Modelling the oil price volatility and macroeconomic variables in South Africa using MGARCH Models

BNY Sekati

orcid.org/0000-0002-3012-7809

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Supervisor: DR J.T TSOKU

Co-supervisor: DR L.D METSILENG

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Student number: 23773987

DECLARATION

I, Boitumelo Nnoi Yolanda Sekati, hereby declare that this research report titled "Modelling the Oil Price Volatility and Macroeconomic variables in South Africa Using Multivariate GARCH Models" is my own work and all sources have been accurately reported and acknowledged, and that this document has not been submitted at any university.

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B.N.Y SEKATI   **DATE**

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ABSTRACT

This study modelled the oil price volatility and macroeconomic variables in South Africa using Multivariate GARCH models. The data used in the study consists of 114 observations ranging from 1990 Q1 to 2018 Q2. The study assessed the oil price volatility with the independent variables being the macroeconomic variables (GDP, Inflation, Interest rate and Exchange rates) using the ARCH, GARCH, EGARCH and Multivariate GARCH-BEKK models.

The importance of this study is on determining relationship between oil price volatility and macroeconomic variables as it is one of the impacts driving the economic growth of South Africa due to the fact that South Africa depends on imported crude oil and cannot control oil prices.

The results of the ADF and PP tests revealed that all the variables are stationary at first difference. That is integrated to order 1, *I (1)*. Furthermore, the study presented the QQ plot as an important diagnostic test for checking the assumption of normality. The variables passed the diagnostic checks and can be used for further analysis. The results from the ARCH model was found to be statistically significant which means that the equation could be modelled using the GARCH technique. The LM test also confirmed the use of GARCH technique.

The GARCH (1.1) model was fitted and the results revealed that exchange rate and interest rate have a negative effect on oil price while GDP and inflation suggested a positive effect. The sum of $\propto$ and β was found to be greater than 1. This means that the South African oil price is volatile. The diagnostic test for the GARCH model revealed that the model is adequate and can be used for further analysis. The results from the EGARCH (1.1) model revealed that oil price is found to be negatively related to all the macroeconomic variables. This means that a 1% increase in macroeconomic variables may lead to a decrease in oil price. The diagnostic checks showed that the macroeconomic variables on oil price have no ARCH errors. Furthermore, the EGARCH model appeared to be adequate and was used for further analysis.

The Multivariate GARCH model was also examined using the BEKK-GARCH model. The results revealed that all the estimates of the diagonal parameters are statistically significant at 5% level of significance. The residual series of the model portrayed a certain pattern for each of the macroeconomic variables. However, the BEKK-GARCH model showed the presence of autocorrelation in the residuals. The study found that there is no spill-over effect between oil price and the two macroeconomic variables (inflation and exchange rate). The study also found that there is a unidirectional volatility transmission between oil price and GDP; oil price and inflation; oil price and interest rate; oil price and exchange rate; GDP and interest rate; inflation and interest rate; and inflation and exchange rate.

The study contributes to the existing literature on modelling oil price volatility and macroeconomic variables using the GARCH and the Multivariate GARCH models. The study also provided recommendations for future studies.

Keywords: GDP, inflation, exchange rate, interest rate, ARCH, GARCH and Multivariate GARCH Models.

LIST OF ACRONYMS

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroscedasticity
BEKK	Baba, Engle, Kraft and Kroner
CCC	Constant Conditional Correlation
DCC	Dynamic Conditional Correlation
DTI	Department of Trade and Industry
ER	Exchange Rate
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
FDI	Foreign Direct Investment
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
HQIC	Hannan-Quinn information criterion
INF	Inflation
IR	Interest Rate
JB	Jarque-Bera
LM	Lagrange Multiplier
MGARCH	Multivariate General Autoregressive Conditional Heteroscedasticity
MAPE	Mean Absolute Percentage Error

MSE	Mean Squared Error
PP	Phillips–Perron
SIC	Schwarz information criterion
MAPE	Mean Absolute Percentage Error
SAS	Statistical Analysis System
STCC	Smooth Transition Conditional Correlation
SARB	South African Reserve Bank
VEC	Vector
WTI	West Texas Intermediate

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CHAPTER 1

ORIENTATION OF THE STUDY

1.1 INTRODUCTION

Numerous studies have been conducted previously on oil price as it is one of the causes for grief on the impact of economy in South Africa due to the fluctuation of the price. However, the focus of the current study is on modelling the oil price volatility with the macroeconomic variables such as Gross Domestic Product (GDP), inflation, exchange rate and interest rate using the Multivariate General Autoregressive Conditional Heteroscedasticity (Multivariate GARCH) models.

Lipsky (2009) defined oil price as being more unstable than the price of any other commodity or asset. Adelman (2000) also stated that crude oil prices have been more volatile than any other commodity price (although in principle it ought to be less volatile). Nevertheless, it is empirically recognised that oil price is one of the most volatile prices that has a significant impact on macroeconomic behaviour of various developing and developed economies according to Guo and Kliesen (2005).

Narayan and Narayan (2007), Mehrara (2008), Guo and Kliesen, (2005), Salisu and Fasanya (2013) established the volatility clustering and confirmed the presence of asymmetries in oil price volatility. In addition, Apere and Ijomah (2013) indicated that there is a significant relationship between interest rate, exchange rate and oil prices. Aphane (2011) continued by stating that volatility is measured using the standard deviation or the variance of the oil price. Aphane (2011) further stated that volatility is the rate at which the prices fluctuate (increase or decrease) over time. Samuel and Leopoldo (2014) viewed volatility as the variation of price over time, which can also be viewed as a degree of fluctuation in prices.

The crude oil market is significantly larger than that for any other commodity, both in terms of physical production and financial market (Dunn and Holloway, 2012). Sadorsky (2006) stated that crude oil is an essential commodity of modern economies and it can be used as a source of energy or as a source of raw materials. Its components are used to manufacture almost all chemical products, such as plastics, detergents, paints, and even medicines (Wintershall, 2014). Unrefined petroleum is also identified as one of the most important natural resource which is greater than any other commodity.

According to Maslyuk, Rotaru and Dokumentov (2013), the movement of crude oil prices has an impact on the sentiments of the various investors and this issue of price volatility also influences both consumers and producers. For example, price volatility may increase investment and production risks of producers and for consumers, price volatility makes it difficult for them to utilize their choices (budget plan is restricted).

Brent crude oil around the world is mostly supplied from the Middle East. Fifty percent of the world oil is located in the Middle East, though most of the world’s oil reserves are highly concentrated in numerous geographic locations. However, oil is frequently traded on the financial markets and only a small portion/fraction of contracts is set for actual physical delivery. The biggest contributors/ main suppliers to South Africa’s crude oil imports are as follows: - from Saudi Arabia (40%), Nigeria (30%), Angola (16%) and Iran (4%). Crude oil is among the main sources of energy, and one of the most important and widely traded commodities that affects the global economy and international trade (Milonas and Henker, 2001). However in Africa the major oil producers include Nigeria, Angola, Algeria, Egypt, and Libya.

Sadorsky (2006) conducted a study on foreign exchange markets. The success of a particular type of forecasting model applied to one type of market cannot be generalised across other markets. However, the impact of oil price volatility on economic growth has continued to generate controversies among economic researchers and policy makers. Furthermore, higher and more unpredictable volatility may lead to an economic crisis (Acemoglu et al., 2003).

1.2 BACKGROUND OF THE STUDY

The autoregressive conditional heteroscedasticity (ARCH) model was first introduced by Engle in 1982. Engle (1982) developed the ARCH model to model the time-varying volatility that is often observed in economic time series data. According to Gileva (2010), the ARCH models can possibly over-predict volatility as they react slowly to huge isolated shocks to the return series. The research gap in modelling volatility using the ARCH model is its non-negativity constraints whereby the projected parameters cannot be negative. This lead to the introduction of the Generalised ARCH (GARCH) model that was proposed independently by Bollerslev and Taylor in 1986. The GARCH model is most commonly used in modelling financial time series data and has inspired dozens of more sophisticated extensions of the models (Fryzlewics, 2007).

There are many extensions of the standard GARCH models. Black (1976) first observed the exponential GARCH (EGARCH) as one of the extensions of the GARCH model. The EGARCH model is used to model volatility and ensure a non-negative variance and negative parameters can be used. The EGARCH models attempt to address volatility clustering in an innovations process whereby the volatility clustering happens when an innovations process does not show significant autocorrelation.

The limitation of the EGARCH model is on the statistical properties for the (quasi-) maximum likelihood estimator (QMLE). EGARCH lacks an inevitability condition for the returns shocks underlying the model, the occurrence of the logarithmic transformation, as well as the absolute value function. In addition, the threshold GARCH (TGARCH) model used for leverage effect was developed by Zakoian (1994), and it is expressed in quadratic form while the EGARCH on the other hand is expressed in the exponential form.

The model developed by Engle (1982) and Bollerslev (1986) revealed that the GARCH models have the capability to capture volatility clustering and leptokurtosis in a time series. Nonetheless it is incapable to identify leverage effects and also incapable to depict any straight contact between conditional mean and conditional variance. However many researchers have been stimulated to magnify these models to the multivariate dimension (Tse and Tsui, 2000). Hence, this study used Multivariate GARCH model in modelling the oil price volatility with the macroeconomic variables.

Bollerslev, Engle and Wooldridge (1988) first introduced the Multivariate GARCH model in 1988. The model allows the analysis of volatility contagion among several markets, volatility, correlation and transmission of shocks. The Multivariate GARCH model comprises Vector/Diagonal Vector (VEC/DVEC-GARCH) models, Baba, Engle, Kraft and Kroner (BEKK-GARCH) models and the Constant Conditional Correlation (CCC) model.

In the VEC/DVEC-GARCH model, all the lagged conditional variances and covariances are functions of each other, also of lagged squared returns. While the model defined by Baba, Engle, Kraft and Kroner (1990), called (BEKK-GARCH) model, is regarded as another version of the VEC model to confirm the matrix will constantly stay positive definite; also BEKK is the extension of VEC.

In 1990, Bollerslev introduced the CCC model for modelling mainly the conditional covariance matrix ultimately by assessing the conditional correlation matrix and indicating all conditional correlation are constant. Therefore, this study is only limited to the BEKK-GARCH model.

1.3 PROBLEM STATEMENT

South Africa is one of the countries that are importing oil. The economic growth of South Africa depends on imported oil and this leads to the country's oil price volatility. In addition, the oil price volatility and the macroeconomic variables can lead to instability that would affect the South African economic growth; hence the country has a high demand for oil to be imported. Wakeford (2008) argued that an increase in oil prices generated increases in inflation, interest rates as well as exchange rates, however this increase also lead to an increase in import prices of oil to South Africa.

The standard GARCH model is a univariate and does not allow negative parameters. The multivariate GARCH models have the capability of modelling the variables even if the parameter estimates are negative. Therefore, this study is attempting to fill the gap by modelling the price volatility using the multivariate GARCH models.

Roubini and Setser (2004) stated that oil price shocks could slow down the rate of growth in an oil-importing country and could even have recessionary implications. However, South Africa is still importing the crude oil from other countries, as around the world, oil is mostly supplied from the Middle East. Therefore, this study will model the oil price volatility with the macroeconomic variables using the multivariate GARCH models and correlation coefficient test to determine the impact between them based on the economic growth of South Africa and also fill the gap by modelling the price volatility with the Multivariate GARCH model even though the parameter estimates are negative.

1.4 RATIONALE OF THE STUDY

The purpose of this study is to use the Multivariate GARCH models and correlation coefficient test to model the oil price volatility with the macroeconomic variables in South Africa. This is built on previous similar studies that were conducted on oil price volatility by other researchers with different dependent variables to analyse the impact of oil. The motivation to undertake the current study is that the Multivariate GARCH model can be used in the analysis even if the parameter estimates are negative and in a matrix format using the BEKK-GARCH models.

1.5 AIM AND OBJECTIVES OF THE STUDY

1.5.1 AIM OF THE STUDY

The aim of this study is to model the oil price volatility and macroeconomic variables (GDP, inflation, exchange rate, and interest rate) in South Africa using Multivariate GARCH models.

1.5.2 OBJECTIVES OF THE STUDY

The specific objectives of the study are as follows:

- To determine the relationship between the oil price volatility and macroeconomic variables in South Africa.
- To fit the best model depicting the relationship between oil price volatility and macroeconomic variables in South Africa
- To determine the volatility spillovers among oil price volatility and macroeconomic variables in South Africa
- To examine the transmission shocks from the oil price to the macroeconomic variables in South Africa
- To determine the impact of oil price volatility on the macroeconomic variables in South Africa.

- To determine whether forecasting the future oil price volatility can increase economic growth.

1.6 RESEARCH QUESTIONS

Based on the above-mentioned research objectives, the following research questions were formulated:

- What is the relationship between oil price volatility and macroeconomic variables?
- Which volatility model is the best to analyze the relationship between oil price and macroeconomic variables in South Africa?
- Are there volatility spillovers between oil price volatility and macroeconomic variables in South Africa?
- What are the channels of transmission shocks from the oil price to the macroeconomic variables in South Africa?
- What is the impact of oil price volatility on the macroeconomic variables?
- Is the forecasting of oil price volatility tied to the increase in economic growth for future?

1.7 SIGNIFICANCE OF THE STUDY

The importance of this study is on determining the relationship between oil price volatility and macroeconomic variables, as it is one of the impacts driving the economic growth of South Africa. South Africa depends on imported crude oil and cannot control oil prices. In addition, this study contributes to the research gap of little existing literature on oil price volatility in the South African context, as it also shed light on the effect that the oil price volatility has on South African macroeconomic variables. The study of this nature could assist other researchers and scholars in the field of volatility modelling.

1.8 STUDY LIMITATIONS

The study is only limited to the oil prices and the four macroeconomic variables, namely, GDP, inflation, exchange rate and interest rate. The study did not use surveys, questionnaires or interviews. There are studies done before on oil prices but only few have used the combination of the oil price and macroeconomic variables mentioned above and this has led to limited literature. Furthermore, most of the studies were not using the Multivariate GARCH hence literature is limited. Therefore, sources older than 10 years were also reviewed.

1.9 DEFINITION OF TERMS

This section of the study presents the terms used in the study.

VOLATILITY- Is a statistical measure of dispersion (Aphane, 2011).

ECONOMIC GROWTH – Is the annual rate of increase in total production or income in the economy (Mohr et al., 2008).

BRENT CRUDE OIL- Is a major trading classification of sweet light crude oil that serves as a major benchmark price for purchases of oil worldwide.

***PRICE*-** Is the quantity of goods given or received in exchange of another good (Commons, 2000).

MGARCH- Is a multivariate extension of the GARCH model and is the model used for modelling volatility.

***EXCHANGE RATES* -** are quoted as foreign currency per unit of domestic currency or domestic currency per unit of foreign currency (Krugman & Obstfeld, 2006).

GDP- *Is the* total value of all final goods and services produced within the boundaries of a country in a particular period, usually one year (Mohr et al., 2008).

CORRELATION COEFFICIENT TEST- Is the statistical measure for testing the strength of the relationship between the movements of the relative variables.

INFLATION – A continued and considerable rise in prices in general (Mohr et al., 2008).

INTEREST RATE – Is the price of loanable funds (Mohr et al., 2008).

1.10 RESEARCH LAYOUT

The study comprises five chapters. Chapter 1 is the introduction, the background of the study, objectives, problem statement, brief literature review, methodology, significance of study, limitations. Chapter 2 discusses the literature review related to the study. However, the literature review has two sections: firstly, the theoretical review and secondly the empirical review. Chapter 3 outlines the research methodology. It includes data and data sources, stationarity test and model estimation for different models: - the ARCH, GARCH, EGARCH and the Multivariate GARCH models. Chapter 4 provides the data analysis and interpretation of the results and Chapter 5 presents the statistical analyses results, which are discussed in detail in line with the objectives of the study. The conclusion and recommendations for further study are also discussed.

1.11 CHAPTER SUMMARY

This chapter provided the background of the research containing the problem statement, the research aims and objectives as well as its significance. The chapter continued to provide the rationale of the study and the research questions as well as the limitations of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter focuses on the theoretical framework and empirical literature review of the study. The empirical review is divided into two spheres, namely, review on international perspective and the review on South African perspective. The first section of this chapter focuses on the theoretical framework of the study and the second section focuses on the empirical literature review.

2.2 THEORETICAL FRAMEWORK

This theoretical framework section presents the following aspect for the study: stationarity test, ARCH model, GARCH model, EGARCH model, Multivariate GARCH model and forecasting.

2.2.1 Stationarity Test

Several macroeconomic and time series data is non-stationary in nature. According to Hipel and McLeod (1994), the concept of stationarity of a stochastic process can be visualised as a form of statistical equilibrium. Gujarati and Porter (2010) explained that for a series to be stationary its mean and variance should be constant over time. Gujarati and Porter (2010) further explained that the value of covariance between two time periods depends only on the distance or lag between them, and not on the actual time at which the covariance is computed. There are two types of stationarity, which are strict stationarity and weak stationarity. The two types of stationary process are defined as follows: -

Firstly, a process $\{Y(t), t = 0, 1, 2, 3, \ldots\}$ is strongly or strictly stationary if the joint probability distribution function of $\{Y_{t-s}, Y_{t-s+1}, \ldots Y_t, Y_{t+s-1}, Y_{t+s}\}$ is independent of t for all s. Therefore, for a strong stationary process the joint distribution of any possible set of random variables from the process is independent of time (Cochrane, 1997; Hipel and McLeod, 1994). Maddala *et al.* (2000) also state that a strictly stationary time series is further characterised as having a constant mean and constant variance.

Secondly, the stochastic process is said to be weakly stationary of order k if the statistical moments of the process up to that order depends only on time differences and not upon the time of occurrences of the data being used to estimate the moments (Lee, 2006; Cochrane, 1997; and Hipel and McLeod, 1994).

There are two popular principal tests among econometricians to test the null hypothesis of a unit root to establish stationarity. The commonly used methods to test the stationarity are implemented from Dickey and Fuller (1979). Asteriou *et al*. (2007) state the methods as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test. However, Pfaff (2008) recommends that researchers should constantly follow the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test since it puts the hypothesis of interest as the alternative as compared to other tests of stationarity. As mentioned above that stationarity has two types, being the strict and weak stationarity the process of weak stationarity is determined by the mean, variance and auto-covariance structure not changing over time (being constant) and the following are the conditions:

$$\mathrm{E}(\mathrm{Y_t}) = \mu \quad , \text{ for all t} \qquad (2.1).$$
$$\mathrm{VAR}(\mathrm{Y_t^2}) = \sigma^2 \quad , \text{ for all t} \qquad (2.2).$$
$$\rho_{t,s} = \mathrm{COV}(\mathrm{Y_t}, \mathrm{Y_s}) \quad , \qquad \text{for all t, s} \qquad (2.3).$$

where $\mathrm{Y_t}$ is the stochastic process and $\mathrm{Y_s}$ denotes the set of distributions of all finite values of the $\mathrm{Y_t}$ process, and μ is the expected value of the process at time t.

On the other hand, strict stationarity is if the random variables have the same joint distribution $(t_1, \ldots, t_n)$ for all set of indices and for all the integers $\tau \; and \; n > 0$, and can be written as:

$$(\mathrm{Y_t}, \ldots, \mathrm{Y_{tn}})^{\mathrm{T}} \stackrel{\mathrm{m}}{=} (\mathrm{Y_1}, \mathrm{Y_{1+\tau}})^{\mathrm{T}} \qquad (2.4).$$

where $\stackrel{\mathrm{m}}{=}$ denotes the means are equal in distribution. The next Subsection 2.2.2 discusses the ARCH model.

2.2.2 Autoregressive Conditional Heteroscedasticity (ARCH) Model

Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) model and it was the first model that provided a way to model conditional heteroscedasticity in volatility. The ARCH model is the combination of an autoregressive (AR) and moving average (MA) model. However, the strength of the ARCH model is that it manages to model the volatility clustering and the mean reverting characteristics, but on the other hand the weakness is that it requires a high order to accurately be able to model the conditional variance. In a time series, the ARCH model treats heteroscedasticity as the variance that can be modelled and the model is also used to describe a changing probably volatile variance.

The disadvantages of this model is that the ARCH (q) is likely to over-predict the volatility given that the model reacts slowly to huge isolated shocks to the return series (Matei, 2009). Secondly, the restriction of the model is for the conditional variance to follow a pure AR process and it may require to more adequately denote the conditional variance process in comparison with other more generalized models. Hence, Bollerslev (1986) extended the ARCH model to the generalization of an ARCH model and called it GARCH, which allows the conditional variance to be dependent in terms of lags.

The general ARCH equation is given as:

$$\sigma_t^2 = \mathrm{c} + \left(\sum_{\mathrm{i}=1}^{\mathrm{m}} \alpha_i u_{t-1}^2\right) + \omega_{\mathrm{t}} \qquad (2.5).$$

where σ_t^2 the conditional variance of the errors at time t, c denotes the constant term, u_{t-1}^2 is the squared error at time $t-q$, α_i is ARCH terms (volatility shocks from prior periods) and ω_{t} is a white noise process (Hamilton, 1994). Subsection 2.2.3 below discusses the extension of the ARCH model.

2.2.3 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is the extension of the ARCH model introduced by Bollerslev (1986). This model has quite similar key properties to the ARCH model, although the GARCH model requires fewer parameters to effectively model the volatility process. Bollerslev (1986) established the GARCH model as a solution for the limitations, and strict assumptions of the traditional linear regression model, and to improve the weaknesses of the ARCH model. However, the purpose of the GARCH method is to identify the volatility bunches and thus to offer a consistent technique for estimating upcoming volatility.

The GARCH models are used to describe the AR process, for example exchange rate volatility, if interested in the stochastic process of short-term volatility (Hviding *et al.,* 2004). In addition, the multivariate GARCH models are used to model forecast volatility. Matei (2009) continued to support Bollerslev (1986) on the GARCH model, which has three parameters compared to the ARCH model that will allow for an infinite numbers of squared roots to influence the current conditional variance.

The ARCH model is improved by the GARCH model by adding the general feature of conditional heteroscedasticity to the model. The parameters *p* and *q* in GARCH (*p,q*) are commonly used for modelling the volatility of financial returns, and the model generates good estimates with few parameters (Engle, 1982). The GARCH model is expressed as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \left(\beta_j \varepsilon \sigma_{t-j}^2\right) \qquad (2.6).$$

where ε_i denotes the ARCH terms (volatility shocks from prior periods), β_j is the GARCH term (the persistence of volatility), ω is the constant term, q is the number of lagged errors (ε^2) and p is the number of lagged conditional variance terms(σ^2).

However, there are different types of GARCH models such as Integrated GARCH (IGARCH), Exponential GARCH (EGARCH), Quadratic GARCH (QGARCH) and Nonlinear Asymmetric GARCH (NAGARCH). The IGARCH model was introduced by Engle and Bollerslev (1986). The IGARCH model deals with the persistent parameters to sum up to one and imports a unit root in the GARCH process, while the EGARCH model introduced by Nelson (1991) captures the size and sign effects of shocks in a nonlinear formulation. The QGARCH model developed by Sentana (1995) is used for modeling asymmetric effects of positive and negative shocks present in the model.

The NAGARCH model developed by Higgins and Bera (1992) is the model that allows asymmetric effects of negative and positive innovations, which means that the parameterization has the impact on the innovations for the conditional variance that is asymmetric.

2.2.4 Exponential Autoregressive Conditional Heteroscedasticity (EGARCH) Model

The Exponential autoregressive conditional heteroscedasticity (EGARCH) model is another form of the GARCH model by Nelson (1991) as one of the GARCH asymmetric models to capture the leverage effect. The EGARCH models do not have limitations on the parameters in the model, as opposed to the GARCH models. The EGARCH model consistently produces a positive conditional variance independently of the indications of the estimated parameters in the model. However, the model is also used when the GARCH model now and then reflects or creates problems when estimated parameters violate the inequality constraints. Furthermore, Nelson (1991) stated that the EGARCH model is an extension of the GARCH and it deals with overcoming the weakness encountered in using the standard GARCH. The advantage of using the EGARCH model is that the positivity of the parameters is guaranteed and also there are no restrictions on the parameters.

2.2.5 Multivariate Generalized Autoregressive Conditional Heteroscedasticity (Multivariate GARCH) Model

The Multivariate GARCH model is the model developed by Bollerslev, Engle and Wooldridge (1988). The Multivariate GARCH models mostly accomplishes positive definitiveness with the conditional variance matrix by indicating a strong assurance structured model. This model has different types, namely: Vector GARCH (VEC) model, the BEKK model (named after Baba, Engle, Kraft and Kroner), Constant Conditional Correlation (CCC) model, Dynamic Conditional Correlation (DCC) model and the Smooth Transition Conditional Correlation (STCC) model. The different types of multivariate GARCH are discussed in the following subsections,

2.2.5.1 Vector GARCH (VEC-MVGARCH) Model

Bollerslev, Engle, and Wooldridge (1988) suggested the VEC model, which is the very first Multivariate GARCH model for the conditional variance-covariance matrix. However this model is the univariate GARCH extended as description to a multivariate setting with the diagonal VEC model. The advantage of the VEC model is that the model is very elastic; though there is a disadvantage which means that it would be very difficult to impose the positive definiteness of the variance-covariance matrix.

The general VEC-MVGARCH Model is given as:

$$VEC(H_t) = C + \sum_{i=1}^{q} A_i.VEC(\varepsilon_{t-i}\varepsilon_{t-i}) + \sum_{j=1}^{p} B_j.VEC\left(\Sigma_{t-j}\right) \quad (2.7).$$

where H_t is the covariance matrix of residuals, C the vector that denotes constant covariances components , VEC is an operator, A_i and B_j are parameter matrices,t is index of the t^{th} observation, N represents number of observations and ε is an $N \times 1$ vector.

2.2.5.2 Baba, Engle, Kraft and Kroner (BEKK-MVGARCH) Model

The Baba-Engle-Kraft-Kroner (BEKK) model was developed by Engle and Kroner (1995). The BEKK model can be observed as a restricted version of the VEC model. The BEKK model has been classified that the conditional variance-covariance matrix is positive definite by construction, hence the study of Xu and Sun (2010) preferred the application of the BEKK-MVGARCH (p,q) model in examining the volatility spillover effects. The BEKK-MVGARCH model is given as:

$$H_t = H_t^{\frac{1}{2}} Z_t \quad (2.8).$$

where $t = 1, \dots, T$ and Z_t is the sequence of random variables, $H_t^{\frac{1}{2}}$ is the symmetric square root of X_t formula which is expressed further in equation (3.12) in Chapter 3.

2.2.5.3 Constant Conditional Correlation (CCC-MVGARCH) Model

Bollerslev (1990) explained the Constant Conditional Correlation (CCC) GARCH model as the simplest multivariate correlation model that is nested in the other conditional correlation models. However, the CCC-MVGARCH models are easier to estimate than many of their counterparts and their parameters (correlations) have a natural interpretation. Chan and McAleer (2003) have proved that the CCC-MVGARCH model is also employed to test for an independent relationship between the conditional volatilities as standard GARCH does not test the interdependence. The advantage of this model is that it has fewer parameters and is simple to estimate. The CCC-MVGARCH model equation is given by Nakatani and Terasvirta (2009) as:

$$\mathrm{Y_t} = \mu + \varepsilon_t \qquad (2.9).$$

With ε_t computed as

$$\varepsilon_t = \mathrm{D_t z_t} \qquad (2.10).$$

where $\mathrm{Y_t}$ is the stochastic $(\mathrm{N} \times 1)$ vector, $\mathrm{D_t}$ is the diagonal matrix whose diagonal elements consists of conditional standard deviation of ε_t, μ is $(\mathrm{N} \times 1)$ intercept vector and the $\mathrm{Z_t}$ is the stochastic vector sequence which is independent.

2.2.5.4 Dynamic Conditional Correlation (DCC-MVGARCH) Model

Engle (2002) introduced the most popular extension of the CCC–MVGARCH model as the DCC–MVGARCH model. The model is used to capture the empirically detected dynamic contemporaneous correlations of asset returns. The DCC structure is similar to the VEC–MVGARCH model. The general equation for DCC model matrix by Engle and Sheppard (2001) is expressed as:

$$H_t = D_t R_t D_t \qquad (2.11).$$

where H_t is the conditional covariance matrix, R_t is the time-varying correlation matrix and the D_t = $k \times k$ diagonal matrix of time varying standard deviations from the univariate GARCH models.

2.2.5.5 Smooth Transition Conditional Correlation (STCC–MVGARCH) Model

Silvennoinen and Terasvirta (2005) extended the CCC–MVGARCH into a STCC–MVGARCH model in which the correlations fluctuate according to a transition variable. The STCC–MVGARCH model is only recognised when the correlations are changing and the standard asymptotic theory is not valid. The proposed STCC–MVGARCH model can capture the conditional correlations assumed to change smoothly over time depending on a transition variable. The equation for STCC-MVGARCH is given as:

$$P_t = (1 - G_t)\mathrm{P}_1 + \mathrm{G}_\mathrm{t}\mathrm{P}_2 \qquad (2.12).$$

where G_t is the transition function with values which are constrained between 0 and 1, P_1 and P_2 are positive definite correlation matrices and the P_t denotes a correlation matrix that should be positive definite with the probability of 1 due to the fact that the structure has two positive definite matrix convex combinations.

2.2.6 Forecasting

Matei (2009) stated that ARCH or GARCH models are most appropriate measures when forecasting volatility, especially when having large observations. However, Akgiray (1989) was the first author to forecast volatility using the GARCH model. Akgiray (1989) explained that GARCH models produce better forecasts than most of the other forecasting methods such as Random Walk (RW), MA and Exponential Smoothing (ES) when applied to monthly United States (US) stock market data.

The Multivariate GARCH formulations to forecast are similar to that of the GARCH model, it is used to analyse a number of different types of financial data for instance, macroeconomic data. Nonetheless, the covariances together with the variances are permitted to be time-varying in the multivariate GARCH model. There are different forms of checking the forecasting accuracy such as the mean squared error (MSE) and mean absolute percentage error (MAPE). Yaffee and McGee (1999) defined the forecasting accuracy as follows: MAPE as the average of the sum of the absolute values of the percentage errors, and MSE on the other side is defined as the sum of squared errors divided by its degrees of freedom, and the outcome will be mean square error or error variance.

2.3 EMPIRICAL LITERATURE REVIEW

In this section of the literature review, the study reviews the empirical studies appropriate to this study based on both international perspectives and the South African perspective.

2.3.1 International Perspective

A number of studies have been conducted with different methods and this section is about to review a brief summary of methods carry out by other researchers. The study by Englama *et al.* (2010) used the monthly data from the year 1999 to 2009 looking at the effects of oil price volatility, and external reserves on exchange rate volatility and demand for foreign exchange in Nigeria. The study utilised the vector error correction model (VECM) and cointegration technique to model the data. The study revealed that a 1% rise in the international price of oil results in an increase of exchange rate volatility in the long run by 0.54%, and in the short run by 0.02%.

Serra (2011) examined transmission among oil, ethanol and sugar prices with the vector error correction model Multivariate GARCH for volatilities. The study used the weekly data ranging from 2000 to 2008.The finding revealed that the increase in oil prices had an impact on the ethanol markets to accomplish higher equilibrium prices, although this caused just short run instability in sugar prices driving some volatility.

Jin (2008) conducted a comparative study between linear and nonlinear GARCH models on the impact of oil price shock and exchange rate volatility on the economic growth. The study found the economic growth was led by the increase in oil prices in China and Japan while Russia's economic growth resulted in a positive impact. However, a 10% surplus on the international prices of oil was linked with a 5.2% growth of Russia's GDP and a decline of 1.1% on Japan's GDP. Therefore, the increase of real exchange rate assumed a positive relationship to Russia's GDP, and China's and Japan's GDP resulted in a negative relationship.

In another study, Wei, Wang and Huang (2010) captured the volatility features of two crude oil markets, these being Brent and West Texas Intermediate (WTI). The study used daily prices data ranging from 1992/01/06 to 2009/12/31 with the linear and nonlinear GARCH models. However, it revealed that the non-linear GARCH models are capturing long memory and/or asymmetric volatility and show more superior forecasting accuracy than the linear models, particularly in volatility forecasting of about 5 or 20 days. The study further indicated that the linear model and other models cannot consistently outperform each other, except the nonlinear models.

The study by Malik and Ewing (2009) examined volatility transmission between oil prices and three equity sector returns in the US, which are consumer services, healthcare and technology, using the weekly data from 1992 to 2008. Findings from the bivariate GARCH models showed the existence of a negative and significant relationship between the volatility of oil prices and sector index returns. Similarly, Hassan and Malik (2007) studied the volatility transmission between US sectors for the period from 1992 January to 2005 June. The study employed the Multivariate GARCH model to simultaneously estimate the mean and conditional variance using daily returns among different US sector indices. The results showed that it is vital as a financial market participant to know the volatility transmission mechanism over time and across sectors, as significant transmission of shocks and volatility among different sectors was observed.

Narayan, Kumar and Narayan (2007) investigated the crude oil price volatility using the EGARCH model. The study used the daily price data ranging from 3 August 1991 to 5 August 2006. The results showed evidence that the shocks have permanent effects and asymmetric effects on volatility. Ramzan *et al.* (2012) modelled exchange rate dynamics in Pakistan using the monthly data from 1981 July to May 2010.The study used the GARCH family models. The study findings showed that GARCH (1,2) was the best as opposed to EGARCH (1,2) model. However, the GARCH (1,2) model was used to remove the persistence in volatility while EGARCH (1,2) successfully overcame the leverage effect in the exchange rate returns under study. In conclusion, the study found that the GARCH family of models captures the volatility and leverage effect in the exchange rate returns and gives fairly good forecasting performance for the model.

The study by Al-Raimony and El-Nader (2012) measured the volatility and the effect of macroeconomic by applying ARCH/GARCH, and their overall outcomes were that the

ARCH was found statistically significant. However, during the period 1991-2010, the GARCH was found to be statistically insignificant. In addition, the study by Jansky and Rippel (2011) evaluated ARCH models on six world stock indices and modelling 1-day onward VaR forecasting. Jansky and Rippel (2011) used data in the time period between 2004 and 2009 from 6 world stock indices fitting the models to the data from less volatile periods and forecasting with ones that are more volatile. The study found that the GARCH process is the most adequate to capture the volatility in the indices.

Katircioglu *et al.* (2015) studied the association between the changes in oil prices and macroeconomic variables (GDP, CPI and unemployment) among 26 OECD economies. The study used Durbin-H panel cointegration to analyse the data, starting from 1980 to 2011. The findings showed that the changes in oil price have an inverse effect on macroeconomic variables.

Taghizadeh-Hessary *et al.* (2015) investigated the impact of oil price volatility on economic sectors in Japan utilizing the vector autoregressive model. The study used quarterly data from Quarter 1 of 1990 until Quarter 1 of 2014. The study found that industrial and transport sectors were strongly sensitive to the drastic oil price volatility.

Nazlioglu *et al.* (2012) studied the price volatility spillovers between oil and agricultural commodities (corn, wheat, soybeans, and sugar) using the univariate GARCH and causality tests with daily data from 1986 to 2011.The outcomes specified that there is a link between oil price and agricultural markets due to the increase in food crisis.

The study by Danmola (2013) in Nigeria examined the relationship between exchange rate volatility and macroeconomic variables for the period of 1980 to 2010. The study examined the presence of unit root utilizing the ADF and PP. The study further used Granger causality test, ordinary least square (OLS), and the correlation matrix to examine this relationship. The study revealed that GDP, Trade Openness and foreign direct investment (FDI) have a positive effect on exchange rate volatility and in addition showed that all variables are stationary at difference level of significance and order of integration.

Similarly, Akide (2007) employed the Granger Causality test using the quarterly data from 1970 to 2000 to investigate the impact of oil price volatility on economic growth indicators in Nigeria. Akide (2007) established that within the period of study, oil price shocks did not affect output and inflation in Nigeria; however they significantly influenced the real exchange rate. Jouini (2013) studied the link between world oil price and stock sectors in Saudi Arabia using weekly data in the period from 2007 to 2011. The study also used the VAR-GARCH technique and found that there is volatility transmission between oil price and stock sectors.

The study by Agnolucci (2009) compared the predictive capability of two methods that can be utilized to forecast volatility using the daily returns of generic light sweet crude oil from West Texas Intermediate (WTI) (31 December 1991 to 02 May 2005). The study utilised the GARCH-type models and an implied volatility model. Agnolucci (2009) concluded that the GARCH-type seemed to perform better as the implied volatility and shocks to the conditional variance of the series were found to be highly persistent.

Busse *et al.* (2010) investigated volatilities of agricultural commodities with multivariate GARCH to model the returns of rapeseed and crude oil. The study used daily datasets for the period 1999 to 2009. The study revealed collective correlation between oil prices and rapeseed, which indicated a high combination between these two and with reactions from the rapeseed market to oil market fluctuations.

Malik and Hammoudeh (2007) also used a Multivariate GARCH to model the volatility in the Gulf stock markets, in a case of Saudi Arabia. The study used yearly data ranging from the year 1994 to 2001. The study revealed that Gulf stock markets obtain volatility mainly from oil markets. Due to the circumstance that the volatility spillover takes transfer from the Saudi stock market to oil market, emphasizes the bigger role Saudi Arabia has in the global oil market.

The study by Belaid and Abderrahmani (2013) explored the relation between oil prices, electricity consumption and economic growth in Algeria for the period 1971 to 2010 using the multivariate cointegration technique. The study found no evidence of neutrality hypothesis.

Aloui and Jammazi (2009) used France, Japan and United Kingdom (UK) covering the period from 1987 January to 2007 December, developing a two-regime Markov-switching EGARCH model to the interdependence between crude oil shocks and stock returns. The findings showed that the net oil prices play a crucial role in determining the volatility of real returns and the probability of transition across regimes.

Abdulkareem and Abdulhakeem (2016) analysed oil price and macroeconomic volatility in Nigeria using GARCH model and its variants (Multivariate GARCH, TGARCH and EGARCH) with different data sets (quarterly, monthly and daily). The study revealed that the macroeconomic variables reflected (oil price, exchange rate, interest rate, and real gross domestic product) high volatility. In conclusion, the asymmetric models (TGARCH model) suggested that oil price is a major source of economic volatility in Nigeria.

2.3.2 South African Perspective

Looking at the South African perspective, Kin and Courage (2014) examined the impact of the oil prices in South Africa on the nominal exchange rate. The study used the GARCH model with the monthly data from 1994 to 2012. The outcomes revealed that rise in oil prices leads to decrease of the exchange rate. The results more revealed that oil prices are a very important variable in determining the strength of the South African currency and its volatility.

Mpofu (2016) studied real and nominal exchange rate volatility using both bilateral (rand / US dollar) and effective exchange rates for the period from 1986 to 2013. Mpofu (2016) used the GARCH (1, 1) which was augmented with macroeconomic determinants of exchange rate volatility. The study found that the nominal volatility output and gold price volatility are positively related with rand volatility. On the other side, trade openness together with changes in foreign exchange reserves and money supply decrease volatility.

The study by Kutu and Ngalawa (2017) modelled the volatility of South Africa's exchange rate amidst global shocks using the symmetric GARCH model and asymmetric Exponential Generalised autoregressive conditional heteroscedasticity (EGARCH). The study found that the asymmetric EGARCH model outperforms the symmetric GARCH model and should be suggested to policymakers in South Africa. The result of the study also showed that the global shocks affect the exchange rate of South Africa.

Arezki *et al.* (2014) used a VECM to study the relationship between the South African Rand (ZAR) and gold price volatility using monthly data from 1980 to 2010. The outcome of the study showed that gold price volatility is vital in explaining the extreme exchange rate volatility of the ZAR. Similarly, Saghaian (2010) used the VECM and Granger causality test to examined the impact of oil prices on commodity prices to determine whether the variables have a causal relationship or are just strongly correlated, using the monthly data for the period 1996 to 2008. The study found that there is a strong correlation between oil prices and commodity prices, and there is no conclusive evidence of a causal relationship.

Schaling *et al.* (2014) used a Granger causality and cointegration technique to observe whether the South African currency changes parallel with commodity prices. They used the data between 1996 and 2010 to model the long and short run relationship between exchange rates and commodity prices. The study revealed that the two assets are not cointegrated and they are found to be negatively related with strong and significant causality running from commodity prices to exchange rate.

Aye *et al.* (2014) analysed the impact of oil price uncertainty on manufacturing production of South Africa. The bivariate GARCH-in-mean-VAR model was used and the results showed that oil price uncertainty have a significant negative impact on manufacturing production. The study also detected that the responses of manufacturing production to positive and negative shocks are asymmetric.

Chisadza *et al.* (2013) examined the impact of the oil supply and demand shocks on the South African economy with a sign-restriction-based structural VAR model. The study revealed that an oil supply shock has a short-lived significant impact only on the inflation rates which impact negatively on the South African economy, although its impact on other variables is statistically insignificant; however supply disturbances result in a short-term increase in the domestic inflation rate with no response from the monetary policy. In conclusion, the oil price effect on GDP showed a negative effect in the short run and a positive effect in the long run.

Oberholzer and Von Boetticher (2015) investigated the inter-market relationship between the South African Rand and the 5 main indices of the Johannesburg Stock Exchange. The authors used the daily closing values from 2002 January to the end of September 2014, and they employed the CCC-MVGARCH (1,1) to test the spillover effects and the impact of shocks on both markets. The results showed that the Rand is more volatile to market shocks compared to the JSE/FTSE's All Share Index (J203), Top 40 Index (J200), Midcap Index (J201), but less volatile to market shocks than JSE/FTSE's Small Cap Index (J202) and Fledgling Index (J204). Oberholzer and Von Boetticher (2015) concluded that the ones that were less volatile to market shocks have an effect on the volatility of the Rand.

The study by Kumar (2013) examined the volatility spillovers between exchange rates and stock prices, and involved the main emerging economies popularly known as IBSA countries (India, Brazil and South Africa). Kumar (2013) used the VAR framework and multivariate GARCH to investigate the relationships between the markets. The results of the multivariate GARCH model revealed that in IBSA countries, there is a bi-directional relationship among the equity and foreign exchange variables, which shows a complete integration of financial markets in the particular countries. Additionally, India, Brazil and South African equity and currency markets displayed return and volatility spillovers.

2.4 CHAPTER SUMMARY

This chapter reviewed different studies on oil price volatility and macroeconomic variables as used in the international context as well as the South African context. Authors such as Akide (2007), Danmola (2013), Jouini (2013), Nazlioglu *et al.* (2012) and Wei, Wang and Hung (2010) reported that volatility has an impact on the economic growth of the countries. In addition, the studies of Hassan and Malik (2007), Serra (2011), Malik and Hammoudeh (2007) and Busse *et al.* (2010) used the

Multivariate GARCH model to investigate the volatility in different forms. All the mentioned authors found that Multivariate GARCH model is the best model in modelling the volatility in different markets. However, many previous studies used the ARCH, GARCH, VAR, Granger causality and cointegration technique models as opposed to the Multivariate GARCH. This is a sign that the application of this framework has not been exhausted in the field of statistics. Hence, this study expands the analysis of volatility using the extension of GARCH model (Multivariate GARCH).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter looks at the statistical methods to model the oil price volatility and selected macroeconomic variables in the South African perspective. The chapter discusses and explains the data type, method used, model estimation and diagnostic checks. Furthermore, the chapter will also discuss the stationarity tests and forecasting technique.

The structure of this chapter is as follows: Section 3.2 Explains the Ethical Consideration, Section 3.3 is the data source; unit roots (testing for stationarity) are discussed in Section 3.4. Section 3.5 presents the model estimation and Section 3.6, the diagnostic checks. Forecasting is highlighted in Section 3.7, and lastly Section 3.8 gives the summary of the chapter.

3.2 ETHICAL CONSIDERATIONS

This study complied with the North-West University academic rules such as correct referencing style which is done to avoid plagiarism, therefore the North West University ethical considerations processes were followed to attain ethical clearance. Moral issues are important to consider in a research, therefore ethical issues on this study are addressed by guaranteeing that the data, sources and interpretations are not deliberately misleading others. Permission to conduct the study was obtained from the Faculty of Economic and Management Sciences through the supervisors. The study is focusing only on secondary data and there is no need for any ethical issues relating to animals, humans or the environment in the study.

3.3 DATA SOURCE

The study utilised secondary quarterly time series data from January 1990 to June 2018, and that is 114 observations. The data were obtained from the South African Reserve Bank (SARB) and the Department of Trade and Industry (DTI). The statistical software used to analyse the data are Statistical Analysis System (SAS 9.3), E-views version 8 and R-packages (R x64 3.0). The variables used in the study are oil price and the four selected macroeconomic variables. The macroeconomic variables comprise GDP, inflation, exchange rate, and interest rate. The variables were selected based on their importance to the oil price in the South African context. The next section discusses the unit root test.

3.4 TESTING FOR STATIONARITY

Stationarity is a process where the statistical parameters, for instance the mean and standard deviation of the process, do not change with time (Challis & Kitney, 1991). The reasons for testing for stationarity are to avoid spurious results, to show time series plots that determine the behaviour of random variables and to evaluate whether the properties of the series are not violated (Baumohl & Lyocsa, 2009). The presence of unit root in this study is tested using the Augmented Dickey Fuller (ADF) test (1979) and Phillips–Perron (PP) test (1988).

However, the ADF test is considered as a good measure in evaluating the stationarity of the series. In addition, Balke (1991) and Leng (2006) support the ADF test according to the assumption that time series is fixed, hence it is recommended as a good measure in evaluating the series stationarity. On other side, the PP test is considered as similar to the ADF test, though the PP includes the DF process to allow autocorrelated residual (Brooks, 2008). The ADF test and the PP test are discussed in the following sub-sections respectively.

3.4.1 Augmented Dickey Fuller (ADF) test

Dickey and Fuller (1979) developed the ADF test model. The testing procedure for the ADF test is the same as for the Dickey–Fuller test. The ADF test for studying unit root in the data uses the following framework:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (3.1).$$

where β is the coefficient, γ is the variable under study, α is a constant and p is the lag order of the autoregressive process. The constraints $\beta = 0$ and $\alpha = 0$ relate to modeling a random walk, and on the other hand, using $\beta = 0$ also links to modeling a random walk with a drift. The hypothesis to be tested is formulated as:

H_0: $\gamma = 0$ (Data is non-stationary)

H_1: $\gamma < 0$ (Data is stationary),

The test statistic for ADF test is given as:

$$ADF_t = \frac{\hat{\gamma} - 1}{SE(\hat{\gamma})} \qquad (3.2).$$

If the test statistics null hypothesis ($\mathrm{H0: Data\ is\ non-stationary}$) is rejected, this means that there is no unit root present. Therefore, the data is stationary. On the other hand, if $\gamma < 0$, the researcher fails to reject the null hypothesis and concludes that the data is non-stationary. If the p-value of the ADF test is less than 5% level of significance, this leads to rejection of the null hypothesis (data is stationary). On the other hand, when the p-value of the ADF test is more than 5% level of significance then the researcher can conclude the data is non-stationary. The same procedure is applied in the PP stationarity test.

3.4.2 Phillips and Perron (PP) tests

Phillips and Perron (1988) developed the Phillips and Perron (PP) stationarity test which is a build-up on the Dickey–Fuller test. The PP test is used to test the null hypothesis that time series is integrated of order 1. The PP test is presented as follows:

$$\Delta y_t = (\rho - 1) y_{t-1} + \mu_t \qquad (3.3),$$

where Δ is the 1st difference operator, y_t represents the time series (t = time and Y= series), ρ is the number of lag order and μ_t is a white noise process. The following hypothesis tests the Phillips and Perron (PP) test:

H_0: $\rho = 1$

H_1: $\rho < 1$

If the p-value is $\leq \alpha$ value, then the null hypothesis is rejected and concludes that there is no unit root for the series. If the p-value$> \alpha$, then the researcher fails to reject H_0 and concludes that there is a unit root for the series.

3.5 MODEL ESTIMATION

The model estimation of the study ranges from the ARCH model to the multivariate GARCH. The first stage of the analysis is to determine the ARCH effects in the model followed by the standard GARCH model, then the multivariate GARCH, the model selection, the diagnostic test and lastly the forecasting.

3.5.1 Autoregressive Conditional Heteroscedasticity (ARCH) Model

The ARCH model is the first model that could systematically model volatility and it was proposed by Engle in 1982. However, Baillie and Bollerslev (1989) explained that variation on error terms has been changed from the constant to be a random sequence. The general form of the ARCH (q) model is:

$$r_t = \mu + \varepsilon_t \quad , t = 1, \dots \dots, T \qquad (3.4).$$

where *T* is number of observations, ε_t represents residuals and μ is the mean of the time series (r_t). However, the residual process of ARCH model indicates that the residuals are assumed as:

$$\varepsilon_t = \sigma_t z_t , \qquad Z_t \sim \mathrm{N}(0,1) \qquad (3.5).$$

The series of σ_t^2 is then modelled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-p}^2 \qquad (3.6).$$

where $\alpha_i \geq 0$ and $\alpha_0 > 0$. The model assumption is that ε_t are assumed to follow a standard normal, student-t or generalized error distribution (Tsay, 2005). The ARCH effect invented by Engle (1982) is similar to the Lagrange Multiplier (LM) test for autocorrelation. Hence, the LM is used in the ARCH model to test the effects, under the null hypothesis that there is no ARCH effect and the alternative being there are

ARCH effects. However, the test statistics is asymptotically distributed as a chi-square distribution with T degrees of freedom. The distribution is given as:

$$\mathrm{LM} = \mathrm{TR}^2 \qquad (3.7).$$

where R denotes the sample multiple correlation of ε_t on constant and T is the sample size or the number of observations.

The ARCH model by Engle (1982) is computed using the following steps:

i. Firstly, run the regression of the model using Ordinary Least Squares (OLS) and collect the residuals (Square the residuals).
ii. Secondly, run the secondary regression and get the R^2 statistic from this regression. The following equation is used when running the secondary regression:

$$\mathrm{u_t}^2 = \alpha_1\ \mathrm{u_{t-1}}^2 + \alpha_2\ \mathrm{u_{t-2}}^2 + \ldots + \alpha_3\ \mathrm{u_{t-p}}^2 + \mathrm{V_t} \qquad (3.8).$$

where p lags are included in this secondary regression and u is the residual from the initial regression.

iii. Lastly, use the statistics test in equation (3.7) to conclude the hypothesis.

3.5.2 Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Model

Bollerslev (1986) and Taylor (1986) proposed the generalised ARCH (GARCH) model, which has been indicated that it better captures the volatility in a return series than the ARCH model. The GARCH model is based on the assumption that forecasts of variance changing in time depend on the lagged variance of the variables, and the advantage of GARCH models is that the model is able to account for volatility clustering (Bauwens *et al*., 2012).

After Engle (1986) proposed the GARCH model, Engle (1986) identified the 3 steps that the GARCH model can be used for:

- To estimate a best-fitting autoregressive model
- For computing autocorrelations of the error term and
- Testing for significance.

The GARCH (p, q) model can be defined and expressed as follows:

$$\mathrm{h}_{\mathrm{t}}^{2} = \mathrm{c} + \sum_{i=1}^{q} \varepsilon_{i}\ \epsilon_{\mathrm{t-i}}^{2} + \sum_{j=1}^{p} b_{j}\ \mathrm{h}_{\mathrm{t-j}}^{2} \qquad (3.9).$$

where $\mathrm{h}_{\mathrm{t-1}}^{2}$ indicates the variance, $\epsilon_{\mathrm{t-j}}^{2}$ is the squared error for the period $t-j$, ε_{i} is the residual coefficient, t denotes time, while j denote the number of lags, c being the intercept, $\sum_{i=1}^{q} \varepsilon_{i}\ \epsilon_{\mathrm{t-i}}^{2}$ represent the ARCH terms and $\sum_{j=1}^{p} b_{j}\ \mathrm{h}_{\mathrm{t-j}}^{2}$ is the GARCH terms. However, the residual coefficient and the intercept in the equation ε_{t} and c have to be more than zero in order to ensure a positive variance (Reider, 2009).

However, the GARCH models have a few disadvantages, such as not allowing leverage effects and limitations on parameters which should be indicated to ensure positivity for unconditional variance that might distract the estimation process. Hence, the study further applies the Exponential GARCH model and Multivariate GARCH model.

3.5.3 Exponential Autoregressive Conditional Heteroscedasticity (EGARCH) Model

Nelson (1991) firstly introduced the exponential GARCH model to capture the asymmetric response of volatility. This model is a discrete-time estimate to a continuous-time stochastic volatility process that is expressed in the form of logarithms and conditional volatility that is certain to be positive without any limitations on the parameters.

The EGARCH (p,q) model may be defined as:

$$\log \sigma_{\mathrm{t}}^{2} = \omega + \sum_{k=1}^{q} \beta_{k} g(z_{t-k}) + \sum_{k=1}^{p} \sigma_{k} \log \sigma_{\mathrm{t-k}}^{2} \qquad (3.10).$$

where σ_t^2 is the conditional variance, ω is a constant parameter, β indicates the past coefficient, p is the order of the ARCH component model while q is the order of the GARCH component model, $\sum_{k=1}^{q} \beta_k g(z_{t-k})$ represent the fixed variance from the past period where z_t is the standard normal variable.

3.5.4 Multivariate GARCH Model

Bollerslev, Engle and Wooldridge in 1988 first introduced the Multivariate GARCH model. The model allows the inspection of the transmission of shocks, volatility contamination between data sets and correlation. The general Multivariate GARCH model is described as:

$$Y_t = \mu_t + \varepsilon_t \qquad (3.11).$$

where μ_t is the vector of conditional expectation of Y_t at time period *t* while ε_t denotes the vector shocks at time *t*. The multivariate GARCH model includes VEC/DVEC-GARCH, BEKK, DCC and CCC models. Bauwens *et al.* (2006) classified present multivariate GARCH models into three non-mutually exclusive categories:

- Direct generalizations of the univariate GARCH model of Bollerslev (1986) which include the VEC model and the BEKK model.
- Linear combinations of univariate GARCH models which is the factor models.
- Nonlinear combinations of univariate GARCH models which is the CCC model.

However, the study is only limited to the first category, which is the BEKK model, in order to address the objectives stated in chapter 1. The BEKK model is discussed in the following subsection.

3.1.1.1 The BEKK model

Baba *et al*. (1990) developed the BEKK model, which is classified as another version of the VEC model. Padhi and Lagesh (2012) stated that the BEKK model captures the persistence of volatility within each series.

The BEKK model formula is expressed as follows:

$$X_t = CC' + \sum_{j=1}^{p}\sum_{k=1}^{k} A'_{kj}\, \varepsilon_{t-j}\, \varepsilon'_{t-j}\, A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{k} B'_{kj}\, X_{t-j} B_{kj} \qquad (3.12).$$

where $\mathrm{A_{kj}}$, $\mathrm{B_{kj}}$ and C are $\mathrm{N} \times \mathrm{N}$ parameter matrices and C is a lower triangular matrix which indicates that all the entries above the main diagonal are zero as represented:

$$c = \begin{bmatrix} \ell_{1,1} & \cdots & 0 \\ \ell_{2,1} & \ell_{2,2} & \vdots \\ \ell_{3,1} & \ell_{3,2,} & \ell_{n,n} \end{bmatrix} \quad \text{e.g} \quad c= \begin{bmatrix} 1 & 0 & 0 \\ 2 & 8 & 0 \\ 4 & 9 & 7 \end{bmatrix} \qquad (3.13).$$

$\mathrm{A_{kj}}$ and $\mathrm{B_{kj}}$ matrices are $\mathrm{N} \times \mathrm{N}$ diagonal parameter matrices and are represented as:

$$\mathrm{A_{kj}} \text{ and } \mathrm{B_{kj}} = \begin{bmatrix} C_{1,1} & C_{1,2} & C_{1,,3} \\ C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,1} & C_{3,2} & C_{3,3} \end{bmatrix} \quad \text{e.g} \quad \mathrm{A_{kj}} \text{ and } \mathrm{B_{kj}} = \begin{bmatrix} C_{1,1} & 0 & 0 \\ 0 & C_{2,2} & 0 \\ 0 & 0 & C_{3,3} \end{bmatrix} \qquad (3.14).$$

The formula of BEKK equation in (3.12) is represented as follows: the symmetric parameterization of the model $\mathrm{X_t}$ is surely positive definite provided that $CC'^{'}$ is positive definite, as the BEKK is the extension of VEC and the required condition for the covariance stationarity of the BEKK model is having the eigenvalues.

3.6 MODEL DIGNOSTICS

Moroke (2005) suggested that the diagnostics checks must be computed to define the model adequacy after model estimation is done. Hence, in this study the normality test, Portmanteau test and Lagrange Multiplier (LM) test are to be used to determine the model adequacy. The tests are discussed in the subsequent sections.

3.6.1 Normality Test

The most commonly applied test for normality is the Jarque-Bera (JB) test (Brooks 2008). The study also used the JB test to test the normality of the data set. Jarque and Bera (1980) explain the test as used as a measure of the differences in kurtosis and skewness of a variable compared to those of the normal distribution. The null and alternative hypothesis for JB test is formulated as:

H_0: Skewness and excess kurtosis are zero – normal distribution
H_1: Skewness or excess kurtosis are not zero – non-normal distribution

The test statistic of JB test is described as:

$$\mathrm{JB} = \frac{\mathrm{n-k}}{6}\left(\mathrm{S}^2 + \frac{1}{4}(\mathrm{c}-3)^2\right) \quad (3.15).$$

where S is the sample skewness, n is the number of observations, C is the sample kurtosis and K is the number of estimated parameters. The S and C are computed using the following equations:

$$\mathrm{S} = \frac{1}{\mathrm{n}}.\frac{\sum_{\mathrm{i-1}}^{\mathrm{n}}(\mathrm{x_i}-\bar{\mathrm{x}})^3}{\left(\hat{\sigma}^2\right)^{\frac{3}{2}}} \quad (3.16).$$

$$\mathrm{K} = \frac{1}{\mathrm{n}}.\frac{\sum_{\mathrm{i-1}}^{\mathrm{n}}(\mathrm{x_i}-\bar{\mathrm{x}})^4}{\left(\hat{\sigma}^2\right)^{2}} \quad (3.17).$$

where n are sample values, x_i is the i^{th} value, $\bar{x}$ is the sample mean and $\hat{\theta}^2 = \frac{1}{\mathrm{n}}.\ \sum_{\mathrm{i-1}}^{\mathrm{n}}(\mathrm{x_i}-\bar{\mathrm{x}})$. If the test statistic is large as measured by the upper quantiles of the chi-square distribution, the H_0 hypothesis is rejected in the favour of H_1.

3.6.2 Portmanteau Test

Box and Pierce (1970) introduced the portmanteau statistic to test for the adequacy of fitted models established on the asymptotic distribution of the residual autocorrelations.
The proposed equation is given as:

$$\mathrm{Q_{BP}} = \mathrm{n}\sum_{\mathrm{k=1}}^{\mathrm{m}}\hat{\mathrm{r}}^2{}_{\mathrm{k}} \quad (3.18).$$

where

$$\hat{r}^2{}_k = \frac{(n+2)}{(n-k)} r_k^2 \qquad (3.19).$$

After some conversation of the test statistics introduced by Box and Pierce (1970) about the limited sample distribution, a modification of new test statistics was suggested by Ljung and Box (1978). The test statistic by Ljung and Box improved the sample performance of the first test statistics by modifying it based on improving the finite sample performance of Box and Pierce (1970) by introducing a modified statistic based on standardizing the residual autocorrelations and the equation is given as:

$$Q_{LB} = n(n+2) \sum_{k=1}^{m} (n-k)^{-1} \hat{r}_k^2 \qquad (3.20).$$

where m is the number of lags being tested n is the sample size and $\hat{r}_k^{\,2}$ is the sample autocorrelation of order k of the residual.

3.6.3 Lagrange Multiplier (LM) Test

Engle (1982) recommended the use of the LM test for ARCH disturbances; therefore, the study used the LM test to test for the presence of heteroscedasticity in the residuals of the model. The hypotheses for the LM test are stated as:

H_0: The is no serial correlation
H_1: There is the presence of serial correlation

The test statistic for the LM test is formulated as:

$$LM_E = nR^2 \qquad (3.21).$$

where LM represents the Lagrange multiplier, n denotes number of observations and R^2 the coefficient of determination for the augmented residual regression and is given as:

$$R^2 = 1 - \frac{SSR}{SST} \qquad (3.22).$$

where SSR indicates the sum squared regression error and SST represents the sum squared total error.

3.7 FORECASTING

Forecasting is the process of predicting the future (Ykhlef, 2009). The study has an objective that is to forecast the future oil price volatility. Hence, this section of the study discusses the forecast of the models individually, based on the estimated parameters of the models. This is done to compare the one-step ahead forecast variance of the GARCH, EGARCH and the Multivariate GARCH-BEKK model.

3.8 CHAPTER SUMMARY

This chapter presented the methodology of the study that will be used to analyse the data in order to address the research objectives of the study. The chapter discussed the data source and the unit roots test. The unit root test will be tested using the ADF test and PP test. The chapter further discussed the ARCH, GARCH and the multivariate tests, namely the BEKK model. The diagnostics checks using normality test, the Jarque-Bera test, Portmanteau test and the LM for accuracy were also discussed. Furthermore, the forecasted values for each model will be assessed to determine the best model. The next chapter presents the data analysis and the interpretation of results.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION OF RESULTS

4.1 INTRODUCTION

This chapter is about data analysis and interpretation of results obtained using the methodology presented in chapter 3.The chapter is organised as follows: Section 4.2 present the preliminary data analysis results, Section 4.3 is stationary test, Section 4.4 is QQ Plots, Section 4.5 is estimation results, diagnostics checks and forecasting, and Section 4.6 is the chapter summary.

4.2 PRELIMINARY DATA ANALYSIS RESULTS

The study utilizes the time series data, and R-package software is used to run the descriptive statistics used to describe the dataset in the study. However the results show that the data has114 observations on each of the 5 macroeconomic variables (Oil price, GDP, Exchange rate, Interest rate and Inflation) with no missing values.

4.2.1 Descriptive Statistics

This section provides the descriptive statistics that describe the data being studied. The descriptive statistics comprise the mean, median, maximum and minimum values, standard deviation, skewness, kurtosis, the Jarque-Bera statistic and its probability value. The descriptive statistics of the 5 variables are presented in Table 4.1 below.

Table 4.1: Descriptive statistics results

	OIL	INTEREST_RATE	INFLATION	GDP	EXCHANGE_RATE
Mean	73.453	10.715	7.219	0.578	7.240
Median	34.547	10.833	6.367	0.621	6.999
Maximum	1213.483	21.687	16.167	1.837	15.857
Minimum	11.487	5.000	0.433	-1.530	2.534
Std. Dev.	148.070	4.382	3.551	0.681	3.272
Skewness	5.793	0.373	0.774	-0.529	0.543
Kurtosis	39.609	1.928	3.187	3.040	2.658
Jarque-Bera	7003.771	8.097	11.539	5.330	6.156

	OIL	INTEREST_RATE	INFLATION	GDP	EXCHANGE_RATE
Probability	0.000	0.018	0.003	0.070	0.046
Sum	8373.661	1221.474	822.933	65.890	825.331
Sum Sq. Dev.	2477.493	2170.131	1425.149	52.472	1209.850
Observations	114	114	114	114	114

According to the results in Table 4.1, the probability value of the Jarque-Bera (JB) test statistic for all the variables except GDP are less than 5% significance level, while the p-value for GDP is significant at 10% level of significance. Therefore, we conclude that all variables are normally distributed. The standard deviation of oil price and GDP are higher than their mean values, indicating that the two variables have been unstable and high throughout the sample period.

The oil price is found to be positively skewed with the value of 5.793 indicating that the distribution is highly skewed to the right. Interest rate, inflation and exchange rate are also found to be positively skewed at values of 0.373, 0.774 and 0.543 respectively. This means that these three variables are moderately skewed to the right. Furthermore, GDP has negative skewness with value of -0.529 which suggest that it is moderately skewed to the left.

4.2.2 Correlation Test Results

Table 4.2 shows the Pearson's correlation which determines pairwise correlations between the variables.

Table 4.2: Correlation results

	OIL	INTEREST_RATE	INFLATION	GDP	EXCHANGE_RATE
OIL	1	-0.183	-0.013	-0.071	0.166
INTEREST_RATE	-0.183	1	0.666	-0.224	-0.677
INFLATION	-0.013	0.666	1	-0.473	-0.465
GDP	-0.071	-0.224	-0.473	1	-0.018
EXCHANGE_RATE	0.166	-0.677	-0.465	-0.018	1

Table 4.2 presents pairwise correlations between the oil price, Interest rate, Inflation, GDP and Exchange rate. According to the results, the correlation coefficient ranges

from -0.68 to 0.67. The oil price shows a weak negative linear relationship with all the variables excluding Exchange rate, as with this variable there is a weak positive linear relationship. On the other hand, inflation has a moderate negative relationship with GDP and exchange rate, while the interest rate results show that it has a moderate positive relationship with inflation. There is a weak negative linear relationship between GDP and two variables, interest rate and exchange rate. However, exchange rate and interest rate show a strong negative linear relationship and all relationships among variables show that one variable increases as the other decreases, which means there is an inverse correlation among the variables.

4.3 STATIONARITY TEST RESULTS

The first step in examining the stationarity of the variables is the graphical representation followed by the formal test of stationarity. Figure 4.1 presents the time series plots and Figure 4.2 the differenced plots for all the variables. The formal test of stationarity using the ADF and PP tests are presented in Table 4.3.

4.3.1 Series Plots at Level

Figure 4.1 presents the graphical representation of the five variables at level.

Figure 4.1: Time series plots at level

Time series plots are presented in Figure 4.1. By eye inspection, the plots for all the variables (Oil price, GDP, Exchange rate, Interest rate and Inflation) seem to be nonstationary at level. The oil price plot is shown to be non-stationary with values revolving around zero, though around 2006 and 2010 there is a large increase, which means by that time there was a lot of oil price volatility effect in the country.

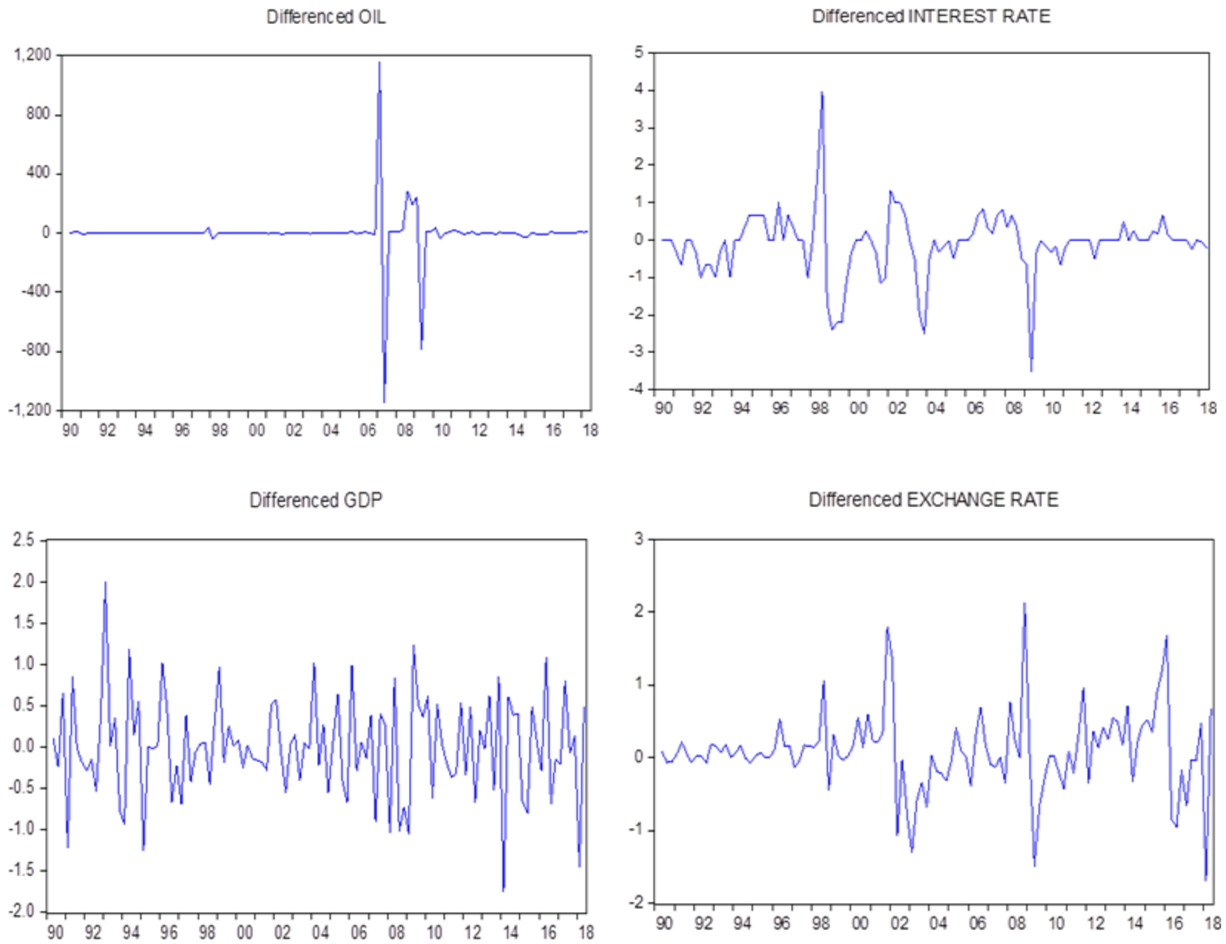
The plot of the Interest rate seems to be non-stationary since it measured decreasing trends which start on the year 1999. On the other hand, the GDP series appears to have an irregular trend though it seems to be stationary at level.

The Exchange rate series revealed an upward cyclical trend from 1990 onwards and the series therefore results to being non-stationary. This upward trend could be the result of democracy on the South African economy based on the country’s exchange rate as the country’s trade with other countries favours the economy.

In addition, the Inflation series shows a disturbance between the years 2003 and 2005, which rotated around zero. Furthermore, the recession that happened in 2009 could have also influenced disturbances. Differencing was then applied and the results are presented in Figure 4.2.

4.3.2 Series Plots at First Difference

The first differenced series plots are presented in Figure 4.2 below.



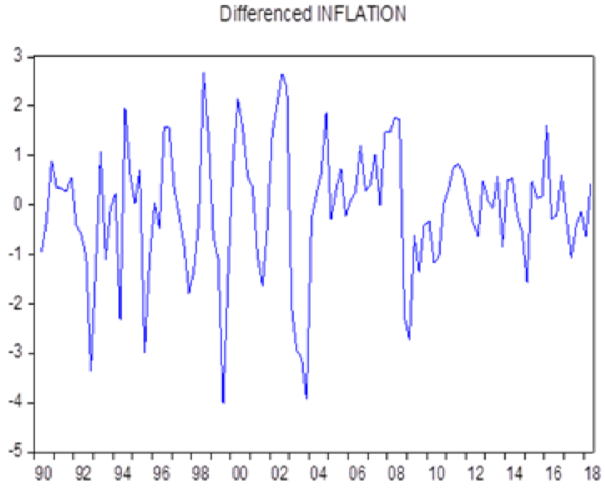


Figure 4.2: Time Series Differenced Plots

Figure 4.2 shows the time series plots results at first difference. The graphical evidence given on the above diagrams demonstrates that all variables are stationary at first difference. The formal tests for stationarity were computed to verify the eye inspection and the results are presented in Table 4.3.

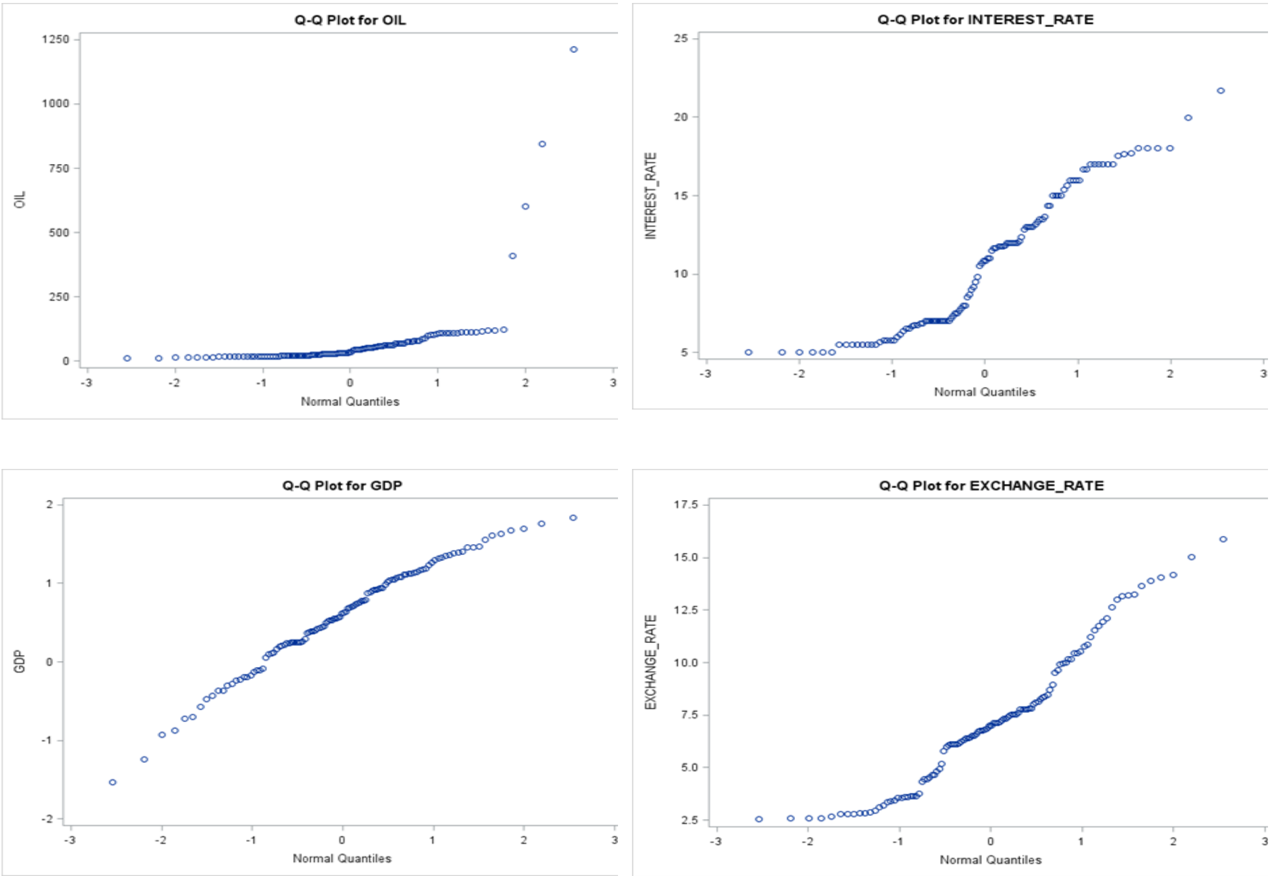
Table 4.3: Stationarity test results

Variables	Level of test	ADF test statistic	P-value	PP test statistic	P-value	Conclusion
Oil	Level	-7.707	<0.001	-7.821	<0.001	**Stationary**
	1st Difference	-8.930	<0.001	-52.828	<0.001	**Stationary**
Interest Rate	Level	-2.019	0.279	-1.702	0.428	**Non Stationary**
	1st Difference	-6.416	<0.001	-5.873	<0.001	**Stationary**
Inflation	Level	-2.929	0.045	-2.248	0.191	**Non Stationary**
	1st Difference	-5.085	<0.001	-7.082	<0.001	**Stationary**
GDP	Level	-5.327	<0.001	-5.314	<0.001	**Stationary**
	1st Difference	-8.901	<0.001	-30.958	<0.001	**Stationary**
Exchange Rate	Level	-0.721	0.836	-0.907	0.783	**Non Stationary**
	1st Difference	-8.528	<0.001	-8.528	<0.001	**Stationary**

Table 4.3 above presents the summary of the results for the ADF and PP tests. The results revealed that oil price and GDP are stationary at level, while interest rate, inflation and exchange rate are non-stationary. However, all the variables became stationary at first difference. This means that the variables are integrated to order 1. Section 4.4 presents the QQ-plots

4.4 TIME SERIES QQ-PLOTS

To test the assumption of normality, the QQ-plots were computed. The results are presented in Figure 4.3.



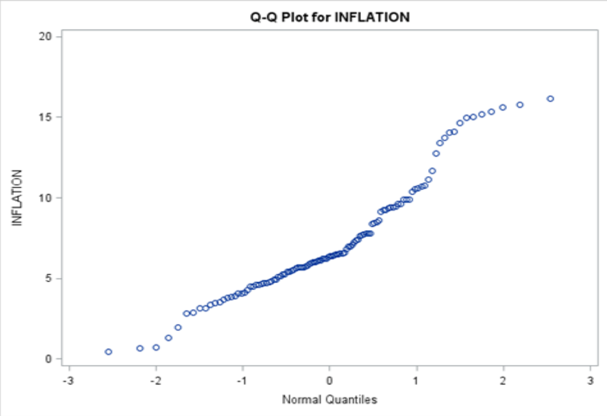


Figure 4.3: Time series QQ plots

A normal quantile-quantile (QQ) plot is an important diagnostic for checking the assumption of normality (Stine, 2016). Based on the graphical presentation in Figure 4.3 above, the results show that the interest rate, GDP, exchange rate and inflation display linearity of the points, which recommends that the series are normally distributed. On the other hand, oil price series provides different results with outliers and this result is because the price of oil is not consistent hence there is a flattened line graph. The next Section 4.5 presents the model estimation results.

4.5 MODEL ESTIMATION, DIAGNOSTICS AND FORECASTING RESULTS

This section provides the results for the ARCH, GARCH and the Multivariate GARCH models. The aim is to construct an ARCH, GARCH and Multivariate GARCH models to determine volatility of oil price using four selected macroeconomic variables.

The study also determines the relationship between the oil price and the macroeconomic variables. This section also identifies the best model for estimating the oil price volatility. The results are presented in Tables 4.4, 4.6 and 4.8. The results for Multivariate GARCH-BEKK model are presented in Tables 4.11, 4.12 and 4.13.

4.5.1 ARCH Model

This section presents the results for ARCH (1) model. The residuals of the ARCH model are presented in Figure 4.4.

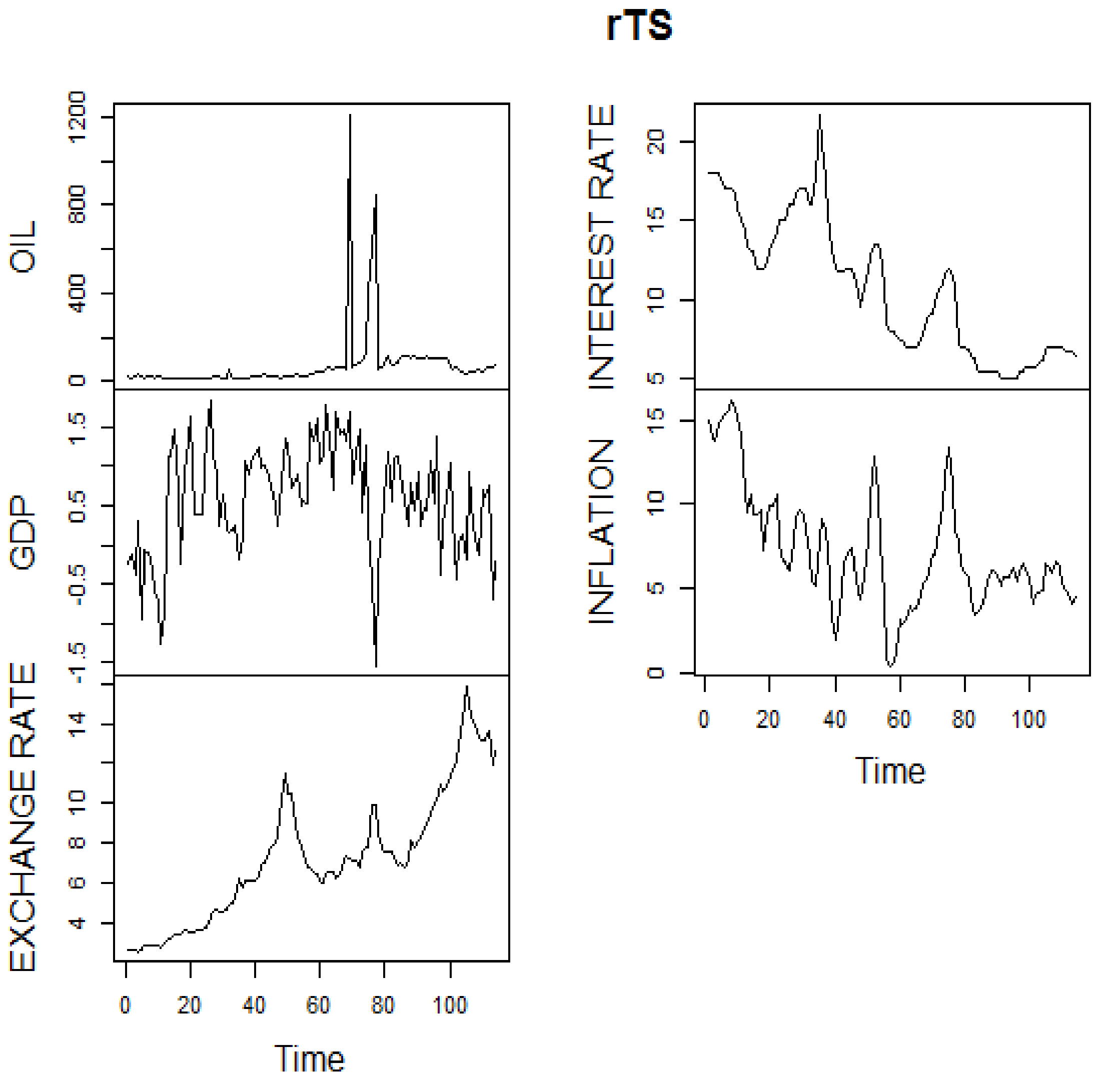


Figure 4.4: Residual time series plots

Figure 4.4 above illustrates the time series plots for the parameter estimations, and further provides the tests for ARCH disturbances using residuals. Table 4.4 below presents the ARCH model estimation results. The series are described by random/irregular, quick changes and are said to be unstable (volatile). The instability appears to change over time as well. For instance, oil price encounters a generally calm period from 1990 to 2006, whereas from 2006 to 2009 it shows an irregular volatility increase trend. On the other hand, exchange rate gives an increasing trend and interest rates a decreasing trend from 1990Q1 to 2018Q2. However, GDP provides similar periods of relative calm followed by increased volatility and drops throughout.

Table 4.4: Estimation results of the ARCH (1) model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDP	61.401	2.408	25.504	<0.001
INFLATION	13.364	0.387	34.521	<0.001
INTEREST_RATE	-16.253	0.342	-47.471	<0.001
EXCHANGE_RATE	-5.453	0.256	-21.296	<0.001
C	148.302	4.787	30.983	<0.001
		Variance Equation		
C	82.995	91.566	0.906	0.365
∝	7.511	0.827	9.083	<0.001

. According to the results in Table 4.4, the ARCH (1) model is estimated as:

$$OIL = 148.302 + 61.401(GDP) + 13.364\ (INF) - 16.253(IR) - 5.453(ER) \qquad (4.1).$$

Equation 4.1 illustrates the Multivariate ARCH (1) model for oil price. According to the results, exchange rate and interest rate have a negative effect on oil price. However, GDP and Inflation have positive coefficients, suggesting that each 1% increase in GDP and inflation leads to an increase in oil price. The ARCH (1) effect is statistically significant with probability value significant at 5% level of significance. Therefore, the equation for oil price could be modelled using the GARCH technique. The ARCH LM-test was also computed to determine the presence of ARCH effects and the results are presented in Table 4.5.

Table 4.5: ARCH LM-test

Chi-squared	Df	p-value
6.267	1	0.012

The results indicate that the p-value is 0.012 which is less than 0.05 level of significance. Therefore, the null hypothesis was rejected and conclude that there is a presence of ARCH (1) effects. Therefore, the oil price can be modelled using the GARCH model and the results are presented in subsection 4.5.2.

4.5.2 GARCH Model

This section provides the results of the GARCH model. The estimated parameters of the GARCH model are displayed below in Table 4.6.

Table 4.6: Estimation results of the GARCH (1, 1) model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
GDP	28.577	1.197	23.869	<0.001
INFLATION	5.721	0.330	17.343	<0.001
INTEREST_RATE	-16.127	0.258	-62.615	<0.001
EXCHANGE_RATE	-7.584	0.037	-206.236	<0.001
C	229.311	1.943	118.019	<0.001
	Variance Equation			
C	4.550	28.399	0.160	0.873
$\propto$	11.838	0.770	15.369	<0.001
$\boldsymbol{\beta}$	-0.0004	<0.001	-0.818	0.413

Table 4.6 presents the parameter estimation results for the GARCH (1, 1) model. Based on the results in Table 4.6, the following GARCH (1, 1) model was formulated:

$$OIL = 229.311 + 28.577\ (GDP) + 5.721\ (INF) - 16.127(IR) - 7.584\ (ER) \qquad (4.2).$$

The GARCH (1, 1) model in equation 4.2 is formed to determine relationships between the variables. According to the results, exchange rate and interest rate have negative values that propose a negative effect on oil price, while GDP and Inflation suggest a positive effect.

GDP and Inflation results provided below shows that these variables have positive coefficients, proposing that each 1% increase in GDP and inflation leads to an increase in oil price. However the negative effect on interest rate and exchange rate led by its negative values implies that a 1% increase in interest rate and exchange rate may lead to a decrease in oil price. The results are in line with the study by Mirchandani (2013), who found similar results. However, in this case the interest value is negative and this may depress the foreign investors, as interest rate is one of the macroeconomic variables that have an effect on oil price volatility which attracts investors. In addition, the coefficients of the $\propto$ and β parameters are 11.838 and -0.000 respectively.

The GARCH (1, 1) model revealed that the p-value of $\propto$ is found to be statistically significant, while the p-value of β is statistically insignificant, meaning that there are ARCH effects and there are no GARCH effects. The sum of $\propto$ and β is found to be greater than 1. This means that the oil price in South Africa is volatile The model results for probability shows that all variables are statistically significant at 5% level of significance, p-value <0.05, thus the null hypothesis that there is no volatility is rejected and accept the alternative hypothesis that in South Africa there is volatility in oil prices. The diagnostic test results for GARCH model are presented in Table 4.7.

Table 4.7: **Diagnostic test results of the GARCH model**

Variables	**Diagnostics Tests**	**Statistics**	**P-value**
GDP	ARCH-LM	0.056	0.814
	JB	3508.024	<0.001
	Box-Pierce test (R)	1.965	0.161
	Box-Ljung test (R^2)	2.178	0.156
Inflation	ARCH-LM	6.20e-05	0.099
	JB	15692.89	<0.001
	Box-Pierce test (R)	2.345	0.126
	Box-Ljung test (R^2)	2.407	0.120
Interest Rate	ARCH-LM	0.009	0.926
	JB	25507.08	<0.001
	Box-Pierce test (R)	0.398	0.528
	Box-Ljung test (R^2)	0.408	0.523
Exchange Rate	ARCH-LM	0.004	0.953

Variables	Diagnostics Tests	Statistics	P-value
	JB	15911.76	<0.001
	Box-Pierce test (R)	0.090	0.764
	Box-Ljung test (R^2)	0.092	0.761

Table 4.7 shows that all the macroeconomic variables on oil price have no ARCH errors since all the p-values for the ARCH-LM test are greater than the 0.05 level of significance. Moreover, all the macroeconomic variables show that the residuals are normally distributed with p-values less than 0.05, whereby the result of the Box-Ljung test (R^2) shows that the residuals of these variables to oil price does not have serial correlation. Therefore, the GARCH (1, 1) model appears to be adequate and can be used for further analysis. The following subsection 4.5.3 presents the forecasts of the GARCH model.

4.5.3 Forecasts of the GARCH Model

Table 4.8 presents the forecasts of the GARCH model.

Table 4.8: Forecasting

Variables	Time (Quarterly)	Mean Forecast	Upper 95% CI	Lower 95% CI
GDP	2018 – 3	0.032	0.986	-1.275
	2018 – 4	0.007	1.141	-1.429
	2019 – 1	-0.020	1.278	-1.567
	2019 – 2	-0.046	1.404	-1.692
Inflation	2018 – 3	5.202	7.891	2.566
	2018 – 4	5.199	9.955	2.034
	2019 – 1	5.198	11.898	1.702
	2019 – 2	5.198	13.828	1.464

Variables	Time (Quarterly)	Mean Forecast	Upper 95% CI	Lower 95% CI
Interest Rate	2018 – 3	6.845	7.911	4.897
	2018 – 4	6.922	9.028	3.690
	2019 – 1	7.001	10.014	2.662
	2019 – 2	7.084	10.876	1.781
Exchange Rate	2018 – 3	14.352	14. 532	11.689
	2018 – 4	14.574	14.821	11.094
	2019 – 1	14.799	15.025	10.615
	2019 – 2	15.026	15.429	10.214

Table 4.8 presents the forecasts for the GARCH (1.1) model of each macroeconomic variable on oil price forecasted for the next 4 quarters (2018Q3, 2018Q4, 2019Q1 and 2019Q2) periods ahead. However, the mean forecasts fall within the 95% confidence interval. The plots of the forecasted values are presented in Figure 4.5 below.

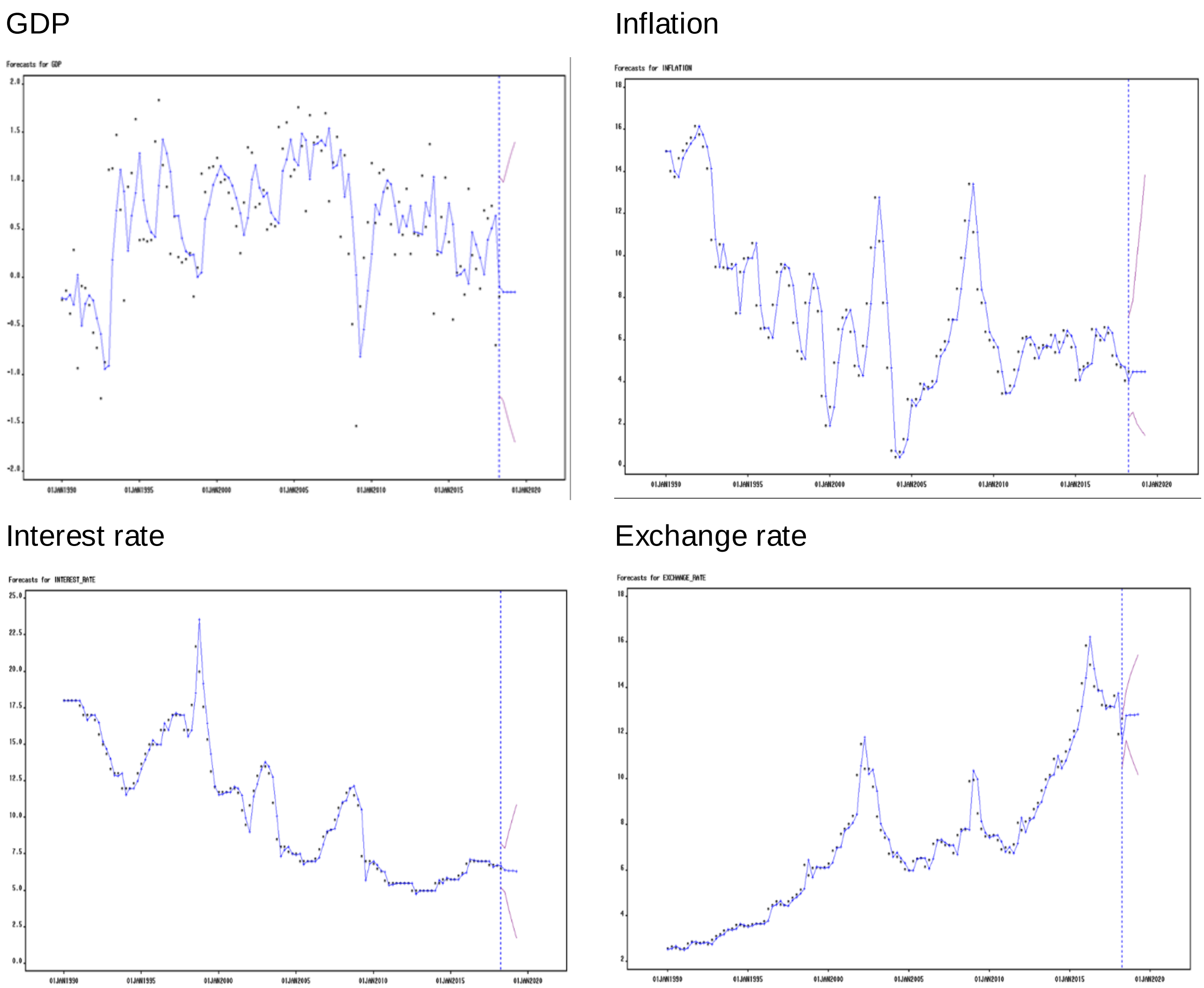


Figure 4.5: Forecasting plots with 95% CI

Figure 4.5 above shows all the four macroeconomic variables (GDP, inflation, interest rate and exchange rate) forecasts plots. According to the figure, all the forecasted values fall within the 95% confidence limit. The next Section 4.5.4 presents the EGARCH model.

4.5.4 EGARCH Model

Table 4.9 provides the results for the EGARCH model. The EGARCH model is used to determine the leverage impact.

Table 4.9: The EGARCH model Estimation results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDP	-0.734	1.045	-0.703	0.482
INFLATION	-0.386	0.380	-1.014	0.311
INTEREST_RATE	-7.228	0.414	-17.470	<0.001
EXCHANGE_RATE	-2.029	0.259	-7.820	<0.001
C	125.816	3.318	37.921	<0.001
		Variance Equation		
$\boldsymbol{\omega}$	-0.540	0.035	-15.386	<0.001
$\propto$	0.744	0.106	7.034	<0.001
$\boldsymbol{\gamma}$	-0.948	0.089	-10.678	<0.001
β	1.068	2.2E-104	4.8E+103	<0.001

The results in Table 4.9 present the EGARCH model parameter estimation. According to results in Table 4.9, the EGARCH model was formulated as:

$$OIL = 125.816 - 0.734\ (GDP) - 0.386\ (INF) - 7.228(IR) - 2.029\ (ER) \qquad (4.3).$$

The EGARCH model results below shows a negative effect on all the macroeconomic variables (GDP, Inflation, Interest rate and Exchange rate) which is led by its negative values, that implies that a 1% increase in this variables may lead to a decrease in oil price, even though the intercept is positive.

The p-values for the $\propto$ and β coefficients are found to be statistically significant at 0.05 level of significance. The sum of $\propto and\ \beta$ coefficient is > 1, which means that the oil price in South Africa is volatile.

Table 4.10: Diagnostic test results of the EGARCH model

Variables	Diagnostics Tests	Statistics	P-value
GDP	ARCH-LM	0.0003	0.987
	JB	2940.838	<0.001
	Box-Pierce test (R)	5.296	0.258
	Box-Ljung test (R^2)	5.540	0.236
Inflation	ARCH-LM	4.81e-08	0.9998
	JB	6255.761	<0.001
	Box-Pierce test (R)	0.546	0.969
	Box-Ljung test (R^2)	0.569	0.966
Interest Rate	ARCH-LM	0.003	0.956
	JB	12060.64	<0.001
	Box-Pierce test (R)	10.216	0.369
	Box-Ljung test (R^2)	10.501	0.033
Exchange Rate	ARCH-LM	0.001	0.978
	JB	6943.282	<0.001
	Box-Pierce test (R)	1.538	0.820
	Box-Ljung test (R^2)	1.597	0.809

The above Table 4.10 displays that all the macroeconomic variables on oil price have no ARCH errors, as all the p-values for the ARCH-LM test are greater than the 0.05 level of significance. Furthermore, it provides that all the macroeconomic variables show that the residuals are normally distributed; in addition the result for the Box-Ljung test (R^2) shows that the residuals of these variables to oil price do not have serial correlation. Therefore, the EGARCH model appears to be adequate and can be used for further analysis.

4.5.5 Forecasts of the EGARCH Model

Table 4.11 below presents the forecasted values of the EGARCH model.

Table 4.11: Forecasting

Variables	Time (Quarterly)	Mean Forecast	Upper 95% CI	Lower 95% CI
GDP	2018 - 3	-0.182	0.956	-1.321
	2018 - 4	-0.167	1.256	-1.591
	2019 - 1	-0.144	1.517	-1.805
	2019 - 2	-0.123	1.857	-1.882
Inflation	2018 - 3	4.701	7.393	2.009
	2018 - 4	5.067	8.691	1.444
	2019 - 1	5.349	9.711	0.987
	2019 - 2	5.821	10.815	0.827
Interest Rate	2018 - 3	6.359	8.568	4.152
	2018 - 4	6.338	8.808	3.868
	2019 - 1	6.329	9.036	3.622
	2019 - 2	6.320	9.246	3.393
Exchange Rate	2018 - 3	12.813	14.221	11.405
	2018 - 4	12.819	14.394	11.244
	2019 - 1	12.821	14.548	11.095
	2019 - 2	12.823	14.689	10.957

Table 4.11 presents the forecasts for the EGARCH model for each of the macroeconomic variables on oil price forecasted for 4 quarters (2018Q3, 2018Q4, 2019Q1 and 2019Q2) periods ahead. However, the mean forecasts results shows that they fall within the 95% confidence interval. The plots for the forecasted values are presented in Figure 4.6 below.

GDP INFLATION

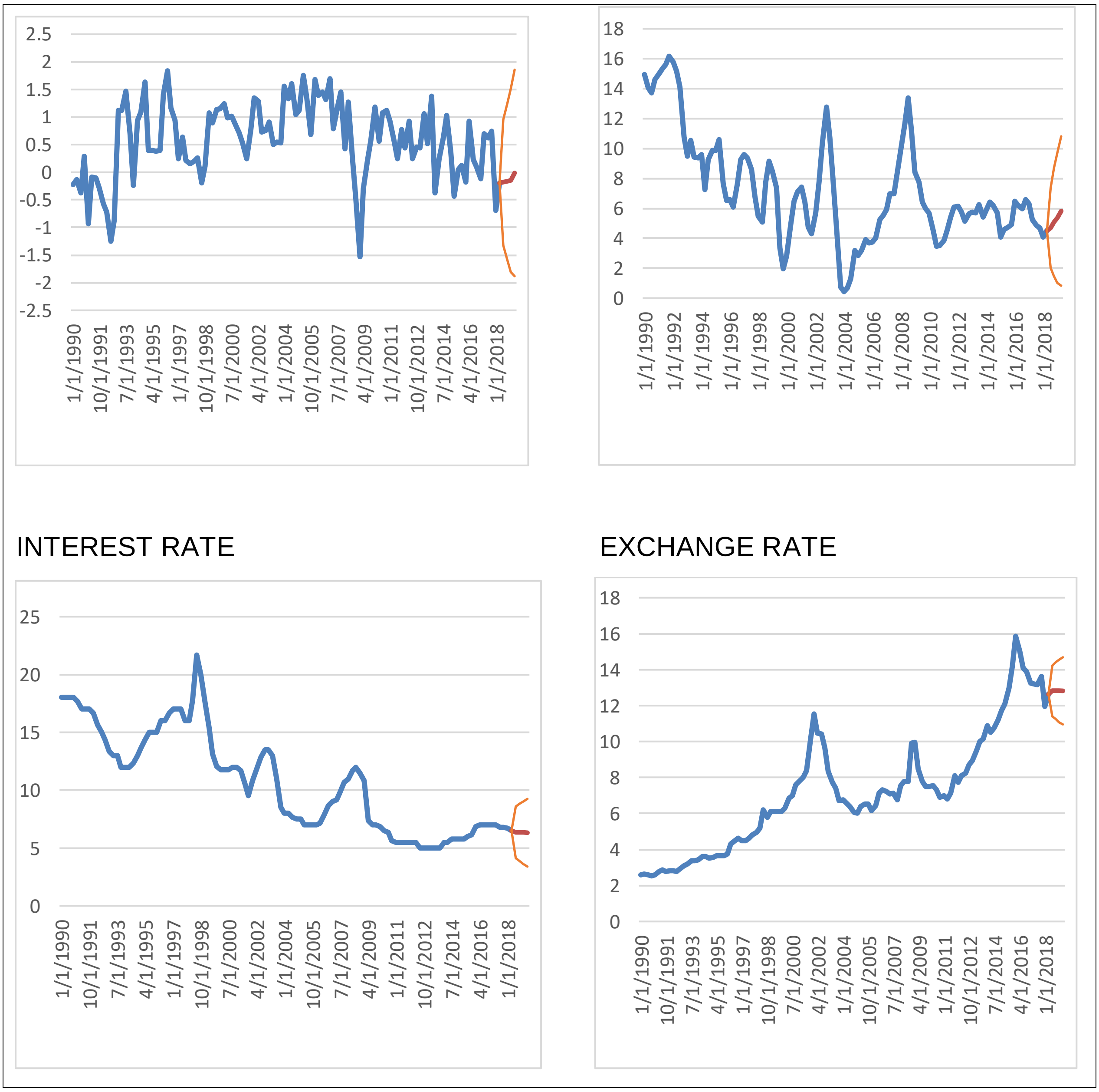


Figure 4.6: Forecasting plots with 95% CI

Figure 4.6 shows all the four macroeconomic variables (GDP, inflation, interest rate and exchange rate) forecasts plots. The figure also indicates that all the forecasted values fall within the 95% confidence limit. The next Section 4.5.5 presents the Multivariate GARCH model.

4.5.6 Multivariate GARCH Model

The section shows the Multivariate BEKK-GARCH model where the triangular Matrix of Constant, ARCH and GARCH effect are presented below. It provides the dynamic relations or the spillovers amongst the macroeconomic variables and oil price.

4.5.5.1 Multivariate GARCH-BEKK model

Tables 4.12– 4.14 show the parameter estimation of the Multivariate GARCH-BEKK model.

Table 4.12: The results for Multivariate GARCH -BEKK model: Triangular matrix of constant

Triangular Matrix of Constant				
Variables	**Coefficients**	**Standard Error**	**t- Statistics**	**P-Value**
A_{11}	53.900	0.137	393.431	<0.001
A_{12}	13.029	0.115	113.296	<0.001
A_{13}	17.031	0.329	51.766	<0.001
A_{14}	-62.414	0.486	-128.424	<0.001
A_{15}	-9.221	0.150	-61.473	<0.001
A_{22}	2.015	0.176	11.449	<0.001
A_{23}	-1.965	0.134	-14.664	<0.001
A_{24}	-13.085	0.115	-113.783	<0.001
A_{25}	4.584	0.319	14.370	<0.001
A_{33}	6.692	0.074	90.432	<0.001
A_{34}	-10.345	0.345	-29.986	<0.001
A_{35}	3.869	0.363	10.658	<0.001
A_{44}	12.007	0.071	169.113	<0.001
A_{45}	1.047	0.024	43.625	<0.001

Triangular Matrix of Constant				
Variables	**Coefficients**	**Standard Error**	**t- Statistics**	**P-Value**
A_{55}	30.018	0.074	405.649	<0.001

Table 4.13: The results for Multivariate GARCH -BEKK model: ARCH effect

ARCH EFFECT				
Variables	**Coefficients**	**Standard Error**	**t- Statistics**	**P-Value**
B_{11}	-20.511	0.090	-227.900	<0.001
B_{12}	-4.660	0.034	-137.059	<0.001
B_{13}	-3.827	0.020	-191.350	<0.001
B_{14}	39.644	0.177	223.977	<0.001
B_{15}	-18.493	0.026	-711.269	<0.001
B_{21}	-0.078	0.109	-0.716	0.476
B_{22}	0.760	0.123	6.179	<0.001
B_{23}	0.137	0.355	0.386	0.701
B_{24}	0.715	0.234	3.056	0.003
B_{25}	-0.492	0.303	-1.624	0.108
B_{31}	1.713	0.087	19.690	<0.001
B_{32}	-0.298	0.272	-1.096	0.276
B_{33}	-4.422	0.420	-10.529	<0.001
B_{34}	7.596	0.351	21.641	<0.001
B_{35}	-6.319	0.376	-16.806	<0.001
B_{41}	-3.183	0.369	-8.626	<0.001
B_{42}	0.340	0.314	1.083	0.282
B_{43}	0.716	0.190	3.768	<0.001
B_{44}	17.973	0.292	61.551	<0.001
B_{45}	-12.882	0.066	-195.182	<0.001
B_{51}	-4.330	0.075	-57.733	<0.001
B_{52}	-0.565	0.405	-1.395	0.167

ARCH EFFECT				
Variables	Coefficients	Standard Error	t- Statistics	P-Value
B_{53}	-1.490	0.259	-5.753	<0.001
B_{54}	9.206	0.233	39.511	<0.001
B_{55}	-6.891	0.405	-17.015	<0.001

Table 4.14: The results for Multivariate GARCH -BEKK model: GARCH effect

GARCH EFFECT				
Variables	Coefficients	Standard Error	t- Statistics	P-Value
C_{11}	-1.345	0.127	-10.591	<0.001
C_{12}	-0.331	0.011	-30.091	<0.001
C_{13}	-0.275	0.021	-13.095	<0.001
C_{14}	3.605	0.157	22.962	<0.001
C_{15}	-1.849	0.087	-21.253	<0.001
C_{21}	-1.292	0.040	-32.300	<0.001
C_{22}	-0.811	0.042	-19.310	<0.001
C_{23}	-0.597	0.041	-14.561	<0.001
C_{24}	7.197	0.524	13.735	<0.001
C_{25}	-3.533	0.281	-12.573	<0.001
C_{31}	-1.812	0.168	-10.786	<0.001
C_{32}	-0.264	0.012	-22.000	<0.001
C_{33}	-0.445	0.029	-15.345	<0.001
C_{34}	2.459	0.254	9.681	<0.001
C_{35}	-1.227	0.121	-10.140	<0.001
C_{41}	-2.482	0.116	-21.397	<0.001
C_{42}	-0.619	0.002	-309.500	<0.001
C_{43}	-0.587	0.005	-117.400	<0.001
C_{44}	6.955	0.066	105.379	<0.001
C_{45}	-3.603	0.051	-70.647	<0.001
C_{51}	-3.398	0.126	-26.968	<0.001
C_{52}	-0.798	0.009	-88.667	<0.001

GARCH EFFECT				
Variables	**Coefficients**	**Standard Error**	**t- Statistics**	**P-Value**
C_{53}	-0.789	0.003	-263.000	0.000
C_{54}	9.458	0.106	89.226	0.000
C_{55}	-4.954	0.068	-72.853	0.000

Tables 4.12 to Table 4.14 display the parameter estimations of the Multivariate GARCH model. According to the results in the tables, most of the variables are statistically significant at 0.01, 0.05 and 0.1. The estimated Multivariate GARCH-BEKK model is presented using the following matrices:

$$\mathbf{A} = \begin{pmatrix} 53.900 & 0 & 0 & 0 & 0 \\ 13.029 & 2.015 & 0 & 0 & 0 \\ 17.031 & -1.965 & 6.692 & 0 & 0 \\ -62.414 & -13.085 & -10.345 & 12.007 & 0 \\ -9.221 & 4.584 & 3.869 & 1.047 & 30.018 \end{pmatrix} \quad (4.4).$$

$$\mathbf{B} = \begin{pmatrix} -20.51 & -4.660 & -3.827 & 39.644 & -18.493 \\ -0.078 & 0.760 & 0.137 & 0.715 & -0.493 \\ 1.713 & -0.298 & -4.422 & 7.596 & -6.319 \\ -3.183 & 0.340 & 0.716 & 17.973 & -12.882 \\ -4.330 & -0.565 & -1.490 & 9.206 & -6.891 \end{pmatrix} \quad (4.5).$$

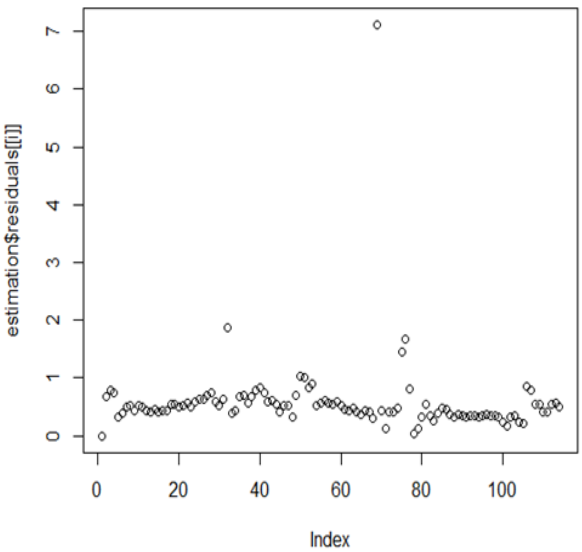
$$\mathbf{C} = \begin{pmatrix} -1.345 & -0.331 & -0.275 & 3.605 & -1.849 \\ -1.292 & -0.811 & -0.597 & 7.197 & -3.533 \\ -1.812 & -0.264 & -0.445 & 2.459 & -1.227 \\ -2.482 & -0.619 & -0.587 & 6.955 & -3.603 \\ -3.398 & -0.798 & -0.789 & 9.458 & -4.954 \end{pmatrix} \quad (4.6).$$

The above Table 4.13 and Table 4.14 present the estimates of the diagonal parameters, which show that all diagonal parameters (B11, B22, B33, B44, B55, C11, C22, C33, C44 and C55) are statistically significant at 5% level of significance. This indicates that the conditional variance of the macroeconomic variables and oil prices are affected by their own conditional volatility meaning that the macroeconomic variables have an influence on the oil price volatility.

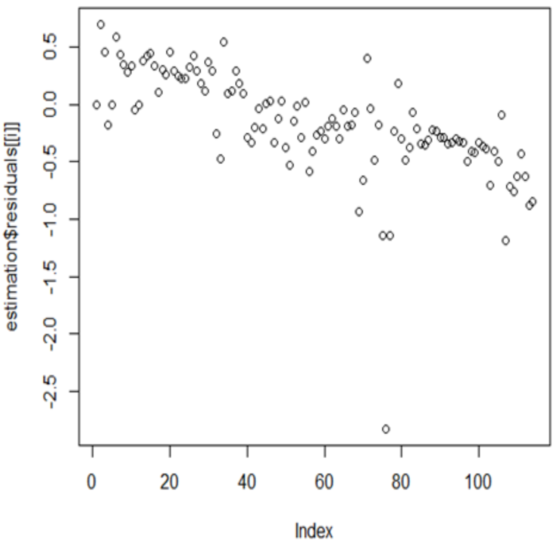
In matrix B, the off diagonal elements for B23 and B25 (inflation-GDP and exchange rate-GDP) are the only parameters that are statistically insignificant, meaning that there is no spillover effect between the two macroeconomic variables (inflation and exchange rate) and oil prices, while the spillover effect is found between the remaining two macroeconomic variables (GDP and interest rate) and the oil price. However, the negative impact of each variable does not affect the oil price. The results further revealed that B12, B13, B14, B15, B24, B34, and C35 are statistically significant. This means that there is a unidirectional volatility transmission between oil price and GDP; oil price and Inflation; oil price and Interest rate; oil price and exchange rate; GDP and Interest rate; Inflation and Interest rate; and Inflation and Exchange rate.

Matrix C has captured the macroeconomic variables and oil prices volatility transmission where all pairs of the off diagonal parameter at 5% level of significance are statistically significant, showing a transmission between the oil price and macroeconomic variables. The next Figure 4.7 illustrates the residual series for Multivariate GARCH-BEKK model.

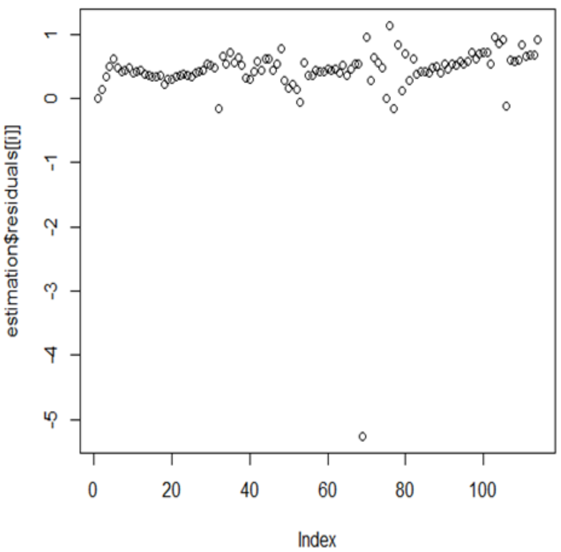
Oil price



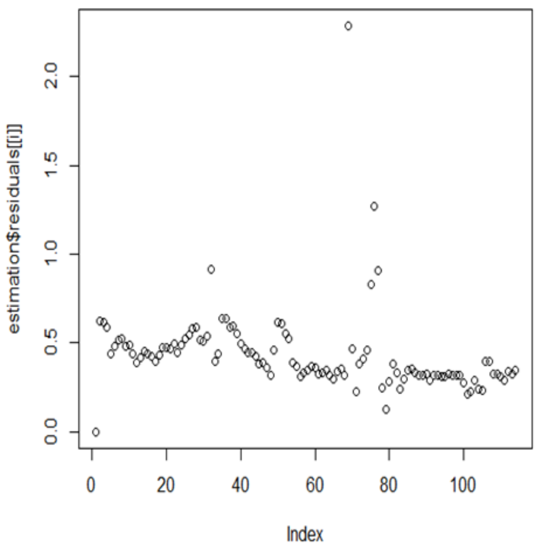
GDP



Exchange rate



Interest rate



Inflation

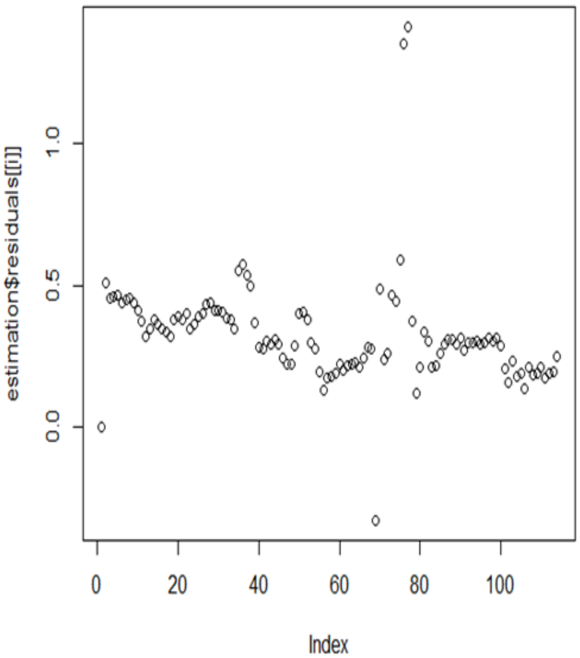


Figure 4.7: Residual series for Multivariate GARCH-BEKK model

Figure 4.7 above displays the residual series of the Multivariate GARCH-BEKK model. The residual series portrays a certain pattern for each of the macroeconomic variables. Therefore, the BEKK-GARCH model shows the presence of autocorrelation in the residuals.

4.6 CHAPTER SUMMARY

The study modelled the oil price volatility and macroeconomic variables using the Multivariate GARCH model to determine the relationship between the oil price and the selected macroeconomic variables, the volatility spillovers effect between oil price volatility and macroeconomic variables, and their impact on South Africa. The results of the study have shown the relationships between the four macroeconomic variables have an effect on the oil price volatility. The next chapter presents the discussion of the results, conclusions and the recommendations for future research.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 INTRODUCTION

The chapter gives the discussion of results interpreted in chapter 4. The chapter also presents the conclusions and recommendations of the study. It paves the way for future studies.

The rest of the chapter is arranged as follows: In Section 5.2, the results of the study are discussed in line with the individual objectives as presented in chapter 4 of the study. Section 5.3 is the conclusion that summarizes the study as whole and section 5.4 provides the recommendations for future studies based on the findings and conclusion of the study.

5.2 DISCUSSION OF RESULTS

The study modelled the oil price volatility and macroeconomic variables in South Africa. The ARCH model, GARCH model, EGARCH model and the Multivariate GARCH models were computed. In terms of the Multivariate GARCH model the technique used was the BEKK model.

The study presented 114 observations of quarterly data from 1990Q1 to 2018Q2. The preliminary data was given where the descriptive statistics showed all the variables are normally distributed and showing that there is an inverse correlation among the variables. However, all the series were stationary on the first differencing meaning that the variables are integrated to order 1.

Brooks (2008) states that the Phillips–Perron and Augmented Dickey Fuller tests frequently provide similar conclusions and have been demonstrated in the study. Furthermore, the study presented the QQ plot as an important diagnostic for checking the assumption of normality, and results shows that the variables display linearity of the points which recommends that the series are normally distributed.

The complete analysis for ARCH, GARCH, EGARCH and Multivariate GARCH-BEEK model estimation, diagnostics and forecasting was given. The expectation was to determine the impact of the oil price volatility on the macroeconomic variables in South Africa and the volatility spillovers between oil price and its explanatory variables.

The **ARCH** model showed statistically significant results which means the mean equation could be fitted using GARCH technique, and the results are supported by Al-Raimony and El-Nader (2012). Furthermore, the LM test further recommends that the oil price can be modelled using the GARCH model.

The **GARCH (1, 1)** model was fitted using the oil price and macroeconomic variables data and showed that the QQ plots pursued a normal distribution with extreme tails. In addition the model estimation, diagnostic tests (goodness of fit test; Ljung-Box (R), Ljung-Box (R2)) and ARCH-LM were used. The estimated result showed that the probability was statistical significant, and the diagnostic results shown that the GARCH (1, 1) model in the *standard* conditional distribution performed adequately, hence the model was utilized for further analysis. According to the results, exchange rate and interest rate have negative values that propose a negative effect on oil price while GDP and inflation suggest a positive effect. The results are supported by the study of Mpofu (2016) and Agnolucci (2009).

The GDP and Inflation results showed that these variables have positive coefficients. Interest rate and exchange rate have a negative effect on oil price. The results are in line with the study by Mirchandani (2013,) stating that currencies with higher interest rates attract more investors in South Africa looking for better opportunities for their investment. However, in this case the interest rate value is negative and may depress the foreign investors as the interest rate is one of the macroeconomic variables that has an effect on oil price volatility which attracts investors. The forecasted results for oil price were displayed and it was discovered that the mean forecasts fall within the 95% confidence interval, adequately capturing the volatility, and these results are supported by Jansky and Rippel (2011).

The **EGARCH (1, 1)** model estimated results revealed that oil price has a negative effect on all the macroeconomic variables (GDP, Inflation, Interest rate and Exchange rate). This means that a 1% increase in these variables may lead to a decrease in oil price. The diagnostic checks showed that the macroeconomic variables on oil price have no ARCH errors as all the p-values for the ARCH-LM test are greater than the 0.05 level of significance. The EGARCH model appeared to be adequate and was used for further analysis. Furthermore the mean forecasts result showed that it falls within the 95% confidence interval. The results are in line with the study by Ramzan *et al.* (2012).

The Multivariate GARCH model was also examined using the **BEKK-GARCH** model, and results demonstrated that at 5% level of significance, all the estimates of the diagonal parameters are statistically significant. The model displayed the residual series of Multivariate GARCH-BEKK model, and portrayed a certain pattern for each of the macroeconomic variables. However, the BEKK-GARCH model showed the presence of autocorrelation in the residuals. The results of this model also revealed that there is no spillover effect between the macroeconomic variables (inflation and exchange rate) and oil prices, meaning that these parameters are statistically insignificant. The spillover effects were found between GDP and interest rate with the oil price. However, the negative impact of each variable does not affect the oil price. The study found that there is a unidirectional volatility transmission between oil price and GDP; oil price and Inflation; oil price and Interest rate; oil price and exchange rate; GDP and Interest rate; Inflation and Interest rate; and Inflation and Exchange rate. The results are supported by the study of Malik and Hammoudeh (2007), and Abdulkareem and Abdulhakeem (2016).

The objectives of the study as stated in chapter one were all met.

5.3 CONCLUSION

This section summarizes the study as a whole and the investigation which is to model the oil price volatility and macroeconomic variables in South Africa.

The present study assessed the oil price volatility with macroeconomic variables in South Africa and the investigation took into consideration the objectives of the study. The ADF and PP tests revealed that all the variables were integrated to order one and the variables were normally distributed and correlated.

The following models were estimated: ARCH, GARCH, EGARCH and Multivariate GARCH-BEKK. The data revealed that there are no spillover effects between the macroeconomic variables (inflation and exchange) and the oil price. The data also revealed that there is a unidirectional volatility transmission between oil price and GDP; oil price and Inflation; oil price and Interest rate; oil price and exchange rate; GDP and Interest rate; Inflation and Interest rate; and Inflation and Exchange rate.

5.4 RECOMMENDATIONS

The recommendations provided below are for future studies based on the findings and conclusion of the study:

- Similar investigations should be undertaken in order to increase the validity and consistency of the results.
- Policy makers should have a view of the impact of oil price volatility on the South African economy.
- One can consider on a small scale using an article to draw comparison between the Multivariate GARCH BEKK model and other competing Multivariate GARCH type models, for example Multivariate GARCH DCC or CCC.
- The study also recommends that further studies should look at a few kinds of Multivariate GARCH models such as DCC, CCC, VEC, etc. and compare them for modelling the oil price volatility.
- The Government Department of Trade and Industry should sponsor research on models relating to other commodities including but not limited to oil price volatility, energy and exchange rates.

5.5 SUMMARY OF THE STUDY

The study was arranged into five chapters in order to address the objectives of the study as stated in chapter one. Chapter 1 provided the background of the study and introduction to the whole research. The chapter also stated the problem statement, research aims and objectives as well as the significance of the study. In addition, the rationale of the study and the research questions as well as the limitations of the study was also presented in Chapter 1. Chapter 2 provided the theoretical framework and empirical literature (international perspective and the review on the South African perspective). Chapter 3 presented the research methodology of the study. The data analysis and interpreted the results were presented in Chapter 4. Chapter 5 provided the conclusion, summary and recommendation for future study.

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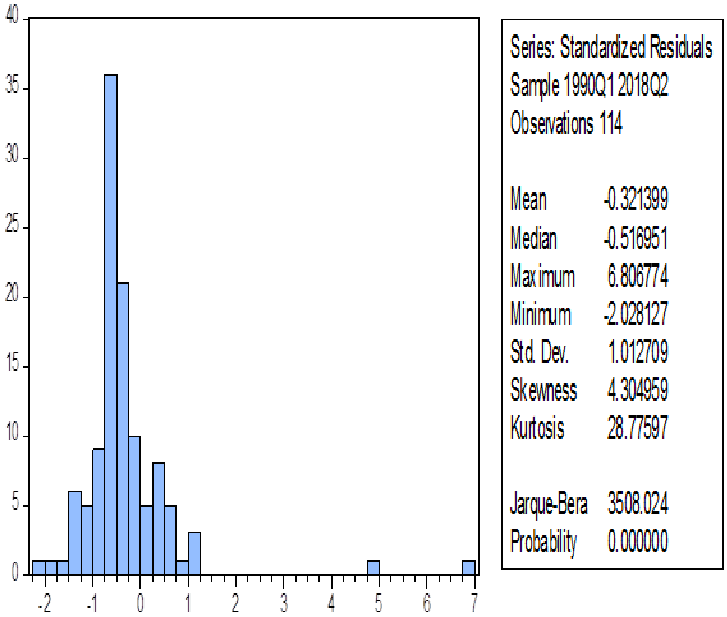
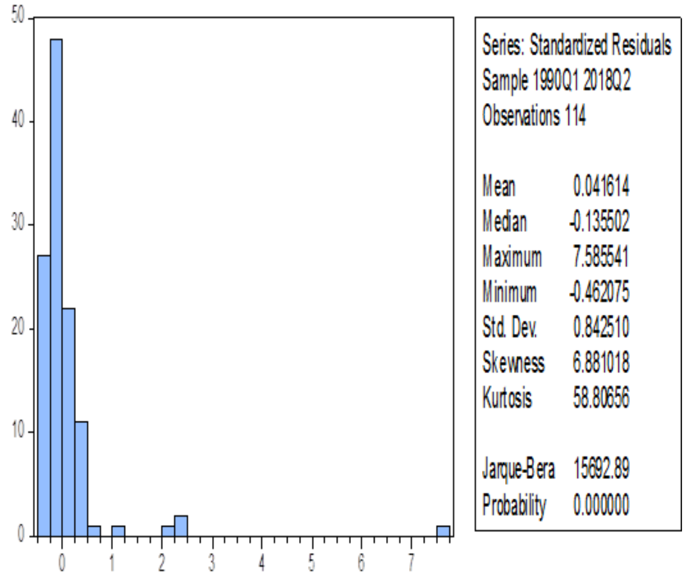
APPENDIXES

Appendix A: GARCH Model

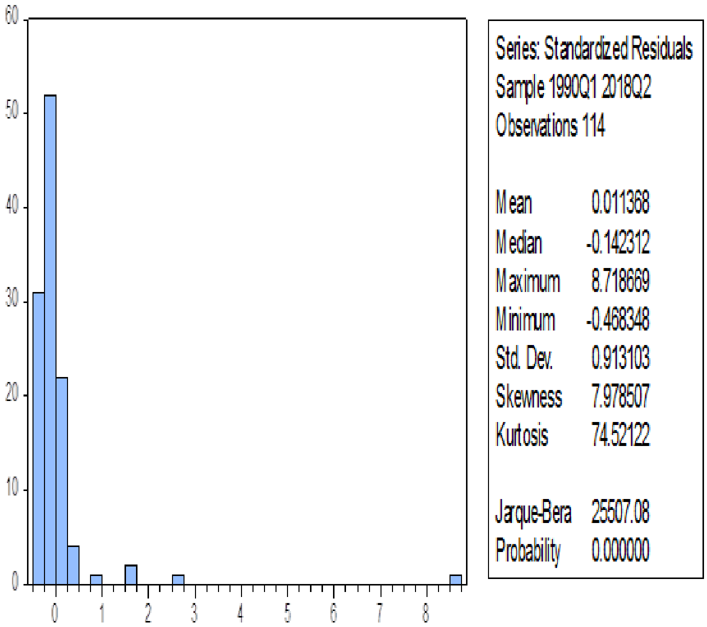
GDP



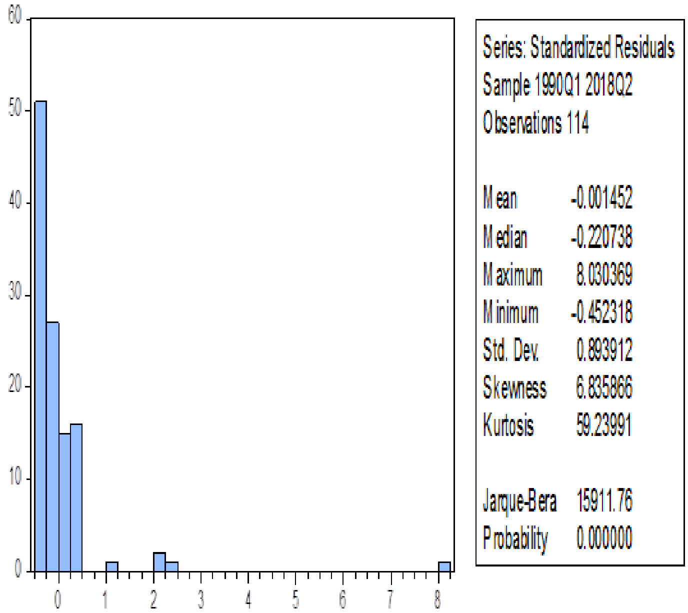
INFLATION



INTEREST RATE

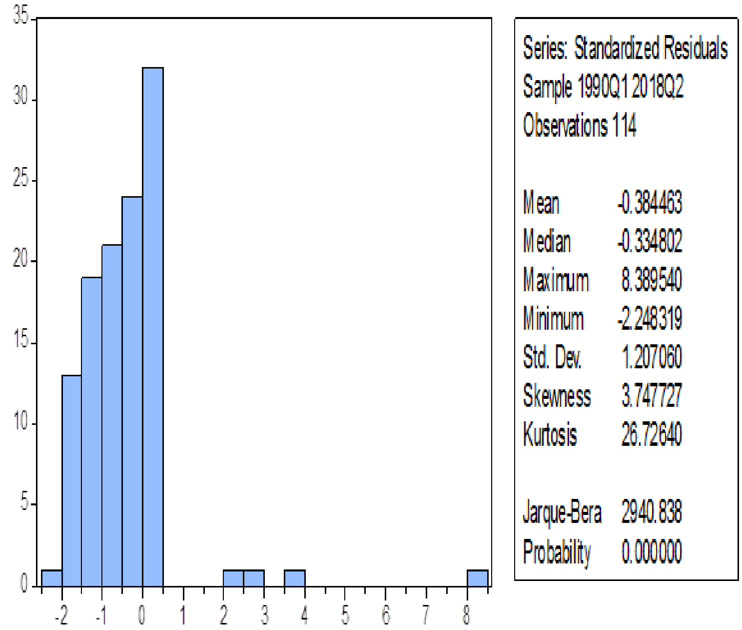


EXCHANGE RATE

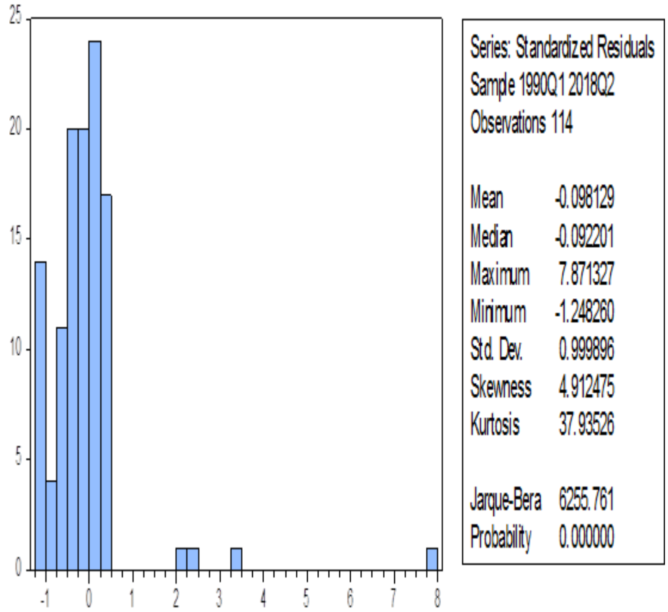


Appendix B: EGARCH Model

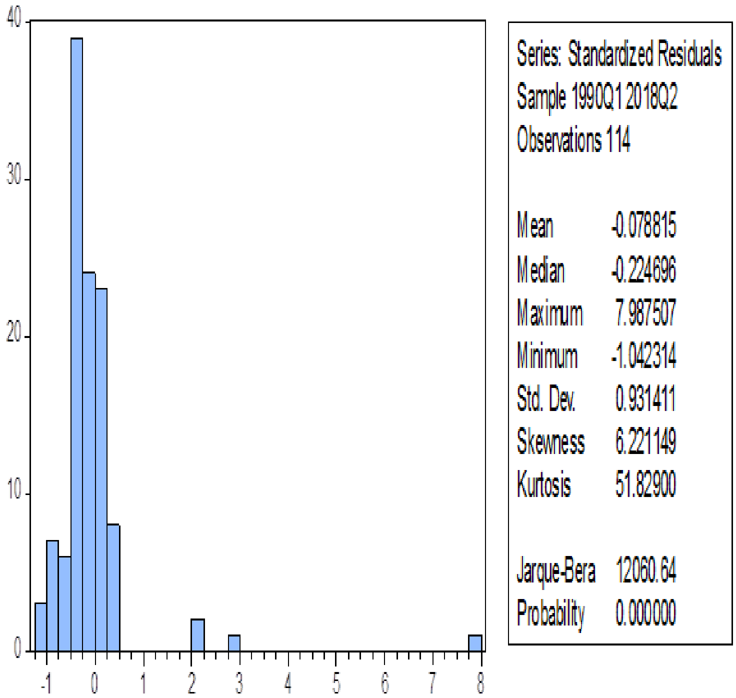
GDP



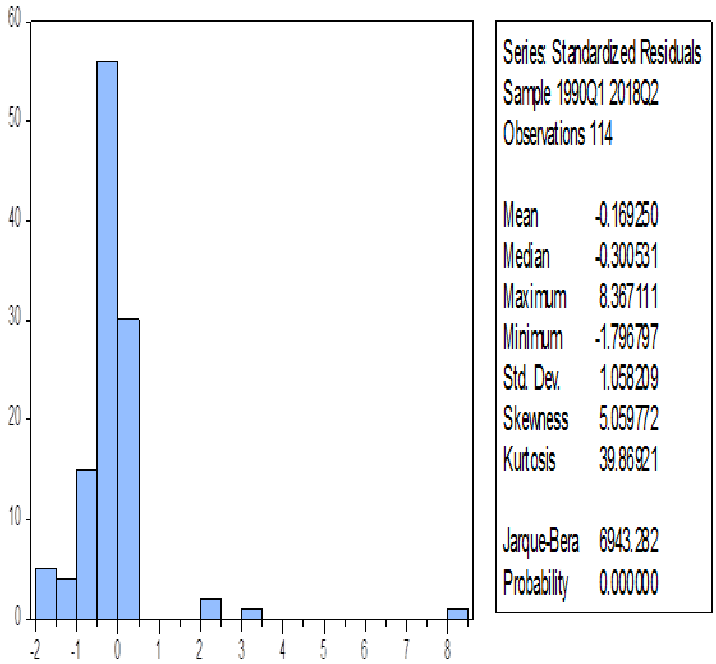
INFLATION



INTEREST RATE



EXCHANGE RATE



Appendix C: Estimation results of the ARCH (1) model

Dependent Variable: OIL
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 07/01/19 Time: 14:28
Sample (adjusted): 1990Q1 2018Q2
Included observations: 114 after adjustments
Convergence achieved after 51 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDP	61.40049	2.407451	25.50435	0.0000
INFLATION	13.36415	0.387126	34.52144	0.0000
INTEREST_RATE	-16.25267	0.342368	-47.47137	0.0000
EXCHANGE_RATE	-5.452790	0.256046	-21.29611	0.0000
C	148.3023	4.786583	30.98291	0.0000
		Variance Equation		
C	82.99513	91.56603	0.906397	0.3647
RESID(-1)^2	7.511069	0.826926	9.083124	0.0000

R-squared	-0.070766	Mean dependent var	73.45317
Adjusted R-squared	-0.110061	S.D. dependent var	148.0700
S.E. of regression	156.0056	Akaike info criterion	11.70638
Sum squared resid	2652816.	Schwarz criterion	11.87439
Log likelihood	-660.2636	Hannan-Quinn criter.	11.77457
Durbin-Watson stat	1.423232		

Appendix D: Estimation results of the GARCH (1, 1) model

Dependent Variable: OIL
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 07/01/19 Time: 14:26
Sample (adjusted): 1990Q1 2018Q2
Included observations: 114 after adjustments
Failure to improve likelihood (non-zero gradients) after 119 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDP	28.57687	1.197227	23.86921	0.0000
INFLATION	5.720594	0.329845	17.34329	0.0000
INTEREST_RATE	-16.12740	0.257566	-62.61463	0.0000
EXCHANGE_RATE	-7.584089	0.036774	-206.2358	0.0000
C	229.3110	1.943002	118.0189	0.0000
		Variance Equation		
C	4.550360	28.39895	0.160230	0.8727
RESID(-1)^2	11.83793	0.770237	15.36921	0.0000
GARCH(-1)	-0.000346	0.000423	-0.818317	0.4132

R-squared	-0.041436	Mean dependent var	73.45317
Adjusted R-squared	-0.079654	S.D. dependent var	148.0700
S.E. of regression	153.8542	Akaike info criterion	11.38391
Sum squared resid	2580150.	Schwarz criterion	11.57593
Log likelihood	-640.8830	Hannan-Quinn criter.	11.46184
Durbin-Watson stat	1.408458		

Appendix E: Estimation results of the EGARCH model

Dependent Variable: OIL
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 07/03/19 Time: 13:32
Sample: 1990Q1 2018Q2
Included observations: 114
Failure to improve likelihood (singular hessian) after 235 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDP	-0.734217	1.044506	-0.702932	0.4821
INFLATION	-0.385727	0.380430	-1.013922	0.3106
INTEREST_RATE	-7.228429	0.413771	-17.46962	0.0000
EXCHANGE_RATE	-2.028717	0.259439	-7.819633	0.0000
C	125.8162	3.317894	37.92050	0.0000
	Variance Equation			
C(6)	-0.540011	0.035099	-15.38554	0.0000
C(7)	0.744289	0.105810	7.034230	0.0000
C(8)	-0.947704	0.088753	-10.67795	0.0000
C(9)	1.067485	2.2E-104	4.8E+103	0.0000

R-squared	-0.057515	Mean dependent var	73.45317
Adjusted R-squared	-0.096323	S.D. dependent var	148.0700
S.E. of regression	155.0373	Akaike info criterion	10.55065
Sum squared resid	2619985.	Schwarz criterion	10.76667
Log likelihood	-592.3873	Hannan-Quinn criter.	10.63832
Durbin-Watson stat	1.335501		

Appendix F: BEKK-GARCH

Parameter estimation matrix

```
       C estimates:
        [,1]      [,2]      [,3]      [,4]      [,5]
[1,] 53.8953 13.029109 17.030990 -62.41437 -9.220754
[2,]  0.0000  2.015088 -1.964522 -13.08456  4.583979
[3,]  0.0000  0.000000  6.691664 -10.34446  3.869361
[4,]  0.0000  0.000000  0.000000  12.00707  1.047350
[5,]  0.0000  0.000000  0.000000   0.00000 30.018055

       ARCH estimates:
             [,1]       [,2]       [,3]       [,4]        [,5]
[1,] -20.51138248 -4.6600428 -3.8269269 39.6439918 -18.4925674
[2,]  -0.07837177  0.7597178  0.1372744  0.7147988  -0.4916216
[3,]   1.71318716 -0.2983702 -4.4222544  7.5955376  -6.3193646
[4,]  -3.18309727  0.3404264  0.7155753 17.9734425 -12.8882061
[5,]  -4.33024467 -0.5652089 -1.4898463  9.2059682  -6.8921926

       GARCH estimates:
          [,1]       [,2]       [,3]     [,4]      [,5]
[1,] -1.346577 -0.3305802 -0.2746339 3.604742 -1.848820
[2,] -1.291606 -0.8109248 -0.5964469 7.197322 -3.532870
[3,] -1.811598 -0.2638026 -0.4447297 2.458941 -1.226852
[4,] -2.481487 -0.6185070 -0.5873285 6.954677 -3.603358
[5,] -3.397697 -0.7975952 -0.7889201 9.457904 -4.953593
```

Standard error matrix

```
      C estimates, standard errors:
          [,1]      [,2]       [,3]       [,4]       [,5]
[1,] 0.1372506 0.1148146 0.32851079 0.48626137 0.15011616
[2,] 0.0000000 0.1760149 0.13353805 0.11456039 0.31874758
[3,] 0.0000000 0.0000000 0.07351774 0.34491252 0.36267442
[4,] 0.0000000 0.0000000 0.00000000 0.07143935 0.02371847
[5,] 0.0000000 0.0000000 0.00000000 0.00000000 0.07371240

      ARCH estimates, standard errors:
           [,1]      [,2]       [,3]      [,4]       [,5]
[1,] 0.09005666 0.0343804 0.01980692 0.1767180 0.02600156
[2,] 0.10933321 0.1233987 0.35515521 0.2337129 0.30316800
[3,] 0.08708114 0.2720080 0.41995095 0.3514382 0.37576809
[4,] 0.36852977 0.3139237 0.18981575 0.2922434 0.06577747
[5,] 0.07517286 0.4044778 0.25931831 0.2328973 0.40477876


      GARCH estimates, standard errors:
           [,1]        [,2]        [,3]       [,4]       [,5]
[1,] 0.12728105 0.011299739 0.020951833 0.15703572 0.08720555
[2,] 0.03953434 0.042422090 0.041209351 0.52405734 0.28140225
[3,] 0.16753259 0.012223807 0.029076808 0.25436559 0.12052113
[4,] 0.11612266 0.001469294 0.004986236 0.06586767 0.05140557
[5,] 0.12562564 0.009434773 0.003210712 0.10640584 0.06763798
```

Appendix G: GARCH FORECASTING

Day	_TYPE_	_LEAD_	OIL	INFLATION	GDP	INTEREST_RATE	EXCHANGE_RATE
2018/07/01	FORECAST	1	30.88681	5.201706776	0.032314	6.84659497	14.35188993
2018/10/01	FORECAST	2	25.99697	5.199311449	0.006566	6.921864727	14.57400622
2019/01/01	FORECAST	3	21.00329	5.198044472	-0.01953	7.001070925	14.79875889
2019/04/01	FORECAST	4	15.90578	5.197905846	-0.04596	7.084213565	15.02614796

Appendix H: GARCH FORECASTING

Day	_TYPE_	_LEAD_	OIL	INFLATION	GDP	INTEREST_RATE	EXCHANGE_RATE
2018/07/01	FORECAST	1	30.88681	4.700772401	-0.18233	6.35964811	12.81267941
2018/10/01	FORECAST	2	25.99697	5.067111292	-0.16725	6.337977253	12.81930644
2019/01/01	FORECAST	3	21.00329	5.349420893	-0.14391	6.329288074	12.82133687
2019/04/01	FORECAST	4	15.90578	5.820881435	-0.01236	6.319601977	12.82305591