | 1 | 0.445 |
| DLSOYABEAN_F does not Granger Cause DLFTSE_JSE40_F | | 0.525 | 0.592 | 0.322 | 1 | 0.571 |
| DLZAR_F does not Granger Cause DLSOYABEAN_F | 1952 | 1.716 | 0.180 | 0.010 | 1 | 0.922 |

| | | | | | | |
|--|------|-------------|----------|--------|----|----------|
| DLWOYABEAN_F does not Granger Cause DLZAR_F | | 0.418 | 0.659 | 0.712 | 1 | 0.399 |
| DLWHEAT_F does not Granger Cause DLSUGAR_F | 1952 | 9.575 | 0.000*** | 19.137 | 2 | 0.000*** |
| DLSUGAR_F does not Granger Cause DLWHEAT_F | | 0.543 | 0.581 | 1.098 | 2 | 0.577 |
| DLFTSE_JSE40_F does not Granger Cause DLSUGAR_F | 1952 | 0.201 | 0.818 | 0.501 | 2 | 0.778 |
| DLSUGAR_F does not Granger Cause DLFTSE_JSE40_F | | 0.271 | 0.763 | 0.648 | 2 | 0.723 |
| DLZAR_F does not Granger Cause DLSUGAR_F | 1952 | 7.819 | 0.000*** | 20.711 | 6 | 0.002*** |
| DLSUGAR_F does not Granger Cause DLZAR_F | | 1.263 | 0.283 | 11.013 | 6 | 0.088* |
| DLFTSE_JSE40_F does not Granger Cause DLWHEAT_F | 1952 | 0.313 | 0.732 | 0.113 | 1 | 0.737 |
| DLWHEAT_F does not Granger Cause DLFTSE_JSE40_F | | 0.411 | 0.663 | 0.576 | 1 | 0.448 |
| DLZAR_F does not Granger Cause DLWHEAT_F | 1952 | 0.488 | 0.614 | 0.059 | 1 | 0.809 |
| DLWHEAT_F does not Granger Cause DLZAR_F | | 0.592 | 0.553 | 0.252 | 1 | 0.616 |
| DLZAR_F does not Granger Cause DLFTSE_JSE40_F | 1952 | 0.420 | 0.657 | 0.692 | 1 | 0.406 |
| DLFTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.522 | 0.594 | 0.534 | 1 | 0.465 |
| | | | | | | |
| Future after crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLCOTTON_F does not Granger Cause DLCORN_F | 1892 | 1.193 | 0.304 | 2.414 | 2 | 0.299 |
| DLCORN_F does not Granger Cause DLCOTTON_F | | 6.301 | 0.002*** | 12.753 | 2 | 0.002*** |
| DLSOYABEAN_F does not Granger Cause DLCORN_F | 1892 | 0.327 | 0.721 | 0.628 | 1 | 0.428 |
| DLCORN_F does not Granger Cause DLSOYABEAN_F | | 0.032 | 0.969 | 0.008 | 1 | 0.928 |
| DLSUGAR_F does not Granger Cause DLCORN_F | 1892 | 1.617 | 0.199 | 3.314 | 1 | 0.069* |
| DLCORN_F does not Granger Cause DLSUGAR_F | | 0.566 | 0.568 | 0.794 | 1 | 0.373 |
| DLWHEAT_F does not Granger Cause DLCORN_F | 1892 | 0.330 | 0.719 | 0.237 | 1 | 0.626 |
| DLCORN_F does not Granger Cause DLWHEAT_F | | 0.413 | 0.662 | 0.275 | 1 | 0.600 |
| DLFTSE_JSE40_F does not Granger Cause DLCORN_F | 1892 | 1.030 | 0.357 | 2.196 | 3 | 0.533 |
| DLCORN_F does not Granger Cause DLFTSE_JSE40_F | | 5.142 | 0.006*** | 10.254 | 3 | 0.017** |
| DLZAR_F does not Granger Cause DLCORN_F | 1892 | 1.041 | 0.353 | 0.001 | 1 | 0.970 |
| DLCORN_F does not Granger Cause DLZAR_F | | 1.198 | 0.302 | 1.295 | 1 | 0.255 |
| DLSOYABEAN_F does not Granger Cause DLCOTTON_F | 1892 | 0.941 | 0.390 | 1.885 | 2 | 0.390 |
| DLCOTTON_F does not Granger Cause DLSOYABEAN_F | | 1.863 | 0.156 | 3.764 | 2 | 0.152 |
| DLSUGAR_F does not Granger Cause DLCOTTON_F | 1892 | 2.635 | 0.072* | 5.663 | 2 | 0.059* |
| DLCOTTON_F does not Granger Cause DLSUGAR_F | | 1.779 | 0.169 | 3.297 | 2 | 0.192 |
| DLWHEAT_F does not Granger Cause DLCOTTON_F | 1892 | 2.414 | 0.090* | 4.909 | 2 | 0.086* |
| DLCOTTON_F does not Granger Cause DLWHEAT_F | | 0.894 | 0.409 | 1.780 | 2 | 0.411 |
| DLFTSE_JSE40_F does not Granger Cause DLCOTTON_F | 1892 | 0.257 | 0.773 | 1.164 | 3 | 0.762 |
| DLCOTTON_F does not Granger Cause DLFTSE_JSE40_F | | 0.546 | 0.579 | 1.647 | 3 | 0.649 |
| DLZAR_F does not Granger Cause DLCOTTON_F | 1892 | 1.016 | 0.362 | 2.001 | 2 | 0.368 |
| DLCOTTON_F does not Granger Cause DLZAR_F | | 0.258 | 0.772 | 0.587 | 2 | 0.746 |
| DLSUGAR_F does not Granger Cause DLSOYABEAN_F | 1892 | 1.445 | 0.236 | 3.043 | 1 | 0.081* |
| DLSOYABEAN_F does not Granger Cause DLSUGAR_F | | 1.228 | 0.293 | 2.127 | 1 | 0.145 |
| DLWHEAT_F does not Granger Cause DLSOYABEAN_F | 1892 | 0.139 | 0.870 | 0.147 | 1 | 0.701 |
| DLSOYABEAN_F does not Granger Cause DLWHEAT_F | | 0.561 | 0.571 | 0.106 | 1 | 0.744 |
| DLFTSE_JSE40_F does not Granger Cause DLSOYABEAN_F | 1892 | 0.239 | 0.787 | 1.518 | 3 | 0.678 |
| DLSOYABEAN_F does not Granger Cause DLFTSE_JSE40_F | | 2.129 | 0.119 | 4.241 | 3 | 0.237 |
| DLZAR_F does not Granger Cause DLSOYABEAN_F | 1892 | 0.220 | 0.803 | 0.235 | 1 | 0.628 |
| DLSOYABEAN_F does not Granger Cause DLZAR_F | | 0.076 | 0.927 | 0.056 | 1 | 0.814 |
| DLWHEAT_F does not Granger Cause DLSUGAR_F | 1892 | 0.972 | 0.379 | 0.203 | 1 | 0.652 |
| DLSUGAR_F does not Granger Cause DLWHEAT_F | | 1.499 | 0.224 | 2.829 | 1 | 0.093* |
| DLFTSE_JSE40_F does not Granger Cause DLSUGAR_F | 1892 | 0.264 | 0.768 | 0.624 | 1 | 0.430 |
| DLSUGAR_F does not Granger Cause DLFTSE_JSE40_F | | 1.240 | 0.290 | 1.868 | 1 | 0.172 |
| DLZAR_F does not Granger Cause DLSUGAR_F | 1892 | 1.476 | 0.229 | 1.235 | 1 | 0.266 |
| DLSUGAR_F does not Granger Cause DLZAR_F | | 0.362 | 0.696 | 0.004 | 1 | 0.947 |
| DLFTSE_JSE40_F does not Granger Cause DLWHEAT_F | 1892 | 0.086 | 0.917 | 0.001 | 1 | 0.974 |
| DLWHEAT_F does not Granger Cause DLFTSE_JSE40_F | | 2.994 | 0.050** | 5.110 | 1 | 0.024** |
| DLZAR_F does not Granger Cause DLWHEAT_F | 1892 | 0.052 | 0.950 | 0.040 | 1 | 0.842 |
| DLWHEAT_F does not Granger Cause DLZAR_F | | 1.248 | 0.287 | 0.000 | 1 | 0.999 |
| DLZAR_F does not Granger Cause DLFTSE_JSE40_F | 1892 | 14.808 | 0.000*** | 28.011 | 3 | 0.000*** |
| DLFTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.491 | 0.612 | 1.345 | 3 | 0.719 |

, **, * indicate significance at a 10%, 5% and 1% level of significance respectively*

Source: Thomson Reuters DataStream and EViews.

APPENDIX B.2: VAR FTSE/JSE Top 40 Index and five soft commodities

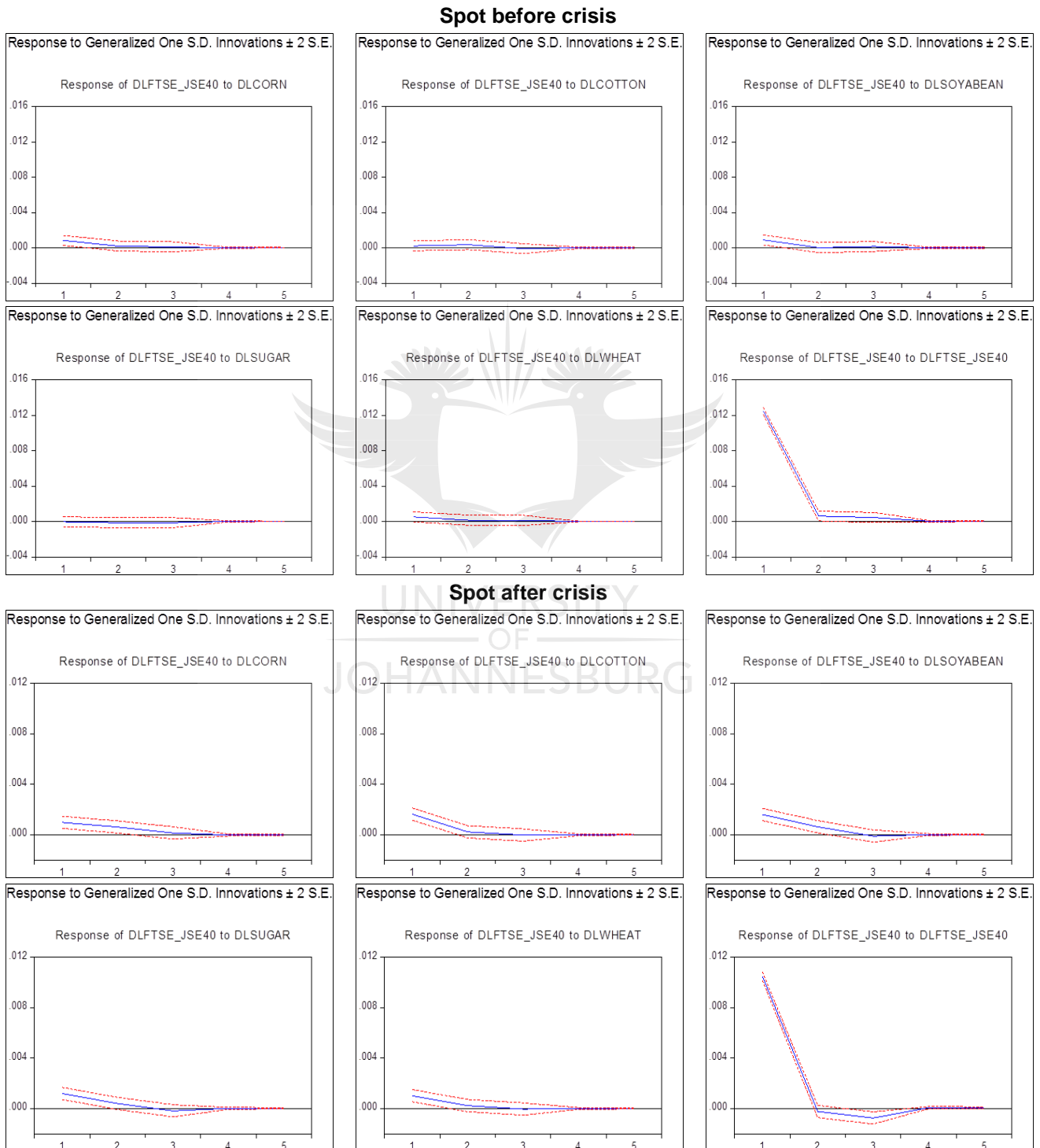
| Spot before crisis | LFTSE_JSE40 | LCORN | LCOTTON | LSOYABEAN | LSUGAR | LWHEAT |
|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| LFTSE_JSE40(-1) | 1.049 (0.023) | 0.004 (0.031) | -0.028 (0.038) | -0.009 (0.028) | 0.042 (0.041) | 0.038 (0.037) |
| | [46.143] | [0.132] | [-0.733] | [-0.321] | [1.024] | [1.023] |
| LFTSE_JSE40(-2) | -0.049 (0.023) | 0.002 (0.031) | 0.031 (0.038) | 0.016 (0.028) | -0.037 (0.041) | -0.029 (0.038) |
| | [-2.163] | [0.066] | [0.802] | [0.555] | [-0.919] | [-0.774] |
| LCORN(-1) | 0.008 (0.021) | 1.022 (0.028) | 0.054 (0.035) | 0.044 (0.026) | -0.005 (0.037) | 0.063 (0.034) |
| | [0.381] | [36.608] | [1.555] | [1.719] | [-0.144] | [1.838] |
| LCORN(-2) | -0.010 (0.021) | -0.029 (0.028) | -0.057 (0.035) | -0.046 (0.026) | -0.002 (0.037) | -0.062 (0.034) |
| | [-0.481] | [-1.035] | [-1.633] | [-1.784] | [-0.067] | [-1.833] |
| LCOTTON(-1) | 0.017 (0.014) | -0.026 (0.018) | 0.886 (0.023) | 0.000 (0.017) | -0.004 (0.024) | 0.024 (0.022) |
| | [1.257] | [-1.419] | [38.818] | [-0.022] | [-0.178] | [1.068] |
| LCOTTON(-2) | -0.018 (0.014) | 0.031 (0.018) | 0.111 (0.023) | 0.010 (0.017) | 0.009 (0.024) | -0.022 (0.022) |
| | [-1.300] | [1.710] | [4.826] | [0.573] | [0.356] | [-0.981] |
| LSOYABEAN(-1) | -0.011 (0.021) | -0.049 (0.028) | -0.023 (0.035) | 0.898 (0.026) | 0.053 (0.038) | -0.069 (0.035) |
| | [-0.528] | [-1.711] | [-0.648] | [34.146] | [1.420] | [-2.002] |
| LSOYABEAN(-2) | 0.012 (0.021) | 0.041 (0.028) | 0.023 (0.035) | 0.086 (0.026) | -0.051 (0.037) | 0.069 (0.035) |
| | [0.555] | [1.452] | [0.638] | [3.291] | [-1.363] | [1.999] |
| LSUGAR(-1) | -0.005 (0.013) | 0.037 (0.017) | -0.013 (0.021) | 0.012 (0.016) | 0.859 (0.023) | 0.014 (0.021) |
| | [-0.393] | [2.193] | [-0.590] | [0.786] | [38.124] | [0.655] |
| LSUGAR(-2) | 0.006 (0.013) | -0.043 (0.017) | 0.009 (0.021) | -0.022 (0.016) | 0.134 (0.023) | -0.021 (0.021) |
| | [0.491] | [-2.528] | [0.406] | [-1.371] | [5.945] | [-0.998] |
| LWHEAT(-1) | 0.004 (0.016) | -0.014 (0.021) | -0.004 (0.026) | -0.021 (0.019) | -0.004 (0.028) | 0.921 (0.026) |
| | [0.259] | [-0.676] | [-0.170] | [-1.076] | [-0.130] | [35.933] |
| LWHEAT(-2) | -0.003 (0.016) | 0.019 (0.021) | 0.006 (0.026) | 0.028 (0.019) | 0.003 (0.028) | 0.066 (0.026) |
| | [-0.180] | [0.892] | [0.235] | [1.435] | [0.116] | [2.568] |
| C | -0.002 (0.011) | -0.026 (0.014) | -0.018 (0.018) | -0.014 (0.013) | -0.019 (0.019) | -0.053 (0.017) |
| | [-0.182] | [-1.859] | [-1.040] | [-1.091] | [-1.017] | [-3.075] |
| R-squared | 0.999 | 0.994 | 0.989 | 0.994 | 0.994 | 0.990 |
| Adj. R-squared | 0.999 | 0.994 | 0.989 | 0.994 | 0.994 | 0.990 |
| Spot after crisis | LFTSE_JSE40 | LCORN | LCOTTON | LSOYABEAN | LSUGAR | LWHEAT |
| LFTSE_JSE40(-1) | 0.962 (0.024) | -0.045 (0.040) | 0.021 (0.041) | -0.033 (0.033) | -0.020 (0.043) | -0.033 (0.054) |
| | [40.870] | [-1.117] | [0.507] | [-0.993] | [-0.466] | [-0.607] |
| LFTSE_JSE40(-2) | 0.035 (0.024) | 0.040 (0.040) | -0.025 (0.041) | 0.031 (0.033) | 0.017 (0.043) | 0.023 (0.054) |
| | [1.472] | [0.993] | [-0.608] | [0.955] | [0.397] | [0.437] |
| LCORN(-1) | 0.023 (0.018) | 1.000 (0.030) | 0.042 (0.031) | 0.030 (0.025) | 0.094 (0.032) | 0.107 (0.041) |
| | [1.278] | [32.980] | [1.345] | [1.218] | [2.929] | [2.635] |
| LCORN(-2) | -0.024 (0.018) | -0.005 (0.030) | -0.048 (0.031) | -0.028 (0.025) | -0.094 (0.032) | -0.104 (0.041) |
| | [-1.333] | [-0.175] | [-1.550] | [-1.130] | [-2.933] | [-2.565] |
| LCOTTON(-1) | 0.003 (0.014) | 0.021 (0.023) | 0.994 (0.024) | 0.034 (0.019) | 0.042 (0.025) | 0.071 (0.031) |
| | [0.247] | [0.914] | [41.651] | [1.785] | [1.705] | [2.271] |
| LCOTTON(-2) | -0.005 (0.014) | -0.023 (0.023) | -0.001 (0.024) | -0.036 (0.019) | -0.040 (0.025) | -0.072 (0.031) |
| | [-0.371] | [-0.970] | [-0.058] | [-1.898] | [-1.620] | [-2.298] |
| LSOYABEAN(-1) | 0.031 (0.020) | -0.023 (0.033) | -0.007 (0.034) | 0.922 (0.027) | -0.019 (0.035) | -0.079 (0.045) |
| | [1.592] | [-0.696] | [-0.196] | [33.853] | [-0.543] | [-1.777] |
| LSOYABEAN(-2) | -0.031 (0.020) | 0.013 (0.033) | 0.000 (0.034) | 0.064 (0.027) | 0.017 (0.035) | 0.086 (0.045) |
| | [-1.571] | [0.402] | [-0.010] | [2.352] | [0.495] | [1.935] |
| LSUGAR(-1) | 0.018 (0.013) | 0.020 (0.022) | 0.028 (0.022) | 0.030 (0.018) | 0.930 (0.023) | 0.020 (0.030) |
| | [1.398] | [0.888] | [1.247] | [1.667] | [39.640] | [0.673] |
| LSUGAR(-2) | -0.019 (0.013) | -0.017 (0.022) | -0.022 (0.023) | -0.028 (0.018) | 0.063 (0.023) | -0.023 (0.030) |
| | [-1.439] | [-0.786] | [-0.995] | [-1.531] | [2.667] | [-0.795] |
| LWHEAT(-1) | -0.006 | 0.010 | -0.008 | 0.021 | -0.005 | 0.903 |

| | | | | | | |
|----------------------|---------------|------------|------------|-------------|------------|------------|
| | (0.012) | (0.021) | (0.021) | (0.017) | (0.022) | (0.027) |
| | [-0.510] | [0.511] | [-0.362] | [1.272] | [-0.220] | [32.850] |
| LWHEAT(-2) | 0.008 | -0.001 | 0.020 | -0.014 | 0.006 | 0.083 |
| | (0.012) | (0.020) | (0.021) | (0.017) | (0.022) | (0.027) |
| | [0.680] | [-0.032] | [0.952] | [-0.837] | [0.289] | [3.012] |
| C | 0.029 | 0.060 | 0.030 | 0.024 | 0.055 | 0.110 |
| | (0.018) | (0.030) | (0.031) | (0.025) | (0.032) | (0.040) |
| | [1.631] | [1.988] | [0.990] | [0.967] | [1.730] | [2.717] |
| R-squared | 0.998 | 0.997 | 0.995 | 0.994 | 0.993 | 0.991 |
| Adj. R-squared | 0.998 | 0.997 | 0.995 | 0.994 | 0.993 | 0.991 |
| Future before crisis | LFTSE_JSE40_F | LCORN_F | LCOTTON_F | LSOYABEAN_F | LSUGAR_F | LWHEAT_F |
| LFTSE_JSE40_F(-1) | 1.058 | -0.002 | 0.006 | -0.016 | 0.025 | -0.008 |
| | (0.023) | (0.028) | (0.033) | (0.027) | (0.051) | (0.030) |
| | [46.526] | [-0.067] | [0.193] | [-0.590] | [0.495] | [-0.277] |
| LFTSE_JSE40_F(-2) | -0.059 | 0.009 | -0.004 | 0.023 | -0.018 | 0.018 |
| | (0.023) | (0.028) | (0.033) | (0.027) | (0.051) | (0.030) |
| | [-2.583] | [0.333] | [-0.133] | [0.866] | [-0.350] | [0.600] |
| LCORN_F(-1) | 0.012 | 1.092 | -0.005 | -0.017 | 0.023 | 0.075 |
| | (0.024) | (0.029) | (0.035) | (0.028) | (0.052) | (0.031) |
| | [0.530] | [37.485] | [-0.134] | [-0.607] | [0.440] | [2.395] |
| LCORN_F(-2) | -0.016 | -0.101 | -0.002 | 0.017 | -0.029 | -0.073 |
| | (0.024) | (0.029) | (0.035) | (0.028) | (0.052) | (0.031) |
| | [-0.666] | [-3.449] | [-0.046] | [0.597] | [-0.564] | [-2.328] |
| LCOTTON_F(-1) | 0.014 | 0.005 | 0.991 | 0.036 | -0.007 | 0.019 |
| | (0.016) | (0.020) | (0.023) | (0.019) | (0.035) | (0.021) |
| | [0.893] | [0.273] | [42.864] | [1.944] | [-0.208] | [0.889] |
| LCOTTON_F(-2) | -0.015 | 0.001 | 0.005 | -0.027 | 0.013 | -0.015 |
| | (0.016) | (0.020) | (0.023) | (0.019) | (0.035) | (0.021) |
| | [-0.926] | [0.045] | [0.215] | [-1.443] | [0.366] | [-0.735] |
| LSOYABEAN_F(-1) | -0.024 | -0.060 | -0.056 | 1.006 | -0.057 | -0.090 |
| | (0.022) | (0.028) | (0.033) | (0.026) | (0.050) | (0.030) |
| | [-1.062] | [-2.157] | [-1.720] | [38.036] | [-1.157] | [-3.052] |
| LSOYABEAN_F(-2) | 0.024 | 0.054 | 0.056 | -0.019 | 0.060 | 0.091 |
| | (0.022) | (0.028) | (0.033) | (0.026) | (0.049) | (0.029) |
| | [1.061] | [1.979] | [1.706] | [-0.721] | [1.206] | [3.094] |
| LSUGAR_F(-1) | 0.002 | -0.003 | -0.023 | -0.004 | 1.017 | -0.010 |
| | (0.010) | (0.013) | (0.015) | (0.012) | (0.023) | (0.013) |
| | [0.197] | [-0.202] | [-1.512] | [-0.329] | [44.924] | [-0.757] |
| LSUGAR_F(-2) | -0.001 | -0.003 | 0.019 | -0.004 | -0.026 | 0.005 |
| | (0.010) | (0.013) | (0.015) | (0.012) | (0.023) | (0.014) |
| | [-0.093] | [-0.243] | [1.288] | [-0.323] | [-1.138] | [0.371] |
| LWHEAT_F(-1) | 0.014 | -0.043 | 0.058 | -0.057 | 0.167 | 0.978 |
| | (0.020) | (0.025) | (0.030) | (0.024) | (0.045) | (0.027) |
| | [0.680] | [-1.704] | [1.945] | [-2.380] | [3.690] | [36.325] |
| LWHEAT_F(-2) | -0.010 | 0.043 | -0.053 | 0.059 | -0.172 | 0.006 |
| | (0.020) | (0.025) | (0.030) | (0.024) | (0.045) | (0.027) |
| | [-0.514] | [1.699] | [-1.771] | [2.450] | [-3.817] | [0.214] |
| C | 0.004 | -0.004 | 0.012 | -0.013 | -0.015 | -0.012 |
| | (0.011) | (0.014) | (0.016) | (0.013) | (0.024) | (0.014) |
| | [0.369] | [-0.313] | [0.739] | [-1.012] | [-0.616] | [-0.860] |
| R-squared | 0.999 | 0.993 | 0.990 | 0.994 | 0.992 | 0.992 |
| Adj. R-squared | 0.999 | 0.993 | 0.990 | 0.994 | 0.992 | 0.992 |
| Future after crisis | LFTSE_JSE40_F | LCORN_F | LCOTTON_F | LSOYABEAN_F | LSUGAR_F | LWHEAT_F |
| LFTSE_JSE40_F(-1) | 0.997 | -0.003 | -0.001 | -0.001 | -0.004 | -0.009 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) |
| | [636.857] | [-1.204] | [-0.517] | [-0.403] | [-1.360] | [-3.034] |
| LCORN_F(-1) | -0.001 | 0.992 | -0.006 | 0.004 | 0.001 | 0.000 |
| | (0.002) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) |
| | [-0.388] | [260.684] | [-1.610] | [1.246] | [0.132] | [-0.078] |
| LCOTTON_F(-1) | -0.001 | -0.001 | 0.993 | -0.001 | 0.001 | -0.002 |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) |
| | [-0.954] | [-0.290] | [433.455] | [-0.357] | [0.575] | [-0.641] |
| LSOYABEAN_F(-1) | 0.001 | -0.006 | -0.007 | 0.989 | -0.001 | 0.007 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.005) | (0.005) |
| | [0.387] | [-1.265] | [-1.583] | [265.982] | [-0.211] | [1.478] |
| LSUGAR_F(-1) | -0.001 | 0.003 | 0.006 | 0.001 | 0.993 | -0.003 |
| | (0.002) | (0.003) | (0.003) | (0.002) | (0.003) | (0.003) |
| | [-0.479] | [1.113] | [2.013] | [0.522] | [314.566] | [-0.844] |
| LWHEAT_F(-1) | 0.002 | 0.010 | 0.015 | 0.003 | 0.000 | 0.989 |
| | (0.003) | (0.005) | (0.005) | (0.004) | (0.006) | (0.005) |
| | [0.532] | [2.047] | [3.055] | [0.776] | [-0.038] | [189.168] |
| C | 0.026 | 0.052 | 0.021 | 0.044 | 0.063 | 0.120 |
| | (0.021) | (0.035) | (0.036) | (0.028) | (0.040) | (0.038) |
| | [1.237] | [1.479] | [0.592] | [1.551] | [1.568] | [3.181] |
| R-squared | 0.998 | 0.996 | 0.996 | 0.994 | 0.993 | 0.992 |
| Adj. R-squared | 0.998 | 0.996 | 0.996 | 0.994 | 0.993 | 0.992 |

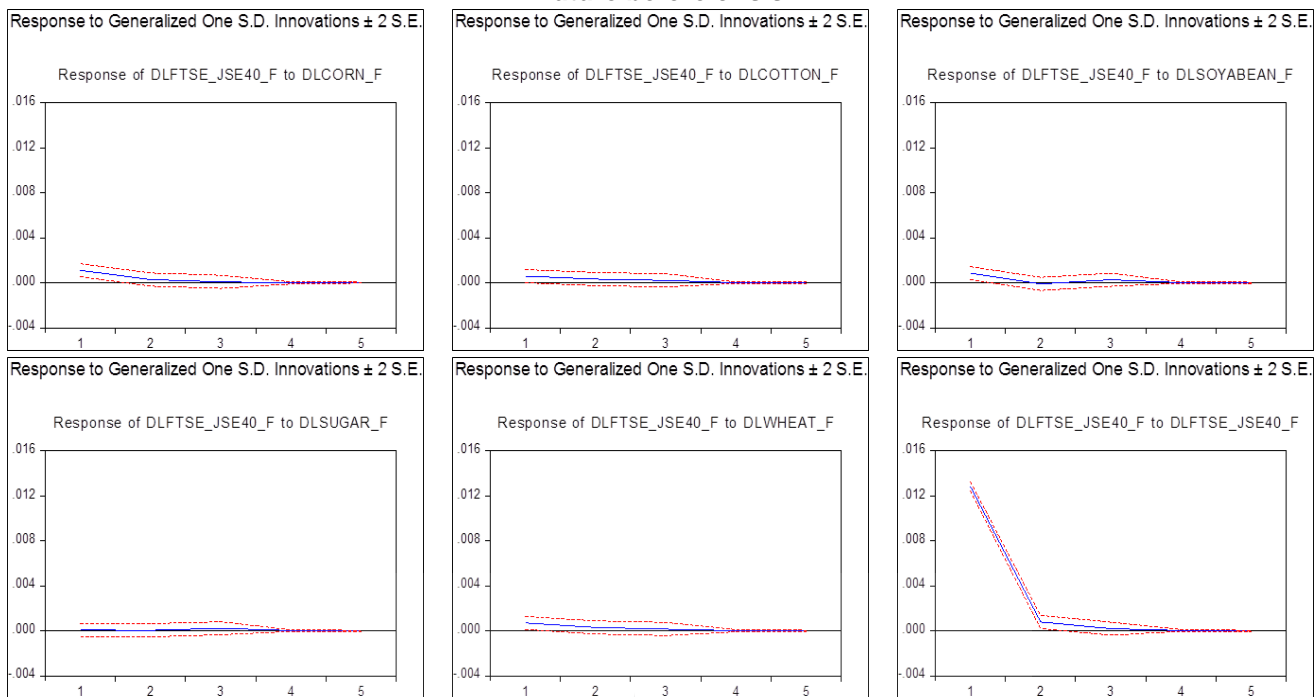
Note: Standard errors in () and t-statistics in []

Source: Thomson Reuters DataStream and EViews.

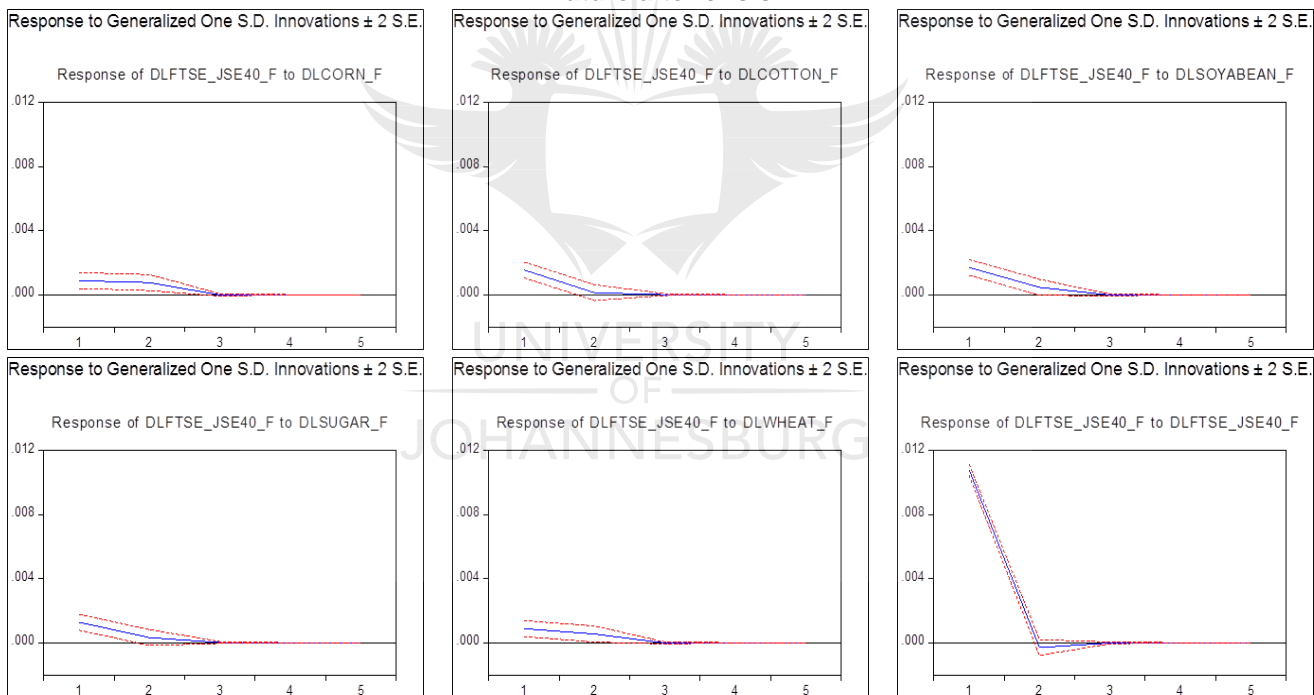
APPENDIX B.3: Impulse response functions and variance decompositions for FTSE/JSE Top 40 Index and five soft commodities



Future before crisis



Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLFTSE_JSE40 | DLCORN | DLCOTTON | DLSOYABEAN | DLSUGAR | DLWHEAT |
|----------------------------|--------|-------|----------------|----------|------------|--------------|-----------|-----------|
| DLFTSE/JSE40 | 1 | 0.012 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.013 | 99.848 | 0.012 | 0.082 | 0.015 | 0.029 | 0.014 |
| DLFTSE/JSE40 | 10 | 0.013 | 99.848 | 0.012 | 0.082 | 0.015 | 0.029 | 0.014 |
| DLFTSE/JSE40 | 20 | 0.013 | 99.848 | 0.012 | 0.082 | 0.015 | 0.029 | 0.014 |
| Spot after crisis | | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.011 | 97.185 | 0.419 | 2.395 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.011 | 96.587 | 0.723 | 2.410 | 0.156 | 0.101 | 0.022 |
| DLFTSE/JSE40 | 10 | 0.011 | 96.587 | 0.723 | 2.410 | 0.156 | 0.101 | 0.022 |
| DLFTSE/JSE40 | 20 | 0.011 | 96.587 | 0.723 | 2.410 | 0.156 | 0.101 | 0.022 |
| Future before crisis | Period | S.E. | DLFTSE_JSE40_F | DLCORN_F | DLCOTTON_F | DLSOYABEAN_F | DLSUGAR_F | DLWHEAT_F |
| DLFTSE/JSE40 | 1 | 0.013 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.013 | 99.760 | 0.003 | 0.076 | 0.100 | 0.024 | 0.037 |
| DLFTSE/JSE40 | 10 | 0.013 | 99.760 | 0.003 | 0.076 | 0.100 | 0.024 | 0.037 |
| DLFTSE/JSE40 | 20 | 0.013 | 99.760 | 0.003 | 0.076 | 0.100 | 0.024 | 0.037 |
| Future after crisis | | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.011 | 96.471 | 0.149 | 0.000 | 1.722 | 0.999 | 0.659 |
| DLFTSE/JSE40 | 5 | 0.011 | 95.952 | 0.391 | 0.000 | 1.718 | 1.030 | 0.908 |
| DLFTSE/JSE40 | 10 | 0.011 | 95.952 | 0.391 | 0.000 | 1.718 | 1.030 | 0.908 |
| DLFTSE/JSE40 | 20 | 0.011 | 95.952 | 0.391 | 0.000 | 1.718 | 1.030 | 0.908 |

Cholesky Ordering spot before crisis: DLFTSE_JSE40 DLCOTTON DLSUGAR DLSOYABEAN DLWHEAT
DLCORN

Cholesky Ordering spot after crisis: DLCOTTON DLCORN DLFTSE_JSE40 DLWHEAT DLSOYABEAN
DLSUGAR

Cholesky Ordering future before crisis: Cholesky Ordering: DLFTSE_JSE40_F DLCOTTON_F DLWHEAT_F
DLCORN_F DLSUGAR_F DLSOYABEAN_F

Cholesky Ordering future after crisis: DLWHEAT_F DLCORN_F DLSOYABEAN_F DLSUGAR_F
DLFTSE_JSE40_F DLCOTTON_F

Source: Thomson Reuters DataStream and EViews.

APPENDIX B.4: VAR ZAR, FTSE/JSE Top 40 Index and five soft commodities

| Spot before crisis | LZAR | LCORN | LCOTTON | LSOYABEAN | LSUGAR | LWHEAT | LFTSE_JSE40 |
|--------------------|-------------------|--------------------|--------------------|--------------------|--------------------|--------------------|-------------------|
| LZAR(-1) | 1.0131 (0.023) | 0.0566 (0.038) | 0.0486 (0.048) | -0.0027 (0.035) | -0.0967 (0.050) | 0.0419 (0.047) | 0.0178 (0.028) |
| | [43.946] | [1.485] | [1.019] | [-0.077] | [-1.915] | [0.899] | [0.628] |
| LZAR(-2) | -0.020 (0.023) | -0.050 (0.038) | -0.052 (0.048) | 0.004 (0.035) | 0.096 (0.050) | -0.035 (0.047) | -0.021 (0.028) |
| | [-0.852] | [-1.325] | [-1.098] | [0.118] | [1.903] | [-0.760] | [-0.742] |
| LCORN(-1) | -0.022 (0.017) | 1.019 (0.028) | 0.055 (0.035) | 0.044 (0.026) | -0.004 (0.037) | 0.061 (0.034) | 0.009 (0.021) |
| | [-1.317] | [36.541] | [1.567] | [1.704] | [-0.115] | [1.778] | [0.411] |
| LCORN(-2) | 0.027 (0.017) | -0.030 (0.028) | -0.056 (0.035) | -0.046 (0.026) | -0.003 (0.037) | -0.063 (0.034) | -0.009 (0.021) |
| | [1.587] | [-1.065] | [-1.600] | [-1.795] | [-0.082] | [-1.863] | [-0.442] |
| LCOTTON(-1) | -0.033 (0.011) | -0.025 (0.018) | 0.886 (0.023) | 0.000 (0.017) | -0.005 (0.024) | 0.025 (0.022) | 0.017 (0.014) |
| | [-3.028] | [-1.361] | [38.782] | [-0.011] | [-0.193] | [1.117] | [1.226] |
| LCOTTON(-2) | 0.030 (0.011) | 0.033 (0.018) | 0.109 (0.023) | 0.010 (0.017) | 0.009 (0.024) | -0.020 (0.022) | -0.019 (0.014) |
| | [2.660] | [1.798] | [4.772] | [0.595] | [0.353] | [-0.902] | [-1.365] |
| LSOYABEAN(-1) | -0.006 (0.017) | -0.047 (0.028) | -0.023 (0.035) | 0.898 (0.026) | 0.052 (0.038) | -0.068 (0.035) | -0.011 (0.021) |
| | [-0.327] | [-1.662] | [-0.646] | [34.127] | [1.389] | [-1.965] | [-0.537] |
| LSOYABEAN(-2) | 0.003 (0.017) | 0.043 (0.028) | 0.021 (0.035) | 0.087 (0.026) | -0.050 (0.037) | 0.071 (0.035) | 0.010 (0.021) |
| | [0.176] | [1.505] | [0.585] | [3.306] | [-1.339] | [2.049] | [0.491] |
| LSUGAR(-1) | -0.007 (0.010) | 0.039 (0.017) | -0.011 (0.021) | 0.012 (0.016) | 0.857 (0.023) | 0.015 (0.021) | -0.005 (0.013) |
| | [-0.681] | [2.280] | [-0.530] | [0.781] | [37.962] | [0.709] | [-0.358] |
| LSUGAR(-2) | 0.007 (0.010) | -0.044 (0.017) | 0.007 (0.021) | -0.022 (0.016) | 0.137 (0.023) | -0.022 (0.021) | 0.006 (0.013) |
| | [0.723] | [-2.593] | [0.335] | [-1.358] | [6.049] | [-1.031] | [0.439] |
| LWHEAT(-1) | 0.005 (0.013) | -0.013 (0.021) | -0.002 (0.026) | -0.021 (0.019) | -0.007 (0.028) | 0.921 (0.026) | 0.005 (0.016) |
| | [0.422] | [-0.636] | [-0.091] | [-1.088] | [-0.234] | [35.891] | [0.325] |
| LWHEAT(-2) | -0.009 (0.013) | 0.017 (0.021) | 0.005 (0.026) | 0.028 (0.019) | 0.006 (0.028) | 0.065 (0.026) | -0.003 (0.016) |
| | [-0.700] | [0.830] | [0.182] | [1.438] | [0.205] | [2.531] | [-0.216] |
| LFTSE_JSE40(-1) | 0.001 (0.019) | -0.002 (0.031) | -0.036 (0.039) | -0.008 (0.029) | 0.055 (0.041) | 0.034 (0.038) | 1.046 (0.023) |
| | [0.063] | [-0.076] | [-0.920] | [-0.291] | [1.333] | [0.896] | [45.312] |
| LFTSE_JSE40(-2) | -0.002 (0.019) | 0.010 (0.031) | 0.038 (0.039) | 0.015 (0.029) | -0.051 (0.041) | -0.024 (0.038) | -0.047 (0.023) |
| | [-0.111] | [0.307] | [0.969] | [0.531] | [-1.232] | [-0.619] | [-2.017] |
| C | 0.0227 (0.012) | -0.0505 (0.020) | -0.0037 (0.025) | -0.0199 (0.018) | -0.0166 (0.026) | -0.0788 (0.024) | 0.0108 (0.015) |
| | [1.910] | [-2.570] | [-0.151] | [-1.089] | [-0.639] | [-3.280] | [0.740] |
| R-squared | 0.997 | 0.994 | 0.989 | 0.994 | 0.994 | 0.990 | 0.999 |
| Adj. R-squared | 0.997 | 0.994 | 0.989 | 0.994 | 0.994 | 0.990 | 0.999 |
| Spot after crisis | LZAR | LCORN | LCOTTON | LSOYABEAN | LSUGAR | LWHEAT | LFTSE_JSE40 |
| LZAR(-1) | 0.987 (0.003) | 0.004 (0.005) | 0.010 (0.006) | 0.003 (0.004) | 0.011 (0.006) | 0.001 (0.007) | 0.010 (0.003) |
| | [330.885] | [0.773] | [1.775] | [0.747] | [1.917] | [0.077] | [3.136] |
| LCORN(-1) | 0.004 (0.002) | 0.994 (0.003) | -0.008 (0.004) | 0.001 (0.003) | -0.002 (0.004) | 0.003 (0.005) | -0.003 (0.002) |
| | [2.171] | [289.126] | [-2.210] | [0.482] | [-0.465] | [0.741] | [-1.302] |
| LCOTTON(-1) | -0.002 (0.001) | -0.001 (0.003) | 0.994 (0.003) | -0.002 (0.002) | 0.004 (0.003) | 0.000 (0.003) | 0.000 (0.001) |
| | [-1.469] | [-0.253] | [389.244] | [-0.845] | [1.502] | [0.005] | [-0.176] |
| LSOYABEAN(-1) | -0.002 (0.003) | -0.009 (0.005) | -0.005 (0.005) | 0.986 (0.004) | 0.000 (0.005) | 0.006 (0.007) | 0.003 (0.003) |
| | [-0.889] | [-1.816] | [-0.963] | [244.470] | [0.090] | [0.936] | [1.025] |
| LSUGAR(-1) | -0.001 (0.002) | 0.002 (0.003) | 0.006 (0.003) | 0.003 (0.003) | 0.992 (0.003) | -0.004 (0.004) | 0.000 (0.002) |
| | [-0.449] | [0.774] | [1.899] | [1.137] | [302.724] | [-0.875] | [-0.211] |
| LWHEAT(-1) | -0.005 (0.002) | 0.011 (0.004) | 0.015 (0.004) | 0.009 (0.003) | 0.004 (0.005) | 0.985 (0.006) | 0.004 (0.002) |
| | [-2.046] | [2.594] | [3.384] | [2.597] | [0.940] | [173.332] | [1.740] |
| LFTSE_JSE40(-1) | 0.013 (0.003) | -0.009 (0.005) | -0.013 (0.006) | -0.004 (0.005) | -0.013 (0.006) | -0.009 (0.007) | 0.988 (0.003) |
| | [4.300] | [-1.592] | [-2.286] | [-0.951] | [-2.300] | [-1.229] | [306.708] |
| C | -0.096 (0.025) | 0.087 (0.046) | 0.091 (0.047) | 0.046 (0.038) | 0.134 (0.049) | 0.109 (0.062) | 0.093 (0.027) |
| | [-3.797] | [1.890] | [1.943] | [1.209] | [2.737] | [1.768] | [3.438] |
| R-squared | 0.999 | 0.997 | 0.995 | 0.994 | 0.993 | 0.991 | 0.998 |

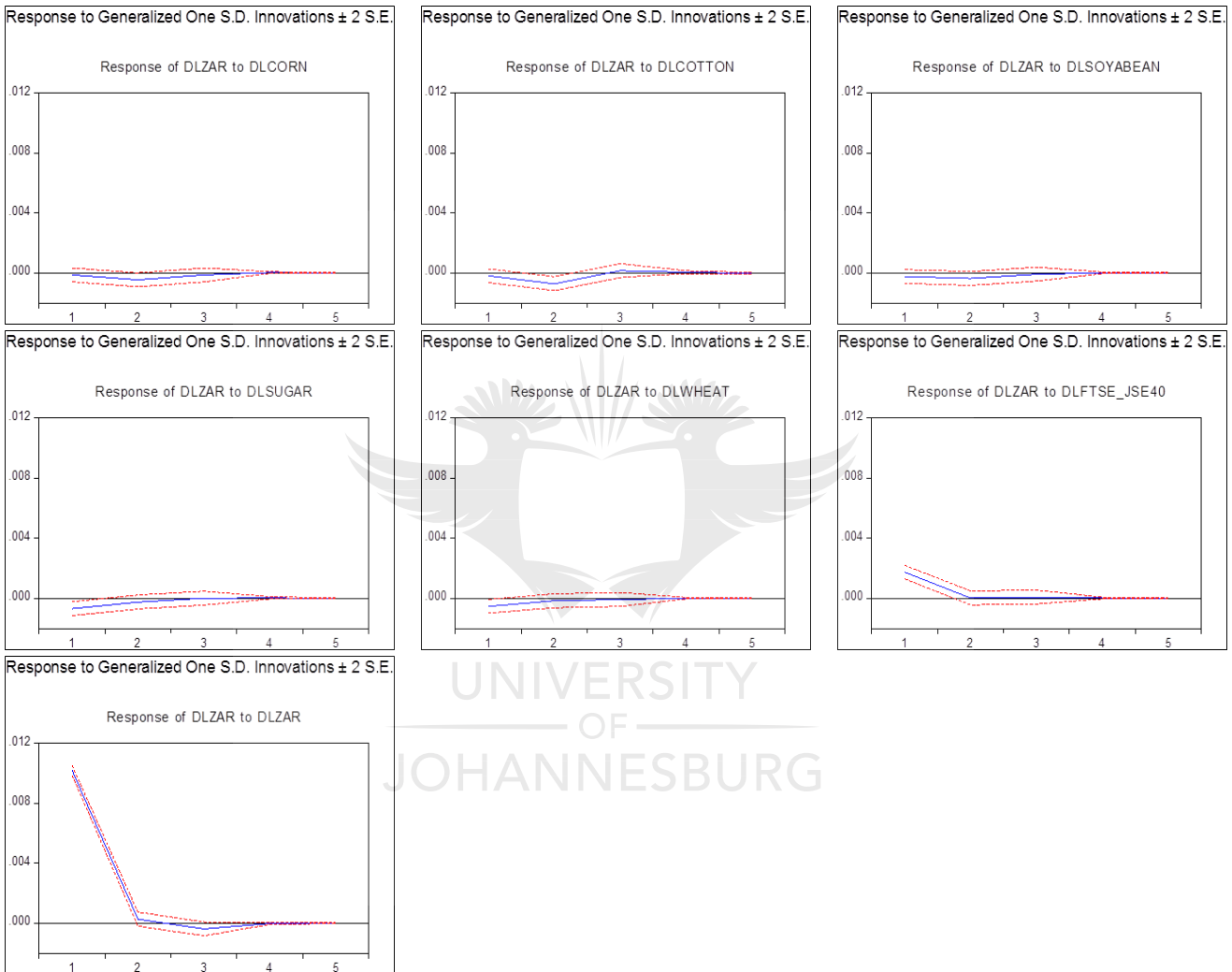
| Adj. R-squared | 0.999 | 0.997 | 0.995 | 0.994 | 0.993 | 0.991 | 0.998 |
|----------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|--------------------------------|
| Future before crisis | LZAR_F | LCORN_F | LCOTTON_F | LSOYABEAN_F | LSUGAR_F | LWHEAT_F | LFTSE_JSE40_F |
| LZAR_F(-1) | 0.988 (0.023) [43.159] | 0.017 (0.033) [0.510] | 0.069 (0.039) [1.773] | 0.010 (0.032) [0.309] | -0.197 (0.059) [-3.332] | 0.012 (0.035) [0.333] | 0.022 (0.027) [0.812] |
| LZAR_F(-2) | 0.005 (0.023) [0.214] | -0.014 (0.033) [-0.431] | -0.075 (0.039) [-1.921] | -0.012 (0.032) [-0.370] | 0.191 (0.059) [3.234] | -0.006 (0.035) [-0.181] | -0.025 (0.027) [-0.946] |
| LCORN_F(-1) | -0.009 (0.020) [-0.444] | 1.092 (0.029) [37.455] | -0.004 (0.035) [-0.127] | -0.017 (0.028) [-0.600] | 0.025 (0.052) [0.479] | 0.074 (0.031) [2.371] | 0.013 (0.024) [0.542] |
| LCORN_F(-2) | 0.014 (0.020) [0.692] | -0.101 (0.029) [-3.459] | -0.001 (0.035) [-0.015] | 0.017 (0.028) [0.608] | -0.029 (0.052) [-0.558] | -0.073 (0.031) [-2.353] | -0.015 (0.024) [-0.640] |
| LCOTTON_F(-1) | -0.025 (0.014) [-1.830] | 0.006 (0.020) [0.319] | 0.992 (0.023) [42.859] | 0.036 (0.019) [1.930] | -0.013 (0.035) [-0.366] | 0.020 (0.021) [0.954] | 0.014 (0.016) [0.874] |
| LCOTTON_F(-2) | 0.022 (0.014) [1.603] | 0.001 (0.020) [0.051] | 0.003 (0.023) [0.108] | -0.028 (0.019) [-1.470] | 0.016 (0.035) [0.451] | -0.015 (0.021) [-0.699] | -0.016 (0.016) [-0.995] |
| LSOYABEAN_F(-1) | -0.007 (0.019) [-0.377] | -0.059 (0.028) [-2.135] | -0.057 (0.033) [-1.740] | 1.005 (0.026) [38.001] | -0.060 (0.049) [-1.204] | -0.089 (0.030) [-3.017] | -0.024 (0.022) [-1.085] |
| LSOYABEAN_F(-2) | 0.002 (0.019) [0.102] | 0.056 (0.028) [2.014] | 0.053 (0.033) [1.620] | -0.020 (0.026) [-0.753] | 0.058 (0.049) [1.174] | 0.093 (0.029) [3.167] | 0.022 (0.022) [0.985] |
| LSUGAR_F(-1) | 0.015 (0.009) [1.769] | -0.002 (0.013) [-0.158] | -0.022 (0.015) [-1.470] | -0.004 (0.012) [-0.330] | 1.013 (0.023) [44.799] | -0.009 (0.014) [-0.702] | 0.002 (0.010) [0.199] |
| LSUGAR_F(-2) | -0.015 (0.009) [-1.766] | -0.003 (0.013) [-0.252] | 0.018 (0.015) [1.174] | -0.004 (0.012) [-0.349] | -0.023 (0.023) [-1.002] | 0.005 (0.014) [0.385] | -0.002 (0.010) [-0.158] |
| LWHEAT_F(-1) | 0.002 (0.017) [0.095] | -0.044 (0.025) [-1.727] | 0.060 (0.030) [1.997] | -0.057 (0.024) [-2.358] | 0.168 (0.045) [3.724] | 0.976 (0.027) [36.261] | 0.015 (0.020) [0.726] |
| LWHEAT_F(-2) | -0.002 (0.017) [-0.127] | 0.042 (0.025) [1.675] | -0.051 (0.030) [-1.723] | 0.060 (0.024) [2.467] | -0.172 (0.045) [-3.803] | 0.005 (0.027) [0.169] | -0.010 (0.020) [-0.470] |
| LFTSE_JSE40_F(-1) | 0.017 (0.020) [0.843] | -0.003 (0.028) [-0.109] | -0.003 (0.034) [-0.080] | -0.018 (0.027) [-0.643] | 0.045 (0.051) [0.894] | -0.008 (0.030) [-0.273] | 1.055 (0.023) [45.989] |
| LFTSE_JSE40_F(-2) | -0.018 (0.020) [-0.905] | 0.011 (0.029) [0.390] | 0.004 (0.034) [0.108] | 0.025 (0.027) [0.902] | -0.039 (0.051) [-0.773] | 0.019 (0.030) [0.628] | -0.056 (0.023) [-2.447] |
| C | 0.046 (0.015) [3.045] | -0.018 (0.022) [-0.831] | 0.041 (0.026) [1.582] | -0.003 (0.021) [-0.142] | 0.020 (0.039) [0.505] | -0.041 (0.024) [-1.744] | 0.023 (0.018) [1.277] |
| R-squared | 0.996 | 0.993 | 0.990 | 0.994 | 0.992 | 0.992 | 0.999 |
| Adj. R-squared | 0.996 | 0.993 | 0.990 | 0.994 | 0.992 | 0.992 | 0.999 |
| Future after crisis | LZAR_F | LCORN_F | LCOTTON_F | LSOYABEAN_F | LSUGAR_F | LWHEAT_F | LFTSE_JSE40_F |
| LZAR_F(-1) | 0.987 (0.003) [318.480] | 0.005 (0.006) [0.822] | 0.013 (0.006) [2.286] | 0.004 (0.005) [0.843] | 0.014 (0.007) [2.159] | -0.004 (0.006) [-0.677] | 0.010 (0.003) [3.058] |
| LCORN_F(-1) | 0.004 (0.002) [1.776] | 0.991 (0.004) [250.071] | -0.009 (0.004) [-2.187] | 0.003 (0.003) [0.947] | -0.002 (0.004) [-0.473] | 0.000 (0.004) [0.099] | -0.003 (0.002) [-1.232] |
| LCOTTON_F(-1) | -0.003 (0.001) [-1.947] | 0.000 (0.003) [0.044] | 0.996 (0.003) [396.287] | 0.000 (0.002) [-0.009] | 0.004 (0.003) [1.410] | -0.002 (0.003) [-0.890] | 0.001 (0.001) [0.366] |
| LSOYABEAN_F(-1) | -0.002 (0.003) [-0.831] | -0.005 (0.005) [-1.052] | -0.005 (0.005) [-1.060] | 0.990 (0.004) [260.015] | 0.001 (0.005) [0.253] | 0.007 (0.005) [1.309] | 0.003 (0.003) [1.035] |
| LSUGAR_F(-1) | 0.000 (0.002) [-0.300] | 0.003 (0.003) [1.111] | 0.006 (0.003) [1.971] | 0.001 (0.002) [0.521] | 0.993 (0.003) [314.603] | -0.002 (0.003) [-0.812] | -0.001 (0.002) [-0.532] |
| LWHEAT_F(-1) | -0.005 (0.003) [-1.634] | 0.012 (0.005) [2.200] | 0.020 (0.005) [3.718] | 0.004 (0.004) [1.046] | 0.005 (0.006) [0.835] | 0.988 (0.006) [172.830] | 0.005 (0.003) [1.717] |
| LFTSE_JSE40_F(-1) | 0.011 (0.003) [3.917] | -0.007 (0.005) [-1.321] | -0.012 (0.005) [-2.254] | -0.004 (0.004) [-0.950] | -0.016 (0.006) [-2.548] | -0.005 (0.006) [-0.900] | 0.989 (0.003) [307.134] |
| C | -0.056 (0.021) [-2.618] | 0.069 (0.040) [1.725] | 0.063 (0.040) [1.572] | 0.057 (0.032) [1.800] | 0.107 (0.045) [2.374] | 0.109 (0.042) [2.562] | 0.059 (0.024) [2.508] |
| R-squared | 0.999 | 0.996 | 0.996 | 0.994 | 0.993 | 0.992 | 0.998 |
| Adj. R-squared | 0.999 | 0.996 | 0.996 | 0.994 | 0.993 | 0.992 | 0.998 |

Note: Standard errors in () and t-statistics in []

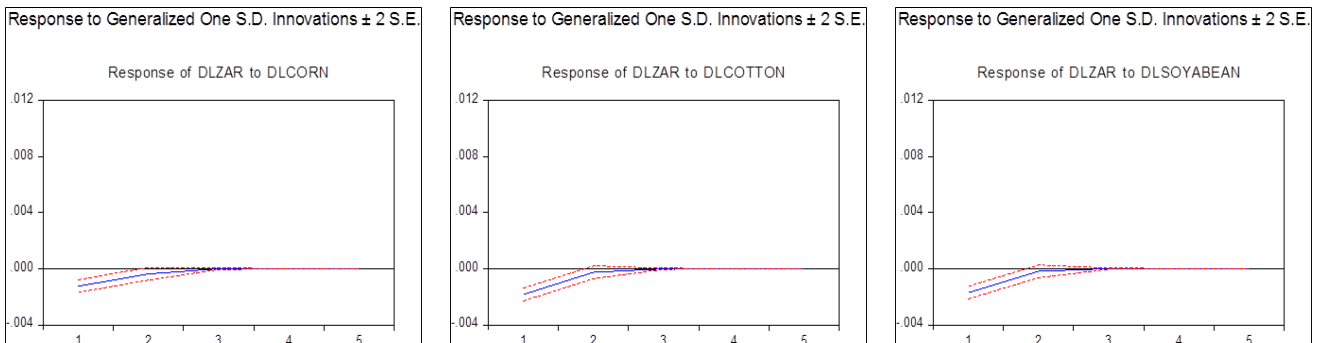
Source: Thomson Reuters DataStream and EViews.

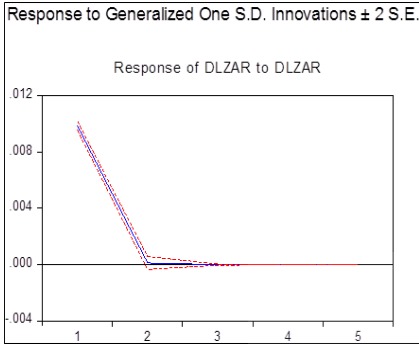
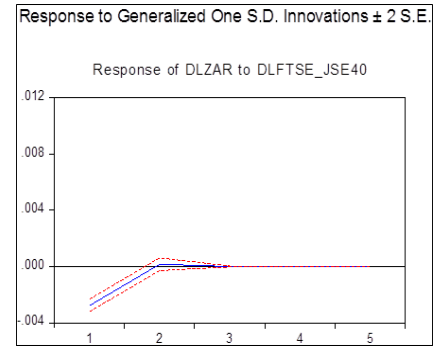
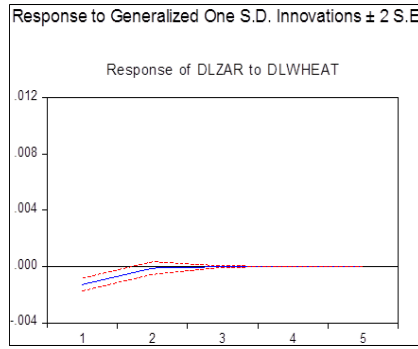
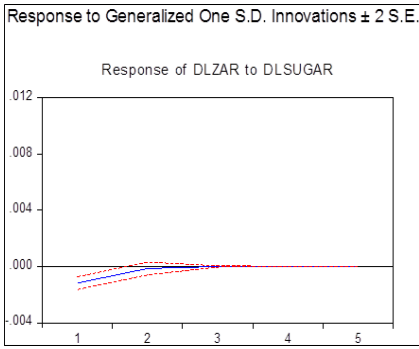
APPENDIX B.5: Impulse response functions and variance decompositions for ZAR, FTSE/JSE Top 40 Index and five soft commodities

Spot before crisis

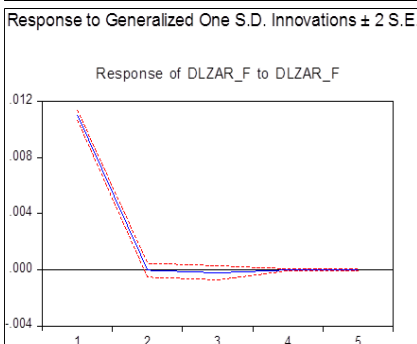
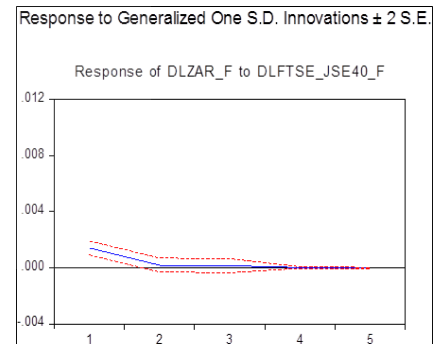
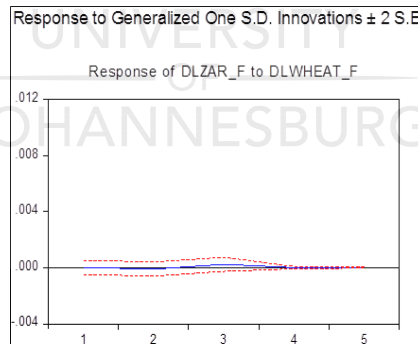
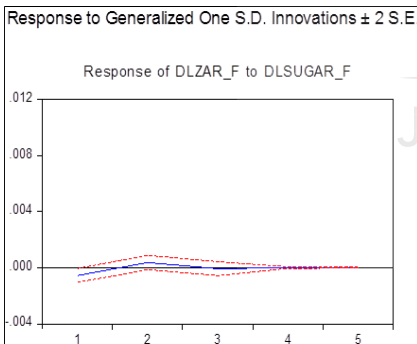
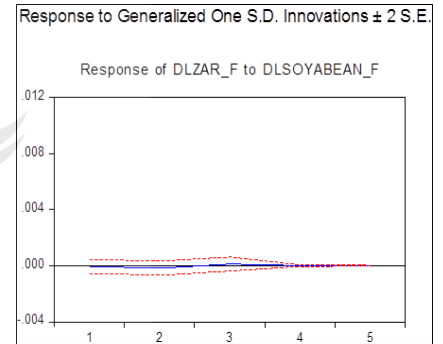
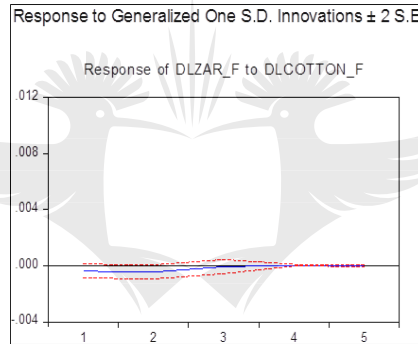
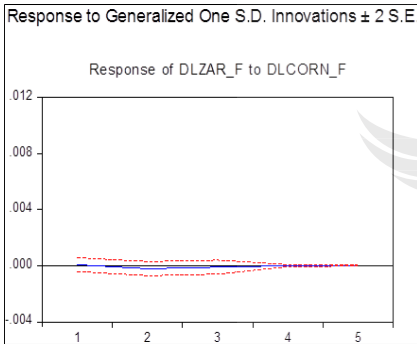


Spot after crisis





Future before crisis



Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLZAR | DLCORN | DLCOTTON | DLSOYABEAN | DLSUGAR | DLWHEAT | DLFTSE_JSE40 |
|-----------------------------|--------|-------|---------|----------|------------|--------------|-----------|-----------|----------------|
| DLZAR | 1 | 0.010 | 96.287 | 0.000 | 0.046 | 0.111 | 0.382 | 0.253 | 2.921 |
| DLZAR | 5 | 0.010 | 95.565 | 0.104 | 0.567 | 0.194 | 0.416 | 0.255 | 2.899 |
| DLZAR | 10 | 0.010 | 95.565 | 0.104 | 0.567 | 0.194 | 0.416 | 0.255 | 2.899 |
| DLZAR | 20 | 0.010 | 95.565 | 0.104 | 0.567 | 0.194 | 0.416 | 0.255 | 2.899 |
| DLFTSE/JSE40 | 1 | 0.017 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 |
| DLFTSE/JSE40 | 5 | 0.017 | 0.027 | 0.012 | 0.082 | 0.015 | 0.032 | 0.012 | 99.820 |
| DLFTSE/JSE40 | 10 | 0.017 | 0.027 | 0.012 | 0.082 | 0.015 | 0.032 | 0.012 | 99.820 |
| DLFTSE/JSE40 | 20 | 0.017 | 0.027 | 0.012 | 0.082 | 0.015 | 0.032 | 0.012 | 99.820 |
| Spot after crisis | | | | | | | | | |
| DLZAR | 1 | 0.010 | 98.422 | 1.578 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR | 5 | 0.010 | 98.180 | 1.710 | 0.033 | 0.000 | 0.004 | 0.013 | 0.059 |
| DLZAR | 10 | 0.010 | 98.180 | 1.710 | 0.033 | 0.000 | 0.004 | 0.013 | 0.059 |
| DLZAR | 20 | 0.010 | 98.180 | 1.710 | 0.033 | 0.000 | 0.004 | 0.013 | 0.059 |
| DLFTSE/JSE40 | 1 | 0.018 | 7.398 | 0.842 | 0.891 | 0.566 | 0.374 | 0.097 | 89.831 |
| DLFTSE/JSE40 | 5 | 0.018 | 7.691 | 1.174 | 0.883 | 0.646 | 0.430 | 0.116 | 89.060 |
| DLFTSE/JSE40 | 10 | 0.018 | 7.691 | 1.174 | 0.883 | 0.646 | 0.430 | 0.116 | 89.060 |
| DLFTSE/JSE40 | 20 | 0.018 | 7.691 | 1.174 | 0.883 | 0.646 | 0.430 | 0.116 | 89.060 |
| Future before crisis | | | | | | | | | |
| Future before crisis | Period | S.E. | DLZAR_F | DLCORN_F | DLCOTTON_F | DLSOYABEAN_F | DLSUGAR_F | DLWHEAT_F | DLFTSE_JSE40_F |
| DLZAR_F | 1 | 0.011 | 98.365 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 1.635 |
| DLZAR_F | 5 | 0.011 | 97.856 | 0.097 | 0.157 | 0.023 | 0.140 | 0.055 | 1.670 |
| DLZAR_F | 10 | 0.011 | 97.856 | 0.097 | 0.157 | 0.023 | 0.140 | 0.055 | 1.670 |
| DLZAR_F | 20 | 0.011 | 97.856 | 0.097 | 0.157 | 0.023 | 0.140 | 0.055 | 1.670 |
| DLFTSE/JSE40_F | 1 | 0.016 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 100.000 |
| DLFTSE/JSE40_F | 5 | 0.016 | 0.042 | 0.006 | 0.064 | 0.100 | 0.021 | 0.051 | 99.716 |
| DLFTSE/JSE40_F | 10 | 0.016 | 0.042 | 0.006 | 0.064 | 0.100 | 0.021 | 0.051 | 99.716 |

| | | | | | | | | | |
|---------------------|----|-------|---------|-------|-------|-------|-------|-------|--------|
| DLFTSE/JSE40_F | 20 | 0.016 | 0.042 | 0.006 | 0.064 | 0.100 | 0.021 | 0.051 | 99.716 |
| Future after crisis | | | | | | | | | |
| DLZAR_F | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR_F | 5 | 0.010 | 99.855 | 0.116 | 0.014 | 0.002 | 0.000 | 0.000 | 0.013 |
| DLZAR_F | 10 | 0.010 | 99.855 | 0.116 | 0.014 | 0.002 | 0.000 | 0.000 | 0.013 |
| DLZAR_F | 20 | 0.010 | 99.855 | 0.116 | 0.014 | 0.002 | 0.000 | 0.000 | 0.013 |
| DLFTSE/JSE40_F | 1 | 0.018 | 3.792 | 0.090 | 0.728 | 1.150 | 0.657 | 0.277 | 93.307 |
| DLFTSE/JSE40_F | 5 | 0.018 | 4.966 | 0.286 | 0.742 | 1.130 | 0.649 | 0.389 | 91.838 |
| DLFTSE/JSE40_F | 10 | 0.018 | 4.966 | 0.286 | 0.742 | 1.130 | 0.649 | 0.389 | 91.838 |
| DLFTSE/JSE40_F | 20 | 0.018 | 4.966 | 0.286 | 0.742 | 1.130 | 0.649 | 0.389 | 91.838 |

Cholesky ordering spot before crisis: DLFTSE_JSE40 DLCOTTON DLISOYABEAN DLWHEAT DLSUGAR DLZAR DLCORN

Cholesky Ordering spot after crisis: DLCORN DLZAR DLCOTTON DLWHEAT DLISOYABEAN DLSUGAR DLFTSE_JSE40

Cholesky Ordering future before crisis: DLFTSE_JSE40_F DLZAR_F DLWHEAT_F DLCORN_F DLCOTTON_F DLISOYABEAN_F DLSUGAR_F

Cholesky Ordering future after crisis: DLZAR_F DLWHEAT_F DLCORN_F DLISOYABEAN_F DLSUGAR_F DLCOTTON_F DLFTSE_JSE40_F

Source: Thomson Reuters DataStream and EViews.



APPENDIX C.1: Pairwise Granger causality test and Toda Yamamoto test

| Spot before crisis Null Hypothesis: | Pairwise Granger causality test | | | Toda Yamamoto test | | |
|---|---------------------------------|-------------|----------|--------------------|----|----------|
| | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLJETKEROSENE does not Granger Cause DLBRENTTOIL | 1951 | 2.032 | 0.108 | 10.052 | 8 | 0.261 |
| DLBRENTTOIL does not Granger Cause DLJETKEROSENE | | 41.062 | 0.000*** | 164.969 | 8 | 0.000*** |
| DLNAPHTHA does not Granger Cause DLBRENTTOIL | 1951 | 2.645 | 0.048** | 12.140 | 8 | 0.145 |
| DLBRENTTOIL does not Granger Cause DLNAPHTHA | | 56.320 | 0.000*** | 207.590 | 8 | 0.000*** |
| DLNATURALGAS does not Granger Cause DLBRENTTOIL | 1951 | 1.755 | 0.154 | 11.699 | 8 | 0.165 |
| DLBRENTTOIL does not Granger Cause DLNATURALGAS | | 3.764 | 0.010*** | 23.977 | 8 | 0.002*** |
| DLFTSE_JSE40 does not Granger Cause DLBRENTTOIL | 1951 | 1.309 | 0.270 | 3.428 | 2 | 0.180 |
| DLBRENTTOIL does not Granger Cause DLFTSE_JSE40 | | 2.511 | 0.057* | 4.959 | 2 | 0.084* |
| DLZAR does not Granger Cause DLBRENTTOIL | 1951 | 0.223 | 0.880 | 0.459 | 1 | 0.498 |
| DLBRENTTOIL does not Granger Cause DLZAR | | 0.634 | 0.593 | 0.592 | 1 | 0.442 |
| DLNAPHTHA does not Granger Cause DLJETKEROSENE | 1951 | 0.971 | 0.405 | 9.071 | 5 | 0.106 |
| DLJETKEROSENE does not Granger Cause DLNAPHTHA | | 16.646 | 0.000*** | 59.920 | 5 | 0.000*** |
| DLNATURALGAS does not Granger Cause DLJETKEROSENE | 1951 | 0.720 | 0.540 | 9.830 | 6 | 0.132 |
| DLJETKEROSENE does not Granger Cause DLNATURALGAS | | 1.056 | 0.367 | 13.052 | 6 | 0.042** |
| DLFTSE_JSE40 does not Granger Cause DLJETKEROSENE | 1951 | 1.311 | 0.269 | 3.934 | 2 | 0.140 |
| DLJETKEROSENE does not Granger Cause DLFTSE_JSE40 | | 1.953 | 0.119 | 2.911 | 2 | 0.233 |
| DLZAR does not Granger Cause DLJETKEROSENE | 1951 | 1.906 | 0.127 | 0.004 | 1 | 0.952 |
| DLJETKEROSENE does not Granger Cause DLZAR | | 2.021 | 0.109 | 0.024 | 1 | 0.877 |
| DLNATURALGAS does not Granger Cause DLNAPHTHA | 1951 | 3.112 | 0.025** | 9.897 | 3 | 0.020** |
| DLNAPHTHA does not Granger Cause DLNATURALGAS | | 2.752 | 0.041** | 8.469 | 3 | 0.037** |
| DLFTSE_JSE40 does not Granger Cause DLNAPHTHA | 1951 | 3.945 | 0.008*** | 15.777 | 5 | 0.008*** |
| DLNAPHTHA does not Granger Cause DLFTSE_JSE40 | | 1.477 | 0.219 | 9.930 | 5 | 0.077* |
| DLZAR does not Granger Cause DLNAPHTHA | 1951 | 0.437 | 0.727 | 1.021 | 1 | 0.312 |
| DLNAPHTHA does not Granger Cause DLZAR | | 1.656 | 0.175 | 0.563 | 1 | 0.453 |
| DLFTSE_JSE40 does not Granger Cause DLNATURALGAS | 1951 | 1.433 | 0.231 | 6.851 | 7 | 0.445 |
| DLNATURALGAS does not Granger Cause DLFTSE_JSE40 | | 0.619 | 0.603 | 11.452 | 7 | 0.120 |
| DLZAR does not Granger Cause DLNATURALGAS | 1951 | 0.859 | 0.462 | 8.136 | 6 | 0.228 |
| DLNATURALGAS does not Granger Cause DLZAR | | 0.267 | 0.849 | 6.158 | 6 | 0.406 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1951 | 0.369 | 0.776 | 0.490 | 1 | 0.484 |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 0.419 | 0.739 | 0.010 | 1 | 0.921 |
| | | | | | | |
| Spot after crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLJETKEROSENE does not Granger Cause DLBRENTTOIL | 1892 | 1.907 | 0.127 | 2.544 | 2 | 0.280 |
| DLBRENTTOIL does not Granger Cause DLJETKEROSENE | | 9.996 | 0.000*** | 22.447 | 2 | 0.000*** |
| DLNAPHTHA does not Granger Cause DLBRENTTOIL | 1892 | 0.691 | 0.557 | 0.135 | 1 | 0.713 |
| DLBRENTTOIL does not Granger Cause DLNAPHTHA | | 1.213 | 0.303 | 3.680 | 1 | 0.055* |
| DLNATURALGAS does not Granger Cause DLBRENTTOIL | 1892 | 1.957 | 0.118 | 8.079 | 7 | 0.326 |
| DLBRENTTOIL does not Granger Cause DLNATURALGAS | | 1.484 | 0.217 | 11.409 | 7 | 0.122 |
| DLFTSE_JSE40 does not Granger Cause DLBRENTTOIL | 1892 | 0.383 | 0.765 | 1.144 | 3 | 0.766 |
| DLBRENTTOIL does not Granger Cause DLFTSE_JSE40 | | 3.647 | 0.012** | 10.260 | 3 | 0.017** |
| DLZAR does not Granger Cause DLBRENTTOIL | 1892 | 0.386 | 0.763 | 0.291 | 1 | 0.589 |
| DLBRENTTOIL does not Granger Cause DLZAR | | 0.433 | 0.730 | 0.954 | 1 | 0.329 |
| DLNAPHTHA does not Granger Cause DLJETKEROSENE | 1892 | 2.538 | 0.055* | 1.360 | 1 | 0.244 |
| DLJETKEROSENE does not Granger Cause DLNAPHTHA | | 0.376 | 0.771 | 0.018 | 1 | 0.892 |
| DLNATURALGAS does not Granger Cause DLJETKEROSENE | 1892 | 2.479 | 0.060* | 13.907 | 8 | 0.084* |
| DLJETKEROSENE does not Granger Cause DLNATURALGAS | | 0.575 | 0.632 | 10.294 | 8 | 0.245 |
| DLFTSE_JSE40 does not Granger Cause DLJETKEROSENE | 1892 | 0.841 | 0.472 | 2.462 | 3 | 0.482 |
| DLJETKEROSENE does not Granger Cause DLFTSE_JSE40 | | 3.114 | 0.025** | 8.720 | 3 | 0.033** |
| DLZAR does not Granger Cause DLJETKEROSENE | 1892 | 1.480 | 0.218 | 4.567 | 1 | 0.033** |
| DLJETKEROSENE does not Granger Cause DLZAR | | 0.436 | 0.727 | 1.061 | 1 | 0.303 |
| DLNATURALGAS does not Granger Cause DLNAPHTHA | 1892 | 4.056 | 0.007*** | 12.041 | 3 | 0.007*** |
| DLNAPHTHA does not Granger Cause DLNATURALGAS | | 0.521 | 0.668 | 1.621 | 3 | 0.655 |
| DLFTSE_JSE40 does not Granger Cause DLNAPHTHA | 1892 | 1.420 | 0.235 | 4.209 | 3 | 0.240 |

| | | | | | | |
|--|------------|--------------------|--------------|---------------|-----------|--------------|
| DLNAPHTHA does not Granger Cause DLFTSE_JSE40 | | 2.869 | 0.035** | 8.207 | 3 | 0.042** |
| DLZAR does not Granger Cause DLNAPHTHA | 1892 | 0.369 | 0.775 | 0.733 | 1 | 0.392 |
| DLNAPHTHA does not Granger Cause DLZAR | | 0.020 | 0.996 | 0.016 | 1 | 0.900 |
| DLFTSE_JSE40 does not Granger Cause DLNATURALGAS | 1892 | 1.819 | 0.142 | 15.740 | 7 | 0.028** |
| DLNATURALGAS does not Granger Cause DLFTSE_JSE40 | | 0.305 | 0.822 | 5.620 | 7 | 0.585 |
| DLZAR does not Granger Cause DLNATURALGAS | 1892 | 0.014 | 0.998 | 1.178 | 5 | 0.947 |
| DLNATURALGAS does not Granger Cause DLZAR | | 0.960 | 0.411 | 2.970 | 5 | 0.705 |
| DLZAR does not Granger Cause DLFTSE_JSE40 | 1892 | 4.592 | 0.003*** | 12.491 | 3 | 0.006*** |
| DLFTSE_JSE40 does not Granger Cause DLZAR | | 0.956 | 0.413 | 2.989 | 3 | 0.393 |
| | | | | | | |
| Future before Crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLNATURALGAS_F does not Granger Cause DLBRENTOL_F | 1952 | 1.053 | 0.349 | 2.138 | 2 | 0.343 |
| DLBRENTOL_F does not Granger Cause DLNATURALGAS_F | | 3.368 | 0.035** | 6.193 | 2 | 0.045** |
| DLFTSE_JSE40_F does not Granger Cause DLBRENTOL_F | 1952 | 2.553 | 0.078* | 5.158 | 2 | 0.076* |
| DLBRENTOL_F does not Granger Cause DLFTSE_JSE40_F | | 2.269 | 0.104 | 4.716 | 2 | 0.095* |
| DLZAR_F does not Granger Cause DLBRENTOL_F | 1952 | 1.263 | 0.283 | 2.101 | 1 | 0.147 |
| DLBRENTOL_F does not Granger Cause DLZAR_F | | 0.883 | 0.414 | 1.497 | 1 | 0.221 |
| DLFTSE_JSE40_F does not Granger Cause DLNATURALGAS_F | 1952 | 0.755 | 0.470 | 1.352 | 2 | 0.509 |
| DLNATURALGAS_F does not Granger Cause DLFTSE_JSE40_F | | 0.634 | 0.531 | 1.571 | 2 | 0.456 |
| DLZAR_F does not Granger Cause DLNATURALGAS_F | 1952 | 0.092 | 0.912 | 0.250 | 1 | 0.617 |
| DLNATURALGAS_F does not Granger Cause DLZAR_F | | 1.096 | 0.334 | 0.086 | 1 | 0.769 |
| DLZAR_F does not Granger Cause DLFTSE_JSE40_F | 1952 | 0.420 | 0.657 | 0.692 | 1 | 0.406 |
| DLFTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.522 | 0.594 | 0.534 | 1 | 0.465 |
| | | | | | | |
| Future after crisis Null Hypothesis: | Obs | F-Statistic | Prob. | Chi-sq | df | Prob. |
| DLFTSE_JSE40_F does not Granger Cause DLBRENTOL_F | 1892 | 1.325 | 0.266 | 2.621 | 3 | 0.454 |
| DLBRENTOL_F does not Granger Cause DLFTSE_JSE40_F | | 17.678 | 0.000*** | 34.600 | 3 | 0.000*** |
| DLNATURALGAS_F does not Granger Cause DLBRENTOL_F | 1892 | 0.174 | 0.840 | 0.350 | 2 | 0.839 |
| DLBRENTOL_F does not Granger Cause DLNATURALGAS_F | | 0.500 | 0.607 | 0.992 | 2 | 0.609 |
| DLZAR_F does not Granger Cause DLBRENTOL_F | 1892 | 1.987 | 0.137 | 4.103 | 2 | 0.129 |
| DLBRENTOL_F does not Granger Cause DLZAR_F | | 3.654 | 0.026** | 7.327 | 2 | 0.026** |
| DLNATURALGAS_F does not Granger Cause DLFTSE_JSE40_F | 1892 | 0.151 | 0.860 | 1.460 | 3 | 0.691 |
| DLFTSE_JSE40_F does not Granger Cause DLNATURALGAS_F | | 0.903 | 0.406 | 2.007 | 3 | 0.571 |
| DLZAR_F does not Granger Cause DLNATURALGAS_F | 1892 | 0.433 | 0.649 | 0.807 | 2 | 0.668 |
| DLNATURALGAS_F does not Granger Cause DLZAR_F | | 1.678 | 0.187 | 3.421 | 2 | 0.181 |
| DLZAR_F does not Granger Cause DLFTSE_JSE40_F | 1892 | 14.808 | 0.000*** | 28.011 | 3 | 0.000*** |
| DLFTSE_JSE40_F does not Granger Cause DLZAR_F | | 0.491 | 0.612 | 1.345 | 3 | 0.719 |

, **, * indicate significance at a 10%, 5% and 1% level of significance respectively*

Source: Thomson Reuters DataStream and EViews.

APPENDIX C.2: VAR FTSE/JSE Top 40 Index and energy commodities

| Spot before crisis | LFTSE_JSE40 | LBRENTOIL | LJETKEROSENE | LNAPHTHA | LNATURALGAS |
|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| LFTSE_JSE40(-1) | 1.039 (0.023) | 0.064 (0.042) | 0.046 (0.038) | 0.081 (0.041) | -0.144 (0.082) |
| | [45.676] | [1.526] | [1.214] | [1.977] | [-1.767] |
| LFTSE_JSE40(-2) | -0.006 (0.033) | -0.114 (0.061) | -0.053 (0.055) | -0.094 (0.059) | 0.137 (0.118) |
| | [-0.185] | [-1.870] | [-0.961] | [-1.590] | [1.164] |
| LFTSE_JSE40(-3) | -0.033 (0.023) | 0.057 (0.042) | 0.006 (0.038) | 0.017 (0.041) | 0.002 (0.082) |
| | [-1.460] | [1.355] | [0.145] | [0.406] | [0.029] |
| LBRENTOIL(-1) | 0.045 (0.014) | 1.005 (0.027) | 0.282 (0.024) | 0.282 (0.026) | 0.184 (0.052) |
| | [3.102] | [37.619] | [11.658] | [10.861] | [3.564] |
| LBRENTOIL(-2) | -0.020 (0.019) | -0.021 (0.035) | -0.205 (0.032) | -0.165 (0.034) | -0.214 (0.068) |
| | [-1.072] | [-0.598] | [-6.422] | [-4.811] | [-3.140] |
| LBRENTOIL(-3) | -0.016 (0.015) | -0.008 (0.028) | -0.040 (0.025) | -0.080 (0.027) | 0.015 (0.054) |
| | [-1.072] | [-0.305] | [-1.582] | [-2.968] | [0.270] |
| LJETKEROSENE(-1) | -0.018 (0.016) | -0.013 (0.030) | 0.834 (0.028) | 0.057 (0.030) | -0.020 (0.059) |
| | [-1.070] | [-0.423] | [30.305] | [1.934] | [-0.346] |
| LJETKEROSENE(-2) | -0.002 (0.021) | 0.037 (0.039) | 0.110 (0.035) | -0.032 (0.038) | 0.105 (0.076) |
| | [-0.073] | [0.938] | [3.102] | [-0.854] | [1.393] |
| LJETKEROSENE(-3) | 0.019 (0.016) | -0.019 (0.030) | 0.010 (0.027) | -0.034 (0.029) | -0.062 (0.058) |
| | [1.162] | [-0.635] | [0.383] | [-1.168] | [-1.077] |
| LNAPHTHA(-1) | -0.032 (0.014) | -0.017 (0.027) | -0.060 (0.024) | 0.806 (0.026) | -0.116 (0.052) |
| | [-2.196] | [-0.624] | [-2.470] | [30.932] | [-2.234] |
| LNAPHTHA(-2) | 0.004 (0.019) | 0.041 (0.035) | 0.083 (0.032) | 0.160 (0.034) | 0.206 (0.067) |
| | [0.231] | [1.190] | [2.641] | [4.738] | [3.060] |
| LNAPHTHA(-3) | 0.019 (0.014) | -0.014 (0.026) | -0.013 (0.024) | -0.001 (0.026) | -0.086 (0.051) |
| | [1.358] | [-0.537] | [-0.526] | [-0.052] | [-1.688] |
| LNATURALGAS(-1) | 0.007 (0.006) | -0.012 (0.012) | 0.007 (0.011) | 0.015 (0.012) | 1.000 (0.023) |
| | [1.072] | [-1.023] | [0.696] | [1.301] | [43.481] |
| LNATURALGAS(-2) | -0.002 (0.009) | 0.033 (0.017) | 0.006 (0.015) | -0.005 (0.016) | -0.163 (0.032) |
| | [-0.243] | [1.983] | [0.398] | [-0.308] | [-5.045] |
| LNATURALGAS(-3) | -0.003 (0.006) | -0.019 (0.012) | -0.013 (0.011) | -0.006 (0.012) | 0.150 (0.023) |
| | [-0.479] | [-1.617] | [-1.177] | [-0.492] | [6.539] |
| C | 0.022 (0.017) | -0.078 (0.031) | 0.085 (0.028) | 0.083 (0.030) | -0.039 (0.060) |
| | [1.334] | [-2.506] | [3.032] | [2.755] | [-0.646] |
| R-squared | 0.999 | 0.997 | 0.997 | 0.997 | 0.988 |
| Adj. R-squared | 0.999 | 0.997 | 0.997 | 0.997 | 0.988 |
| Spot after crisis | LFTSE_JSE40 | LBRENTOIL | LJETKEROSENE | LNAPHTHA | LNATURALGAS |
| LFTSE_JSE40(-1) | 0.943 (0.025) | 0.037 (0.045) | 0.039 (0.038) | 0.071 (0.046) | -0.206 (0.089) |
| | [37.661] | [0.833] | [1.024] | [1.556] | [-2.318] |
| LFTSE_JSE40(-2) | -0.027 (0.034) | -0.057 (0.061) | -0.046 (0.052) | -0.092 (0.063) | 0.133 (0.122) |
| | [-0.785] | [-0.941] | [-0.891] | [-1.466] | [1.090] |
| LFTSE_JSE40(-3) | 0.081 (0.025) | 0.015 (0.045) | 0.004 (0.038) | 0.014 (0.046) | 0.073 (0.089) |
| | [3.251] | [0.330] | [0.094] | [0.314] | [0.821] |
| LBRENTOIL(-1) | 0.041 (0.033) | 1.054 (0.058) | 0.207 (0.049) | 0.146 (0.060) | 0.067 (0.116) |
| | [1.255] | [18.153] | [4.204] | [2.441] | [0.579] |
| LBRENTOIL(-2) | -0.027 (0.043) | -0.039 (0.076) | -0.130 (0.065) | -0.089 (0.078) | -0.190 (0.153) |
| | [-0.624] | [-0.517] | [-2.008] | [-1.130] | [-1.243] |
| LBRENTOIL(-3) | -0.010 (0.033) | -0.013 (0.058) | -0.039 (0.049) | -0.025 (0.060) | 0.153 (0.116) |
| | [-0.299] | [-0.231] | [-0.799] | [-0.419] | [1.313] |
| LJETKEROSENE(-1) | -0.001 (0.035) | -0.058 (0.062) | 0.815 (0.053) | -0.130 (0.064) | 0.005 (0.124) |
| | [-0.039] | [-0.939] | [15.510] | [-2.030] | [0.038] |
| LJETKEROSENE(-2) | 0.054 (0.054) | -0.034 (0.054) | 0.069 (0.054) | 0.084 (0.054) | 0.129 (0.054) |

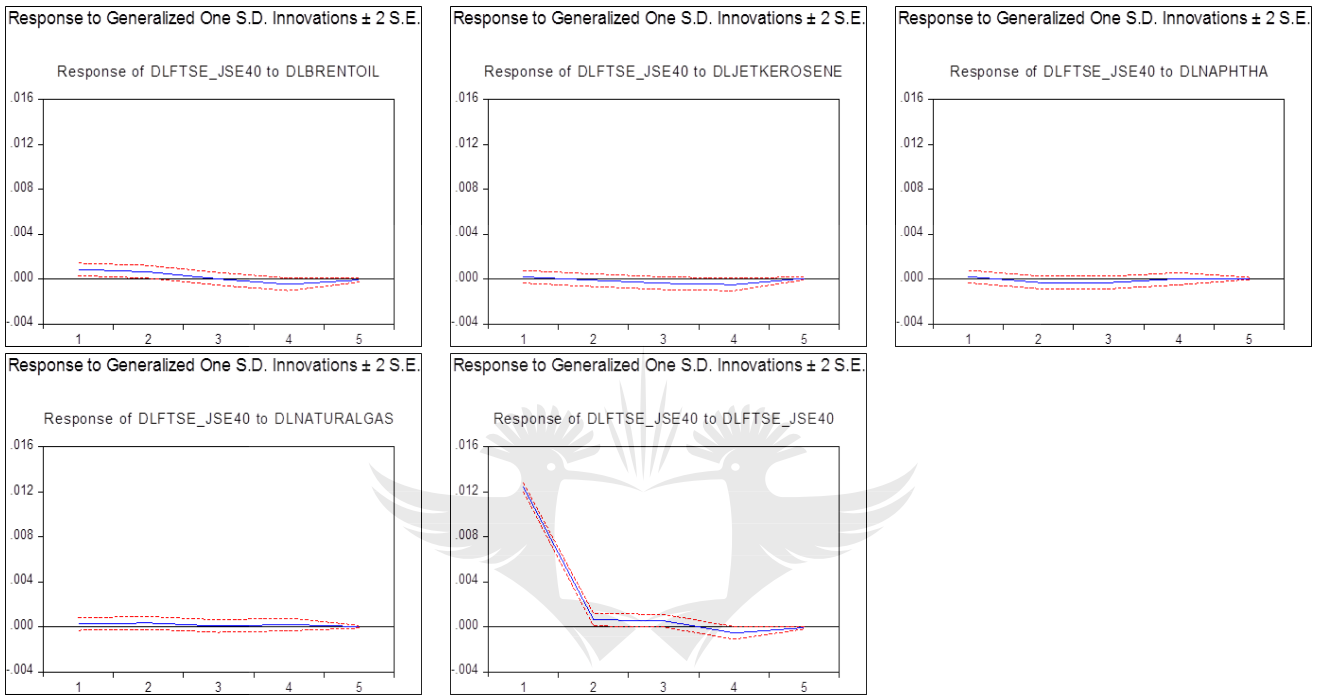
| | | | | | |
|----------------------|---------------|-------------|---------------|-----------|-----------|
| | (0.046) | (0.082) | (0.069) | (0.084) | (0.164) |
| | [1.160] | [-0.410] | [0.990] | [0.999] | [0.786] |
| LJETKEROSENE(-3) | -0.050 | 0.087 | 0.083 | 0.035 | -0.175 |
| | (0.035) | (0.062) | (0.052) | (0.063) | (0.123) |
| | [-1.440] | [1.419] | [1.597] | [0.548] | [-1.426] |
| LNAPHTHA(-1) | 0.005 | 0.021 | -0.030 | 0.961 | -0.012 |
| | (0.023) | (0.041) | (0.035) | (0.042) | (0.082) |
| | [0.234] | [0.521] | [-0.855] | [22.876] | [-0.148] |
| LNAPHTHA(-2) | -0.060 | 0.035 | 0.053 | 0.003 | 0.076 |
| | (0.032) | (0.056) | (0.048) | (0.058) | (0.113) |
| | [-1.894] | [0.625] | [1.106] | [0.055] | [0.671] |
| LNAPHTHA(-3) | 0.047 | -0.056 | -0.033 | 0.009 | -0.050 |
| | (0.023) | (0.041) | (0.035) | (0.042) | (0.082) |
| | [2.055] | [-1.371] | [-0.946] | [0.220] | [-0.615] |
| LNATURALGAS(-1) | 0.000 | 0.019 | 0.016 | 0.029 | 1.131 |
| | (0.006) | (0.011) | (0.010) | (0.012) | (0.023) |
| | [-0.076] | [1.632] | [1.712] | [2.470] | [49.905] |
| LNATURALGAS(-2) | 0.004 | -0.039 | -0.038 | -0.058 | -0.349 |
| | (0.009) | (0.017) | (0.014) | (0.017) | (0.034) |
| | [0.431] | [-2.309] | [-2.633] | [-3.346] | [-10.345] |
| LNATURALGAS(-3) | -0.004 | 0.020 | 0.020 | 0.028 | 0.204 |
| | (0.006) | (0.011) | (0.010) | (0.012) | (0.023) |
| | [-0.638] | [1.724] | [2.064] | [2.437] | [8.994] |
| C | 0.041 | 0.081 | 0.157 | 0.171 | 0.075 |
| | (0.029) | (0.051) | (0.043) | (0.053) | (0.103) |
| | [1.418] | [1.570] | [3.608] | [3.234] | [0.730] |
| R-squared | 0.998 | 0.998 | 0.998 | 0.997 | 0.983 |
| Adj. R-squared | 0.998 | 0.998 | 0.998 | 0.997 | 0.983 |
| Future before crisis | LFTSE_JSE40_F | LBRENTOIL_F | LNATURALGAS_F | | |
| LFTSE_JSE40_F(-1) | 1.056 | 0.069 | 0.040 | | |
| | (0.023) | (0.038) | (0.067) | | |
| | [46.645] | [1.802] | [0.603] | | |
| LFTSE_JSE40_F(-2) | -0.057 | -0.063 | -0.047 | | |
| | (0.023) | (0.038) | (0.067) | | |
| | [-2.505] | [-1.645] | [-0.702] | | |
| LBRENTOIL_F(-1) | 0.027 | 0.938 | -0.089 | | |
| | (0.014) | (0.024) | (0.042) | | |
| | [1.893] | [39.401] | [-2.135] | | |
| LBRENTOIL_F(-2) | -0.027 | 0.055 | 0.101 | | |
| | (0.014) | (0.024) | (0.042) | | |
| | [-1.895] | [2.315] | [2.424] | | |
| LNATURALGAS_F(-1) | 0.004 | 0.022 | 0.977 | | |
| | (0.008) | (0.014) | (0.024) | | |
| | [0.551] | [1.601] | [41.129] | | |
| LNATURALGAS_F(-2) | -0.003 | -0.020 | 0.013 | | |
| | (0.008) | (0.014) | (0.024) | | |
| | [-0.377] | [-1.463] | [0.539] | | |
| C | 0.002 | -0.032 | 0.038 | | |
| | (0.010) | (0.018) | (0.031) | | |
| | [0.225] | [-1.815] | [1.239] | | |
| R-squared | 0.999 | 0.997 | 0.992 | | |
| Adj. R-squared | 0.999 | 0.997 | 0.992 | | |
| Future after crisis | LFTSE_JSE40_F | LBRENTOIL_F | LNATURALGAS_F | | |
| LFTSE_JSE40_F(-1) | 0.928 | 0.064 | -0.061 | | |
| | (0.024) | (0.043) | (0.063) | | |
| | [38.631] | [1.491] | [-0.967] | | |
| LFTSE_JSE40_F(-2) | 0.070 | -0.070 | 0.060 | | |
| | -0.02404 | -0.04316 | -0.0631 | | |
| | [2.894] | [-1.627] | [0.952] | | |
| LBRENTOIL_F(-1) | 0.076 | 0.932 | -0.015 | | |
| | (0.014) | (0.024) | (0.036) | | |
| | [5.627] | [38.344] | [-0.429] | | |
| LBRENTOIL_F(-2) | -0.076 | 0.065 | 0.018 | | |
| | (0.014) | (0.024) | (0.036) | | |
| | [-5.645] | [2.673] | [0.513] | | |
| LNATURALGAS_F(-1) | -0.002 | -0.005 | 0.935 | | |
| | (0.009) | (0.016) | (0.023) | | |
| | [-0.195] | [-0.331] | [40.368] | | |
| LNATURALGAS_F(-2) | 0.001 | 0.004 | 0.057 | | |
| | (0.009) | (0.016) | (0.023) | | |
| | [0.126] | [0.267] | [2.466] | | |
| C | 0.023 | 0.074 | 0.006 | | |
| | (0.015) | (0.027) | (0.039) | | |
| | [1.566] | [2.777] | [0.156] | | |
| R-squared | 0.998 | 0.997 | 0.989 | | |
| Adj. R-squared | 0.998 | 0.997 | 0.989 | | |

Note: Standard errors in () and t-statistics in []

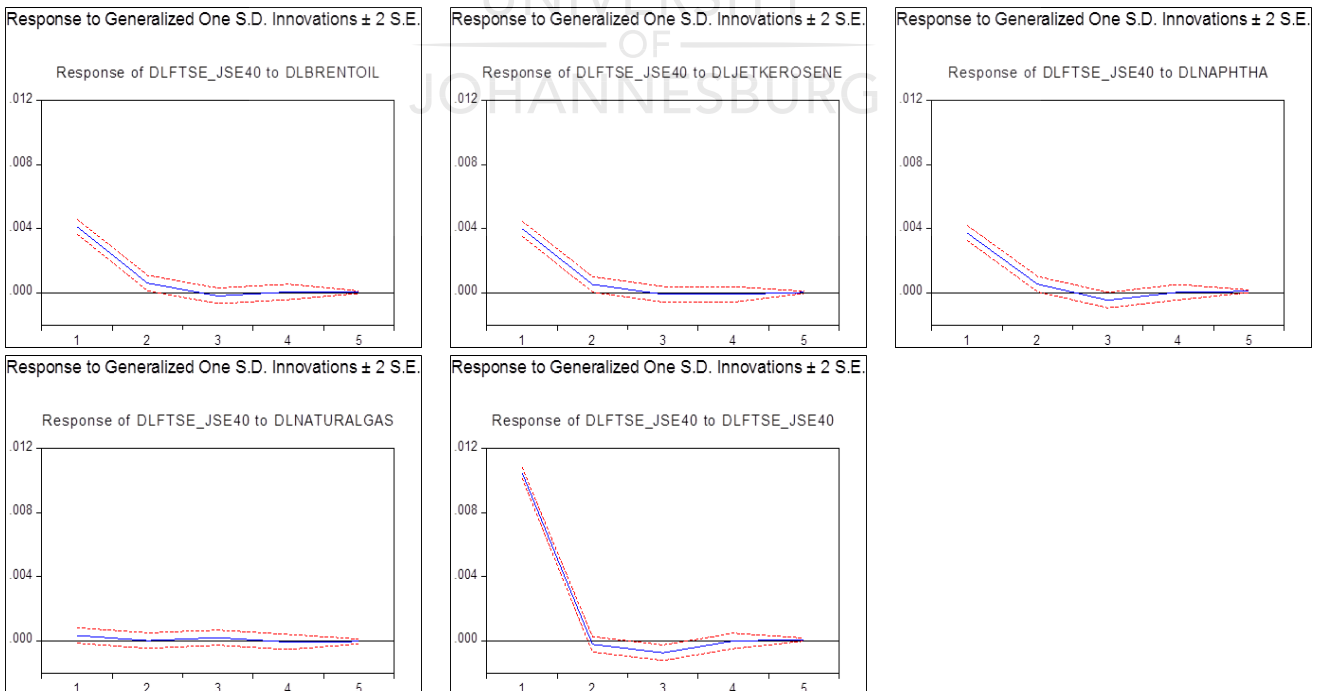
Source: Thomson Reuters DataStream and EViews.

APPENDIX C.3: Impulse response functions and variance decompositions for FTSE/JSE Top 40 Index and energy commodities

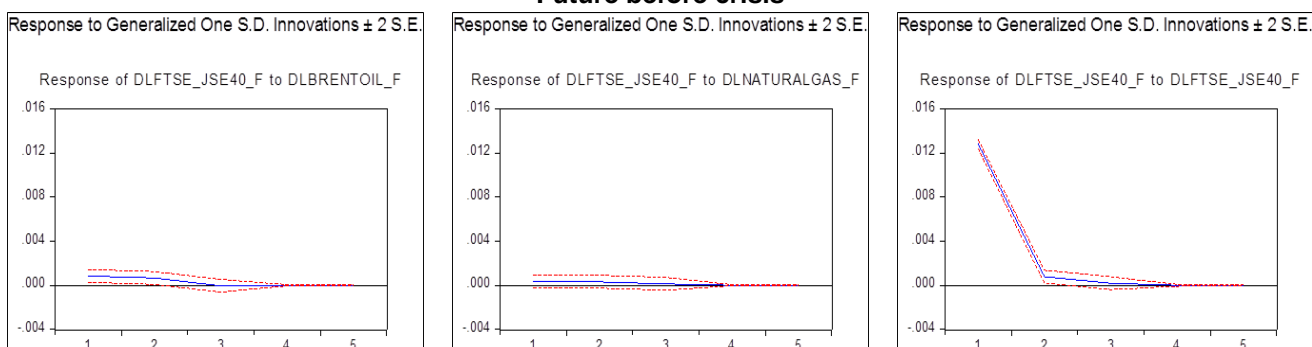
Spot before crisis



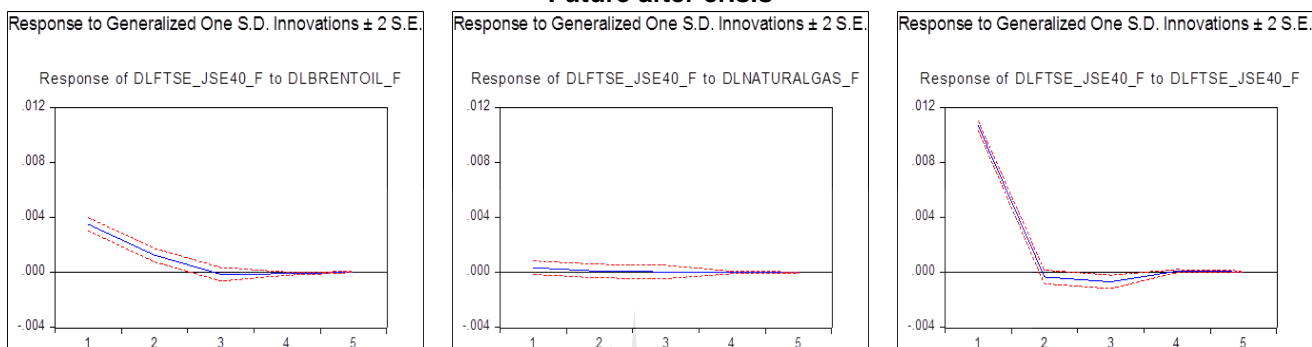
Spot after crisis



Future before crisis



Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLFTSE_JSE40 | DLBRENTTOIL | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS |
|-----------------------------|---------------|----------------|--------------|-------------|---------------|-----------|--------------|
| DLFTSE/JSE40 | 1 | 0.012 | 99.532 | 0.468 | 0.000 | 0.000 | 0.000 |
| DLFTSE/JSE40 | 5 | 0.013 | 98.412 | 0.870 | 0.367 | 0.262 | 0.089 |
| DLFTSE/JSE40 | 10 | 0.013 | 98.408 | 0.870 | 0.368 | 0.263 | 0.092 |
| DLFTSE/JSE40 | 20 | 0.013 | 98.408 | 0.870 | 0.368 | 0.263 | 0.092 |
| Spot after crisis | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.011 | 84.524 | 15.469 | 0.000 | 0.000 | 0.007 |
| DLFTSE/JSE40 | 5 | 0.011 | 83.928 | 15.593 | 0.195 | 0.233 | 0.051 |
| DLFTSE/JSE40 | 10 | 0.011 | 83.926 | 15.593 | 0.195 | 0.233 | 0.053 |
| DLFTSE/JSE40 | 20 | 0.011 | 83.926 | 15.593 | 0.195 | 0.233 | 0.053 |
| Future before crisis | | | | | | | |
| DLFTSE_JSE40_F | DLBRENTTOIL_F | DLNATURALGAS_F | | | | | |
| DLFTSE/JSE40 | 1 | 0.013 | 100.000 | 0.000 | 0.000 | | |
| DLFTSE/JSE40 | 5 | 0.013 | 99.752 | 0.224 | 0.023 | | |
| DLFTSE/JSE40 | 10 | 0.013 | 99.752 | 0.224 | 0.023 | | |
| DLFTSE/JSE40 | 20 | 0.013 | 99.752 | 0.224 | 0.023 | | |
| Future after crisis | | | | | | | |
| DLFTSE/JSE40 | 1 | 0.011 | 89.261 | 10.633 | 0.106 | | |
| DLFTSE/JSE40 | 5 | 0.011 | 88.116 | 11.771 | 0.113 | | |
| DLFTSE/JSE40 | 10 | 0.011 | 88.116 | 11.771 | 0.113 | | |
| DLFTSE/JSE40 | 20 | 0.011 | 88.116 | 11.771 | 0.113 | | |

Cholesky Ordering spot before crisis: DLBRENTTOIL DLFTSE_JSE40 DLNATURALGAS DLJETKEROSENE DLNAPHTHA

Cholesky Ordering spot after crisis: DLBRENTTOIL DLNATURALGAS DLFTSE_JSE40 DLNAPHTHA DLJETKEROSENE

Cholesky Ordering future before crisis: Cholesky Ordering: DLFTSE_JSE40_F DLBRENTTOIL_F DLNATURALGAS_F

Cholesky Ordering future after crisis: DLNATURALGAS_F DLBRENTTOIL_F DLFTSE_JSE40_F

Source: Thomson Reuters DataStream and EViews.

APPENDIX C.4: VAR ZAR, FTSE/JSE Top 40 Index and energy commodities

| Spot before crisis | LZAR | LBRENTOIL | LJETKEROSENE | LNAPHTHA | LNATURALGAS | LFTSE_JSE40 |
|--------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| LZAR(-1) | 1.015 (0.023) | 0.016 (0.052) | 0.015 (0.047) | 0.063 (0.051) | -0.115 (0.101) | 0.023 (0.028) |
| | [43.937] | [0.303] | [0.321] | [1.250] | [-1.136] | [0.832] |
| LZAR(-2) | -0.067 (0.033) | -0.001 (0.074) | 0.110 (0.067) | -0.042 (0.072) | 0.042 (0.144) | -0.026 (0.040) |
| | [-2.035] | [-0.009] | [1.635] | [-0.580] | [0.292] | [-0.653] |
| LZAR(-3) | 0.045 (0.023) | -0.031 (0.052) | -0.139 (0.047) | -0.040 (0.051) | 0.077 (0.101) | 0.000 (0.028) |
| | [1.969] | [-0.592] | [-2.935] | [-0.786] | [0.762] | [-0.012] |
| LBRENTOIL(-1) | 0.014 (0.012) | 1.004 (0.027) | 0.281 (0.024) | 0.282 (0.026) | 0.182 (0.052) | 0.045 (0.014) |
| | [1.147] | [37.568] | [11.633] | [10.867] | [3.507] | [3.118] |
| LBRENTOIL(-2) | 0.002 (0.016) | -0.019 (0.035) | -0.199 (0.032) | -0.164 (0.034) | -0.213 (0.068) | -0.021 (0.019) |
| | [0.157] | [-0.536] | [-6.253] | [-4.785] | [-3.113] | [-1.096] |
| LBRENTOIL(-3) | -0.015 (0.012) | -0.005 (0.028) | -0.040 (0.025) | -0.076 (0.027) | 0.014 (0.054) | -0.015 (0.015) |
| | [-1.222] | [-0.169] | [-1.586] | [-2.790] | [0.264] | [-0.993] |
| LJETKEROSENE(-1) | -0.005 (0.013) | -0.015 (0.030) | 0.832 (0.027) | 0.055 (0.029) | -0.021 (0.059) | -0.018 (0.016) |
| | [-0.403] | [-0.484] | [30.334] | [1.883] | [-0.355] | [-1.079] |
| LJETKEROSENE(-2) | -0.016 (0.017) | 0.036 (0.039) | 0.110 (0.035) | -0.034 (0.038) | 0.106 (0.076) | -0.002 (0.021) |
| | [-0.938] | [0.913] | [3.114] | [-0.899] | [1.403] | [-0.095] |
| LJETKEROSENE(-3) | 0.028 (0.013) | -0.023 (0.030) | 0.005 (0.027) | -0.039 (0.029) | -0.059 (0.058) | 0.018 (0.016) |
| | [2.162] | [-0.775] | [0.181] | [-1.352] | [-1.020] | [1.106] |
| LNAPHTHA(-1) | -0.014 (0.012) | -0.021 (0.027) | -0.066 (0.024) | 0.801 (0.026) | -0.113 (0.052) | -0.033 (0.014) |
| | [-1.164] | [-0.799] | [-2.720] | [30.746] | [-2.171] | [-2.254] |
| LNAPHTHA(-2) | -0.002 (0.015) | 0.041 (0.035) | 0.084 (0.031) | 0.160 (0.034) | 0.204 (0.067) | 0.004 (0.019) |
| | [-0.098] | [1.169] | [2.660] | [4.746] | [3.026] | [0.238] |
| LNAPHTHA(-3) | 0.005 (0.012) | -0.016 (0.026) | -0.013 (0.024) | -0.004 (0.025) | -0.086 (0.051) | 0.019 (0.014) |
| | [0.453] | [-0.614] | [-0.540] | [-0.151] | [-1.680] | [1.316] |
| LNATURALGAS(-1) | 0.003 (0.005) | -0.011 (0.012) | 0.009 (0.011) | 0.017 (0.012) | 0.998 (0.023) | 0.007 (0.006) |
| | [0.539] | [-0.919] | [0.883] | [1.466] | [43.312] | [1.129] |
| LNATURALGAS(-2) | -0.002 (0.007) | 0.033 (0.017) | 0.006 (0.015) | -0.006 (0.016) | -0.162 (0.032) | -0.002 (0.009) |
| | [-0.317] | [1.975] | [0.396] | [-0.352] | [-5.003] | [-0.272] |
| LNATURALGAS(-3) | -0.003 (0.005) | -0.020 (0.012) | -0.014 (0.011) | -0.006 (0.011) | 0.150 (0.023) | -0.003 (0.006) |
| | [-0.515] | [-1.689] | [-1.317] | [-0.564] | [6.541] | [-0.483] |
| LFTSE_JSE40(-1) | -0.004 (0.019) | 0.058 (0.043) | 0.039 (0.039) | 0.068 (0.042) | -0.126 (0.083) | 1.035 (0.023) |
| | [-0.235] | [1.366] | [1.012] | [1.633] | [-1.517] | [44.798] |
| LFTSE_JSE40(-2) | 0.019 (0.027) | -0.113 (0.062) | -0.066 (0.056) | -0.087 (0.060) | 0.129 (0.120) | -0.002 (0.033) |
| | [0.683] | [-1.834] | [-1.178] | [-1.455] | [1.080] | [-0.066] |
| LFTSE_JSE40(-3) | -0.012 (0.019) | 0.069 (0.043) | 0.031 (0.039) | 0.031 (0.042) | -0.010 (0.083) | -0.032 (0.023) |
| | [-0.639] | [1.607] | [0.805] | [0.734] | [-0.119] | [-1.376] |
| C | 0.013 (0.015) | -0.040 (0.033) | 0.118 (0.030) | 0.127 (0.032) | -0.050 (0.065) | 0.030 (0.018) |
| | [0.890] | [-1.210] | [3.902] | [3.899] | [-0.772] | [1.640] |
| R-squared | 0.997 | 0.997 | 0.997 | 0.997 | 0.988 | 0.999 |
| Adj. R-squared | 0.997 | 0.997 | 0.997 | 0.997 | 0.988 | 0.999 |
| Spot after crisis | LZAR | LBRENTOIL | LJETKEROSENE | LNAPHTHA | LNATURALGAS | LFTSE_JSE40 |
| LZAR(-1) | 1.013 (0.025) | -0.010 (0.047) | -0.054 (0.040) | -0.011 (0.048) | -0.047 (0.094) | -0.065 (0.026) |
| | [40.717] | [-0.202] | [-1.341] | [-0.220] | [-0.503] | [-2.468] |
| LZAR(-2) | -0.055 (0.035) | -0.035 (0.067) | 0.042 (0.057) | -0.030 (0.069) | 0.050 (0.133) | 0.030 (0.037) |
| | [-1.571] | [-0.527] | [0.740] | [-0.431] | [0.375] | [0.797] |
| LZAR(-3) | 0.028 (0.025) | 0.047 (0.047) | 0.007 (0.040) | 0.035 (0.049) | -0.001 (0.095) | 0.047 (0.026) |
| | [1.118] | [0.989] | [0.180] | [0.713] | [-0.013] | [1.774] |

| | | | | | | |
|----------------------|------------|-------------|---------------|---------------|-----------|-----------|
| LBRENTOIL(-1) | 0.026 | 1.055 | 0.202 | 0.148 | 0.060 | 0.030 |
| | (0.031) | (0.059) | (0.050) | (0.060) | (0.117) | (0.033) |
| | [0.852] | [18.017] | [4.077] | [2.466] | [0.516] | [0.914] |
| LBRENTOIL(-2) | -0.052 | -0.046 | -0.122 | -0.093 | -0.181 | -0.024 |
| | (0.041) | (0.077) | (0.065) | (0.079) | (0.154) | (0.043) |
| | [-1.288] | [-0.594] | [-1.870] | [-1.172] | [-1.175] | [-0.547] |
| LBRENTOIL(-3) | 0.030 | -0.008 | -0.040 | -0.020 | 0.150 | -0.009 |
| | (0.031) | (0.059) | (0.050) | (0.060) | (0.117) | (0.033) |
| | [0.956] | [-0.145] | [-0.801] | [-0.333] | [1.284] | [-0.280] |
| LJETKEROSENE(-1) | 0.021 | -0.060 | 0.813 | -0.134 | 0.006 | 0.001 |
| | (0.033) | (0.062) | (0.053) | (0.064) | (0.125) | (0.035) |
| | [0.643] | [-0.970] | [15.431] | [-2.098] | [0.048] | [0.040] |
| LJETKEROSENE(-2) | -0.013 | -0.030 | 0.069 | 0.086 | 0.129 | 0.059 |
| | (0.043) | (0.082) | (0.070) | (0.085) | (0.164) | (0.046) |
| | [-0.306] | [-0.362] | [0.992] | [1.022] | [0.786] | [1.276] |
| LJETKEROSENE(-3) | -0.014 | 0.087 | 0.082 | 0.034 | -0.176 | -0.050 |
| | (0.032) | (0.062) | (0.052) | (0.063) | (0.123) | (0.034) |
| | [-0.428] | [1.412] | [1.575] | [-0.532] | [-1.428] | [-1.448] |
| LNAPHTHA(-1) | -0.038 | 0.022 | -0.032 | 0.960 | -0.013 | 0.007 |
| | (0.022) | (0.041) | (0.035) | (0.042) | (0.082) | (0.023) |
| | [-1.753] | [0.541] | [-0.911] | [22.818] | [-0.158] | [0.296] |
| LNAPHTHA(-2) | 0.055 | 0.033 | 0.052 | 0.001 | 0.075 | -0.062 |
| | (0.030) | (0.057) | (0.048) | (0.058) | (0.113) | (0.032) |
| | [1.841] | [0.592] | [1.080] | [0.023] | [0.667] | [-1.962] |
| LNAPHTHA(-3) | -0.017 | -0.055 | -0.031 | 0.010 | -0.049 | 0.051 |
| | (0.022) | (0.041) | (0.035) | (0.042) | (0.082) | (0.023) |
| | [-0.804] | [-1.329] | [-0.887] | [0.245] | [-0.592] | [2.235] |
| LNATURALGAS(-1) | -0.009 | 0.018 | 0.016 | 0.029 | 1.131 | -0.001 |
| | (0.006) | (0.011) | (0.010) | (0.012) | (0.023) | (0.006) |
| | [-1.518] | [1.619] | [1.666] | [2.453] | [49.828] | [-0.152] |
| LNATURALGAS(-2) | 0.013 | -0.039 | -0.037 | -0.058 | -0.348 | 0.004 |
| | (0.009) | (0.017) | (0.014) | (0.017) | (0.034) | (0.009) |
| | [1.421] | [-2.325] | [-2.625] | [-3.352] | [-10.332] | [0.403] |
| LNATURALGAS(-3) | -0.005 | 0.020 | 0.020 | 0.028 | 0.204 | -0.003 |
| | (0.006) | (0.011) | (0.010) | (0.012) | (0.023) | (0.006) |
| | [-0.831] | [1.763] | [2.062] | [2.427] | [8.988] | [-0.431] |
| LFTSE_JSE40(-1) | 0.018 | 0.032 | 0.031 | 0.070 | -0.215 | 0.924 |
| | (0.024) | (0.045) | (0.038) | (0.047) | (0.091) | (0.025) |
| | [0.772] | [0.702] | [0.814] | [1.497] | [-2.366] | [36.353] |
| LFTSE_JSE40(-2) | -0.040 | -0.061 | -0.038 | -0.095 | 0.141 | -0.019 |
| | (0.033) | (0.062) | (0.052) | (0.064) | (0.124) | (0.035) |
| | [-1.214] | [-0.982] | [-0.726] | [-1.488] | [1.145] | [-0.559] |
| LFTSE_JSE40(-3) | 0.034 | 0.022 | 0.006 | 0.023 | 0.072 | 0.084 |
| | (0.024) | (0.045) | (0.038) | (0.047) | (0.091) | (0.025) |
| | [1.415] | [0.477] | [0.166] | [0.487] | [0.792] | [3.292] |
| C | -0.072 | 0.085 | 0.145 | 0.158 | 0.077 | 0.066 |
| | (0.029) | (0.054) | (0.046) | (0.056) | (0.108) | (0.030) |
| | [-2.518] | [1.572] | [3.175] | [2.835] | [0.714] | [2.185] |
| R-squared | 0.999 | 0.998 | 0.998 | 0.997 | 0.983 | 0.998 |
| Adj. R-squared | 0.999 | 0.998 | 0.998 | 0.997 | 0.983 | 0.998 |
| Future before crisis | LZAR_F | LBRENTOIL_F | LNATURALGAS_F | LFTSE_JSE40_F | | |
| LZAR_F(-1) | 0.993 | -0.014 | -0.002 | 0.001 | | |
| | (0.002) | (0.004) | (0.008) | (0.003) | | |
| | [434.778] | [-3.137] | [-0.277] | [0.284] | | |
| LBRENTOIL_F(-1) | -0.001 | 0.984 | 0.009 | 0.000 | | |
| | (0.002) | (0.004) | (0.007) | (0.002) | | |
| | [-0.666] | [237.125] | [1.300] | [0.137] | | |
| LNATURALGAS_F(-1) | -0.002 | 0.002 | 0.990 | 0.002 | | |
| | (0.001) | (0.002) | (0.003) | (0.001) | | |
| | [-2.520] | [0.795] | [295.503] | [1.435] | | |
| LFTSE_JSE40_F(-1) | 0.002 | 0.013 | -0.005 | 0.999 | | |
| | (0.002) | (0.003) | (0.006) | (0.002) | | |
| | [1.064] | [3.804] | [-0.798] | [491.623] | | |
| C | 0.005 | -0.036 | 0.033 | 0.001 | | |
| | (0.009) | (0.017) | (0.031) | (0.010) | | |
| | [0.568] | [-2.062] | [1.060] | [0.136] | | |
| R-squared | 0.996 | 0.997 | 0.992 | 0.999 | | |
| Adj. R-squared | 0.996 | 0.997 | 0.992 | 0.999 | | |
| Future after crisis | LZAR_F | LBRENTOIL_F | LNATURALGAS_F | LFTSE_JSE40_F | | |
| LZAR_F(-1) | 1.044 | -0.083 | -0.046 | -0.091 | | |
| | (0.025) | (0.049) | (0.071) | (0.027) | | |
| | [42.443] | [-1.720] | [-0.647] | [-3.401] | | |
| LZAR_F(-2) | -0.057 | 0.085 | 0.050 | 0.103 | | |
| | (0.025) | (0.048) | (0.071) | (0.027) | | |
| | [-2.324] | [1.752] | [0.709] | [3.825] | | |
| LBRENTOIL_F(-1) | 0.032 | 0.919 | -0.017 | 0.063 | | |
| | (0.013) | (0.026) | (0.037) | (0.014) | | |
| | [2.482] | [35.919] | [-0.446] | [4.471] | | |
| LBRENTOIL_F(-2) | -0.035 | 0.079 | 0.021 | -0.060 | | |

| | | | | |
|--------------------------|-----------------|-----------------|------------------|------------------|
| | (0.013) | (0.026) | (0.037) | (0.014) |
| | [-2.665] | [3.072] | [0.556] | [-4.267] |
| LNATURALGAS_F(-1) | 0.005 | -0.006 | 0.937 | -0.003 |
| | (0.008) | (0.016) | (0.023) | (0.009) |
| | [0.573] | [-0.393] | [40.448] | [-0.326] |
| LNATURALGAS_F(-2) | -0.006 | 0.005 | 0.055 | 0.003 |
| | (0.008) | (0.016) | (0.023) | (0.009) |
| | [-0.730] | [0.331] | [2.390] | [0.312] |
| LFTSE_JSE40_F(-1) | -0.022 | 0.056 | -0.069 | 0.915 |
| | (0.022) | (0.043) | (0.063) | (0.024) |
| | [-1.012] | [1.290] | [-1.085] | [38.017] |
| LFTSE_JSE40_F(-2) | 0.034 | -0.063 | 0.065 | 0.074 |
| | (0.022) | (0.043) | (0.063) | (0.024) |
| | [1.531] | [-1.451] | [1.017] | [3.085] |
| C | -0.078 | 0.081 | 0.027 | 0.074 |
| | (0.021) | (0.041) | (0.060) | (0.023) |
| | [-3.749] | [1.966] | [0.443] | [3.272] |
| R-squared | 0.999 | 0.997 | 0.989 | 0.998 |
| Adj. R-squared | 0.999 | 0.997 | 0.989 | 0.998 |

Note: Standard errors in () and t-statistics in []

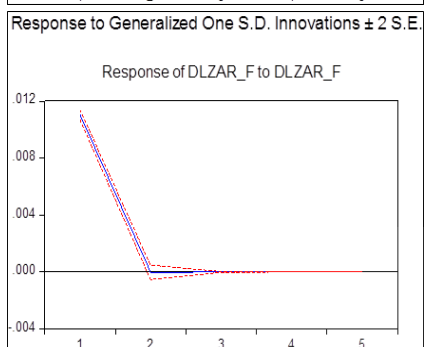
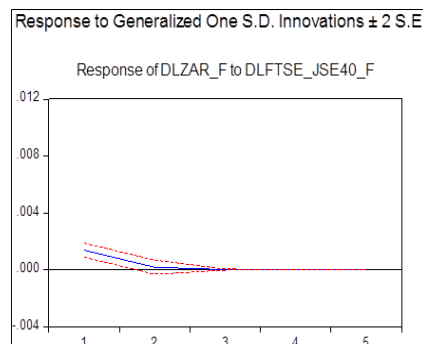
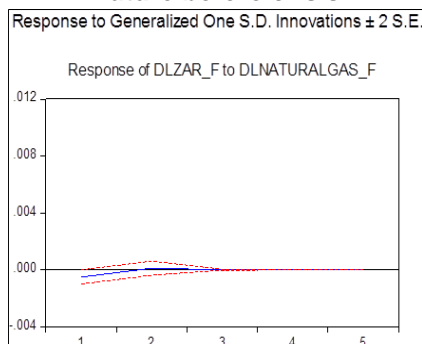
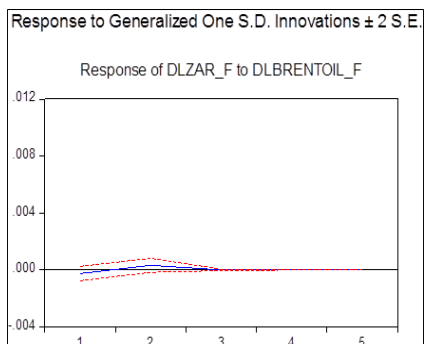
Source: Thomson Reuters DataStream and EViews.



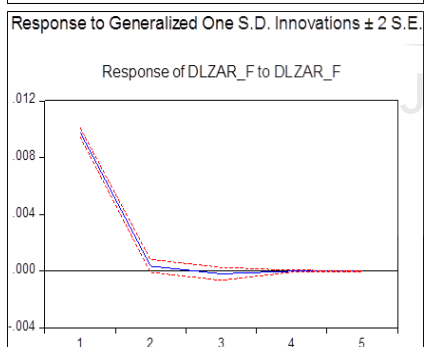
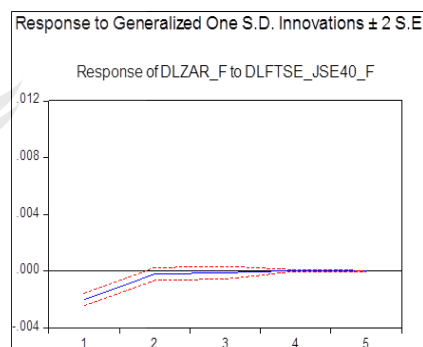
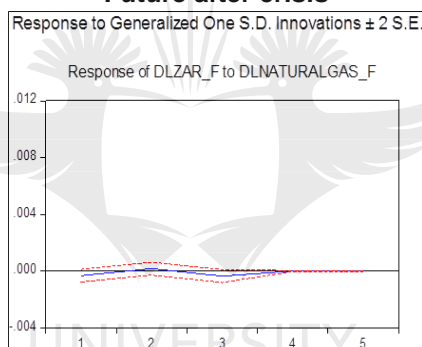
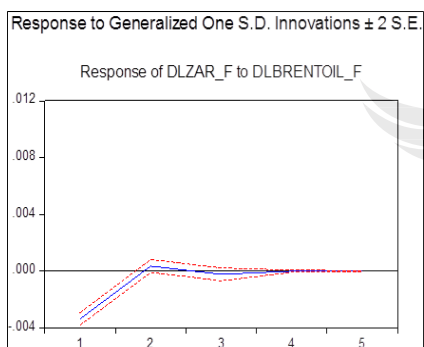
APPENDIX C.5: Impulse response functions and variance decompositions for ZAR, FTSE/JSE Top 40 Index and energy commodities



Future before crisis



Future after crisis



Response to generalised one S.D. innovations

Source: Thomson Reuters DataStream and EViews.

Variance decomposition results

| Spot before crisis | Period | S.E. | DLZAR | DLBRENTA | DLJETKEROSENE | DLNAPHTHA | DLNATURALGAS | DLTSE_JSE40 |
|----------------------|--------|-------|---------|----------|---------------|-----------|--------------|-------------|
| DLZAR | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR | 5 | 0.010 | 99.220 | 0.102 | 0.385 | 0.188 | 0.016 | 0.090 |
| DLZAR | 10 | 0.010 | 99.212 | 0.106 | 0.387 | 0.190 | 0.016 | 0.090 |
| DLZAR | 20 | 0.010 | 99.212 | 0.106 | 0.387 | 0.190 | 0.016 | 0.090 |
| DLTSE/JSE40 | 1 | 0.023 | 2.703 | 0.627 | 0.000 | 0.000 | 0.000 | 96.670 |
| DLTSE/JSE40 | 5 | 0.023 | 2.765 | 1.056 | 0.355 | 0.264 | 0.087 | 95.473 |
| DLTSE/JSE40 | 10 | 0.023 | 2.767 | 1.056 | 0.356 | 0.266 | 0.089 | 95.466 |
| DLTSE/JSE40 | 20 | 0.023 | 2.767 | 1.056 | 0.356 | 0.266 | 0.089 | 95.466 |
| Spot after crisis | | | | | | | | |
| DLZAR | 1 | 0.010 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR | 5 | 0.010 | 99.324 | 0.074 | 0.109 | 0.211 | 0.166 | 0.114 |
| DLZAR | 10 | 0.010 | 99.321 | 0.075 | 0.109 | 0.212 | 0.168 | 0.115 |
| DLZAR | 20 | 0.010 | 99.321 | 0.075 | 0.109 | 0.212 | 0.168 | 0.115 |
| DLTSE/JSE40 | 1 | 0.019 | 8.171 | 9.886 | 0.000 | 0.000 | 0.001 | 81.943 |
| DLTSE/JSE40 | 5 | 0.019 | 8.467 | 9.884 | 0.199 | 0.236 | 0.045 | 81.170 |
| DLTSE/JSE40 | 10 | 0.019 | 8.467 | 9.884 | 0.199 | 0.236 | 0.047 | 81.167 |
| DLTSE/JSE40 | 20 | 0.019 | 8.467 | 9.884 | 0.199 | 0.236 | 0.047 | 81.167 |
| Future before crisis | | | | | | | | |
| DLZAR_F | 1 | 0.011 | 100.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DLZAR_F | 5 | 0.011 | 99.891 | 0.068 | 0.012 | 0.012 | 0.029 | 0.029 |
| DLZAR_F | 10 | 0.011 | 99.891 | 0.068 | 0.012 | 0.012 | 0.029 | 0.029 |
| DLZAR_F | 20 | 0.011 | 99.891 | 0.068 | 0.012 | 0.012 | 0.029 | 0.029 |
| DLTSE/JSE40_F | 1 | 0.022 | 1.586 | 0.000 | 0.094 | 0.094 | 98.320 | 98.320 |
| DLTSE/JSE40_F | 5 | 0.022 | 1.650 | 0.195 | 0.170 | 0.170 | 97.985 | 97.985 |
| DLTSE/JSE40_F | 10 | 0.022 | 1.650 | 0.195 | 0.170 | 0.170 | 97.985 | 97.985 |
| DLTSE/JSE40_F | 20 | 0.022 | 1.650 | 0.195 | 0.170 | 0.170 | 97.985 | 97.985 |
| Future after crisis | | | | | | | | |
| DLZAR_F | 1 | 0.010 | 88.199 | 11.693 | 0.108 | 0.108 | 0.000 | 0.000 |
| DLZAR_F | 5 | 0.010 | 87.879 | 11.760 | 0.268 | 0.268 | 0.093 | 0.093 |
| DLZAR_F | 10 | 0.010 | 87.879 | 11.760 | 0.268 | 0.268 | 0.093 | 0.093 |
| DLZAR_F | 20 | 0.010 | 87.879 | 11.760 | 0.268 | 0.268 | 0.093 | 0.093 |
| DLTSE/JSE40_F | 1 | 0.019 | 0.981 | 10.483 | 0.103 | 0.103 | 88.434 | 88.434 |
| DLTSE/JSE40_F | 5 | 0.019 | 1.564 | 11.558 | 0.110 | 0.110 | 86.767 | 86.767 |
| DLTSE/JSE40_F | 10 | 0.019 | 1.564 | 11.558 | 0.110 | 0.110 | 86.767 | 86.767 |
| DLTSE/JSE40_F | 20 | 0.019 | 1.564 | 11.558 | 0.110 | 0.110 | 86.767 | 86.767 |

Cholesky ordering spot before crisis: DLZAR DLBRENTA DLTSE_JSE40 DLNATURALGAS DLJETKEROSENE DLNAPHTHA

Cholesky Ordering spot after crisis: DLZAR DLBRENTA DLNATURALGAS DLTSE_JSE40 DLNAPHTHA DLJETKEROSENE

Cholesky Ordering future before crisis: DLZAR_F DLNATURALGAS_F DLTSE_JSE40_F DLBRENTA_F

Cholesky Ordering future after crisis: DLNATURALGAS_F DLBRENTA_F DLZAR_F DLTSE_JSE40_F

Source: Thomson Reuters DataStream and EViews.