Modeling return volatility on the JSE sectors

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DECLARATION

I declare that this dissertation titled:

Modelling return volatility on the JSE sectors

is my own work and that all the resources used or quotes have been duly acknowledged by means of in-text citations and complete references, and that I have not previously submitted the dissertation for degree purposes at another university.

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To whom it may concern

This is to confirm that I, the undersigned, have language edited the **dissertation** of

Katleho Makoko

for the degree

Masters of Commerce in Risk Management

entitled:

Modelling return volatility on the JSE sectors

The responsibility of implementing the recommended language changes rests with the author of the dissertation.

Yours truly,

Linda Scott

DEDICATION

To my late father, Teboho Makoko, beloved mother, Sylvia Makoko, and brother, Thabang Makoko.

“*Don’t stop when you are tired, stop when you are done*”

(Marilyn Monroe)

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ABSTRACT

Keywords: modelling, volatility, Johannesburg Stock Exchange, ARCH, GARCH, EGARCH, TGARCH, JSE sectors, models

Modelling and forecasting volatility are essential functions in different fields of finance, particularly in the quantitative risk management departments of banks and insurance companies. Volatility within the stock market can be forecasted. However, the debate is centred around how far ahead one can accurately forecast and to what extent changes to volatility can be made. Volatility has an impact on investment decisions, risk management, monetary policy decisions and security valuation. This study aims to unpack the impact of volatility on investment decisions. Investment is very low in the South African economy because South Africa is perceived as an economy of spenders with little savings and investments, which results in low economic growth rates and a stagnant economy. Volatility exists in various economic sectors, which makes it difficult for investors to make decisions as to which sector to invest in. As a result, it is important to be able to forecast volatility on investment decisions, so that investors can make decisions that are more informed.

The study primarily focused on modelling the most volatile sector in the top five JSE sectors according to market capitalisation. The primary objective was achieved with the use of volatility models, namely the autoregressive conditional heteroscedastic (ARCH); generalised autoregressive conditional heteroscedastic (GARCH); threshold autoregressive conditional heteroscedastic/ Glosten-Jagannathan-Runkle (TGARCH/ GJR); and exponential generalised autoregressive conditional heteroscedastic (EGARCH) models to determine the most volatile JSE sector.

The study used a quantitative approach with secondary data ranging over a period of 13 years starting from January 2002 to December 2015. The sample used in the study consists of daily data obtained from McGregor INET/ BFA, the JSE and the South African Reserve Bank (SARB). The study examined the most volatile JSE sector amongst the top five JSE sectors according to market capitalisation. This was achieved by using the above-mentioned ARCH/ GARCH volatility models. The results of this study revealed that according to the descriptive statistics, the JSE consumer goods sector is the most volatile sector due to its standard deviation value and the deviation of this sector's returns to its mean value, the standard deviation is the most accurate measure of volatility.

Furthermore, for model selection, the EGARCH and TGARCH models were classified as the best volatility capturing models. This was determined by the model criteria of having the lowest Akaike information criterion (AIC) and Schwarz information criterion (SC) values. The EGARCH model was best suited for consumer goods and financial sectors and TGARCH model was best suited for industrial, basic materials and consumer services' sectors.

The information gained from the volatility models will guide investors with valuable information about which sector to invest in and how best to diversify their investment portfolios according to their risk appetites as well as guiding investors with information, such as which sector is the most volatile to generate higher returns, as well as understanding the correlational relationship between the sectors and if there is a spill-over effect between the sectors.

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LIST OF ABBREVIATIONS

AIC	: Akaike information criterion
H1	: Alternative hypothesis
AR	: Autoregressive
ARCH	: Autoregressive conditional heteroscedasticity
ARMA	: Autoregressive moving average model
BIC	: Bayesian information criterion
BRICS	: Brazil, Russia, Indi, China, South Africa
CBOE	: Chicago Board Options Exchange
DCC	: Dynamic Conditional Correlation
EGARCH	: Exponential generalised conditional heteroscedasticity
GARCH	: Generalised autoregressive conditional heteroscedasticity
GARCH M	: Generalised autoregressive conditional heteroscedasticity in mean
GDP	: Gross domestic product
GFC	: Global financial crisis
GJR/ GARCH	: Glosten, Jagannathan and Runkle autoregressive conditional heteroscedasticity
HQ	: Hannan–Quinn
JSE	: Johannesburg Stock Exchange
MPC	: Monetary Policy Committee
MRS-GARCH	: Markov regime-switching generalised autoregressive conditional heteroscedasticity

HO	: Null hypothesis
OECD	: Organisation for Economic Co-operation & Development
P-value	: Probability
SARB	: South African Reserve Bank
SIC	: Schwarz information criterion
TGARCH	: Threshold autoregressive conditional heteroscedasticity
USA	: United States of America
VIX	: Volatility Index

CHAPTER 1: INTRODUCTION, PROBLEM STATEMENT AND STUDY OBJECTIVES

1.1 INTRODUCTION

Volatility is the amount a financial security can increase and decrease in price and is utilised interchangeably with risk (Grouard *et al.*, 2003:2). Markets tend to react with volatility when the economy is going through both a contractionary and expansionary period (Jha, 2014:3). A contraction in the economy may result in low profits for business sectors due to increased monthly expenses, which results in increased decline in corporate earnings (Amadeo, 2016:1). On the other hand, an expansion in the economy results in increased profits for business sectors (Duff, 2016:2). Expansionary periods lead to money being injected into the economy, therefore, increased earnings (Duff, 2016:2). During these periods, stock markets are responsive and can overreact in relation to changes occurring in business sectors (Gillen Markets, 2016:2).

Volatility can be seen as the relative rate at which the price of a market fluctuates around its expected value. The key usage of volatility is the estimation of the value of market risk. The majority of modern option-pricing techniques are reliant on a volatility parameter for price evaluation, which first appeared in the Black-Scholes model for option pricing (Black, 1976:90). Volatility can also be used for various risk management applications and generally in the management of portfolios. It is very important for financial institutions to not only depend on the current values of managed assets' volatility, but also to predict their future values (Masinga, 2015:6).

A link exists between volatility and risk in terms of a straight trade-off between risk and rewards (Saft, 2014:1). Volatility has the potential to fluctuate significantly and affect investor's investment decisions (Saft, 2014:3). Investors end up selling their investments at inappropriate times due to volatility, which is one of the key drivers for investment decisions. Often investors take uninformed investment decisions, for example, selling their investments during declining stock market phases. This results in investors not profiting when the stock markets rise over time. It is ideal for investors to save and invest through stock markets gradually; this indicates that investors accept that volatility exists within stock markets (Gillen Markets, 2016:1).

As a result of uncertainty, volatility makes investors less attracted to holding stocks. Investors end up demanding increased risk premiums as a form of security due to volatility uncertainty. The higher the risk premium, the increase in cost of capital, which results in lower individual investments (Emenike, 2010). Therefore, modelling volatility extends the importance of the intrinsic value of securities measurements. In the process, it becomes convenient to raise funds in the market by firms. Furthermore, volatility determination provides guidance in improved ways of structuring appropriate investment strategies. It is essential for traders and investors to know how the market behaves and volatility is the tool or the indicator that guides investors (Zamani, 2015:1).

The theoretical framework for modelling volatility was traced back to the original autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1991). The theoretical framework captures the variability of time variance returns by suggesting a structure that is autoregressive on the conditional second moment of returns. To address the statistical requirement of a high-order autoregressive structure, a problem that is inherent in the formulation of ARCH, Bollerslev (1986) introduced the generalised autoregressive conditional heteroscedasticity (GARCH) model. The GARCH model extends Engel's model by including lagged conditional variance terms as extra regressors. Several other studies have used ARCH/ GARCH models to model volatility. The study of Gustafsson (2017) incorporates known and future economic data release dates known to cause excess volatility in the GARCH models. The study of Aggarwal *et al*. (1999) examined the various events that result in large movements in the emerging stock markets' volatility. Lastly, the study of Zamani (2015) modelled and forecasted stock return volatility in the JSE securities exchange.

This study is motivated by the absence, or limited number of studies, on volatility measures or analyses in the JSE stock market. Therefore, this study contributes to the literature by providing evidence based on JSE data and top five JSE sectors according to market capitalisation.

1.2 PROBLEM STATEMENT

Volatility within the stock market can be forecast. However, the debate is centred around how far ahead one can precisely forecast and to what extent changes to volatility can be made (Poon *et al.*, 2003:1). Volatility has an impact on investment decisions, risk management, monetary policy decisions and security valuation. This study aims to unpack the impact of volatility on investment decisions. Investments are very low in the South African economy because South Africa is perceived as an economy of spenders, which does not save and invest and this results in low economic growth rates and a stagnant economy (Writer, 2018). Volatility exists in various economic sectors, which makes it difficult for investors to make decisions as to which sector to invest in. As a result, the capability to forecast volatility on investment decisions, so that investors can make decisions that are more informed, is important.

In this study, another key focus is on volatility forecasting in the top five JSE sectors according to market capitalisation. Volatility forecasting is examined and compared based on the results produced by the different GARCH models. Furthermore, the results produced from the different GARCH models guide investors in making informed investment decisions in the top five JSE sectors. A deeper understanding of the results produced by the different types of GARCH models is required for determining the most volatile JSE sector. Although there is no consensus on the best-fit, volatility-capturing model, the results of this study provide more insight.

1.3 OBJECTIVES OF THE STUDY

1.3.1 Primary objective

This study aims to model and determine the most volatile sector in the top five JSE sectors in order to guide individual investment decisions.

1.3.2 Theoretical objectives

In order to achieve the primary objective in Section 1.3.1, the following theoretical objectives are formulated for the study:

- analyse the concept, characteristics, types, indicators and purpose of volatility;
- determine the influence of return volatility in the stock market on investment decisions;
- conduct a sectoral analysis of the South African JSE sectors;
- determine the influence of macroeconomic factors on the top five JSE sectors; and
- determine the influence of volatility due to macroeconomic changes on investment decisions in the top five JSE sectors.

1.3.3 Empirical objectives

In accordance with the primary objective in Section 1.3.1, the following empirical objectives are formulated:

- identify the best model for modelling volatility in each of the top five sectors of the JSE;
- estimate the most volatile sector between the top five sectors of the JSE;
- compare the level of volatility across the top five sectors of the JSE, and
- determine the spill-over effect across the JSE sectors.

1.4 RESEARCH DESIGN AND METHODOLOGY

This study focuses on modelling and comparing the return volatility of the top five JSE sectors. Therefore, a quantitative research approach is followed.

1.4.1 Literature review

The literature review comprised of secondary information, journal articles, textbooks and necessary sources that were utilised to collect and review the theory. The literature review of this study discusses the concepts of return volatility such as characteristics, types, indicators and purpose of volatility. It also provides theoretical concepts linking return volatility and risk and sectorial analysis overview of the top five JSE sectors, providing the conceptualisation of modelling return volatility and, lastly, reviewing studies that have analysed stock return volatility and modelling of volatility.

1.4.2 Empirical study

The empirical portion of this study comprises the following methodological dimensions:

1.4.3 Sample selection

The JSE is made up of 10 sectors, namely consumer goods, consumer services, energy, financial, health care, industrial, information technology, basic materials, telecommunications and utility sectors. However, this study only focused on the JSE top five sectors according to market capitalisation, namely consumer goods, consumer services, financial, industrial and basic materials sectors. The criteria for selecting the top five sectors is a good representation of the JSE sectors because these sectors contributed the highest in terms of market capitalisation in 2015 (analysis start of this study).

1.4.4 Data sources and sample period

The study obtained data from South African Reserve Bank (SARB), Johannesburg Stock Exchange (JSE) and McGregor BFA (Pty) Ltd, which is a financial data feed and analysis online tool. The sample period runs from 2002-2015, making use of daily data. The starting period is 2002 because that is the year most sector data became available and 2015 was the most recent starting year of this analysis. The choice of daily returns is due to the finding that important information regarding volatility is lost at lower frequencies, especially during crisis periods (Edwards, 1998). Brooks (2002:389), emphasised the point that models, which use daily data, are more data-intensive than simple regression; therefore, the chosen models for this study perform better when the data are sampled daily instead of lower frequency.

1.4.5 Statistical analysis

To meet the empirical objectives, the study uses the volatility models, namely ARCH, GARCH, threshold autoregressive conditional heteroscedastic/Glosten-Jagannathan-Runkle (TGARCH/ GJR) and exponential generalised autoregressive conditional heteroscedastic (EGARCH) models to determine the most volatile JSE sector, which was followed by further information on the determination of the models and how each model is expressed. Different models are estimated because each model has its own model requirements for measuring volatility. Therefore, various model measurements are a clear indication of volatility levels.

The purpose of the application of the ARCH models is to run several tests like the descriptive statistics in order to present the data of this study in a more meaningful way. The purpose of correlation analysis is a statistical process that is used to determine whether two variables are associated with each other. In this study, correlation analysis is used to determine whether the JSE sectors are associated. Preliminary investigation displays a brief analysis of how volatile each sector was between the period 2002 and 2015. Unit root testing determines the ARCH effects in all mean equations before estimating and selecting the GARCH model. The volatility determination section determines the most volatile sector as per the econometrics equation criterion (Brooks, 2014). Diagnostic checking is used to confirm if the estimated models are robust or not. Risk premium test is used in order to estimate the best model in the mean. Lastly, the spill-over effects using the dynamic conditional correlation (DCC) model is used to test the movement amongst the sectors. All these tests are practically indicated in Chapter 5 of this study.

The ARCH/ GARCH models are applied to determine the volatility level of each of the JSE top five sectors. The performance of ARCH/ GARCH models depends on the market, period and error measures. Studies like Brooks (2014:441) analysed that the EGARCH model, which is part of the GARCH family models, has some advantages when forecasting stock market volatility. The study results of Poon *et al*. (2003:3) reveal that implied standard deviation models produce the best volatility model forecasts. However, this study focuses on the ARCH, GARCH, TGARCH and EGARCH models to determine the best volatility model.

1.5 ETHICAL CONSIDERATIONS

The data required to complete the analysis of this study are secondary data available to the public from the above-mentioned databases. The ethical considerations of North-West University, Vaal Triangle Campus, are adhered to in order to attain ethical clearance (ECONIT-2017-020).

1.6 CHAPTER CLASSIFICATION

This study comprises of the following chapters:

Chapter 1: Introduction, problem statement and background of the study

The first chapter places focus on the background and the aim of the study, the problem statement, research objectives, as well as the research method to be conducted.

Chapter 2: Literature review

Chapter 2 provides a theoretical framework for volatility. This chapter explains the concept of volatility, characteristics of volatility, various types of volatility, the purpose of volatility models and a review of previous studies on volatility is discussed. Lastly, the influence of return volatility in the stock market on investment decisions is discussed.

Chapter 3: Sectorial analysis of the JSE sectors

This chapter discusses the sectoral analysis of the top five JSE sectors. Chapter 3 explains the history of the South African stock market, the economic sectors of South Africa as well as the influence of macroeconomic variables on the JSE sectors. Lastly, the influence of volatility due to macroeconomic changes on investment decisions in the JSE sectors is clarified.

Chapter 4: Research design and methodology

Chapter 4 describes the sample data used and the methodology used for conducting the analysis. This is achieved by describing the sample period, data collection, different sectors and the different equations, which are used as inputs in explaining each model. The chapter continues by explaining the various volatility models that were used to capture the level of volatility for each sector.

Chapter 5: Empirical results and discussion

The results and findings of the tests conducted in Chapter 5 determine the best volatility model, the most volatile sector, correlation between the JSE sectors and the spill-over effect using the DCC model. The best volatility model and the most volatile sector were identified. A conclusion was reached, which was supported by evidence and data from tests conducted.

Chapter 6: Summary, conclusion and recommendations

In closing, Chapter 6 summarises the entire study, providing further conclusions on the findings, recommendations, limitations of this study and suggestions for future research.

CHAPTER 2: A LITERATURE REVIEW ON VOLATILITY

"We steer clear of the foolhardy academic definition of risk and volatility, recognising, instead, that volatility is a welcome creator of opportunity" Seth Klarman

2.1 INTRODUCTION

The key objective of this study is to model the return volatility of the JSE sectors and to achieve this objective; it is essential to understand the history and features of volatility in the stock market. In this chapter, volatility is linked to risk and return by reviewing previous studies on stock volatility returns based on the JSE. This chapter discusses the concept of volatility, characteristics of volatility, types of volatility, statistical measures of volatility, the purpose of volatility and, lastly, the influence of return volatility on the stock market on investment decisions. The chapter also discusses how a highly volatile sector triggers higher expected return.

2.2 THE CONCEPT OF VOLATILITY

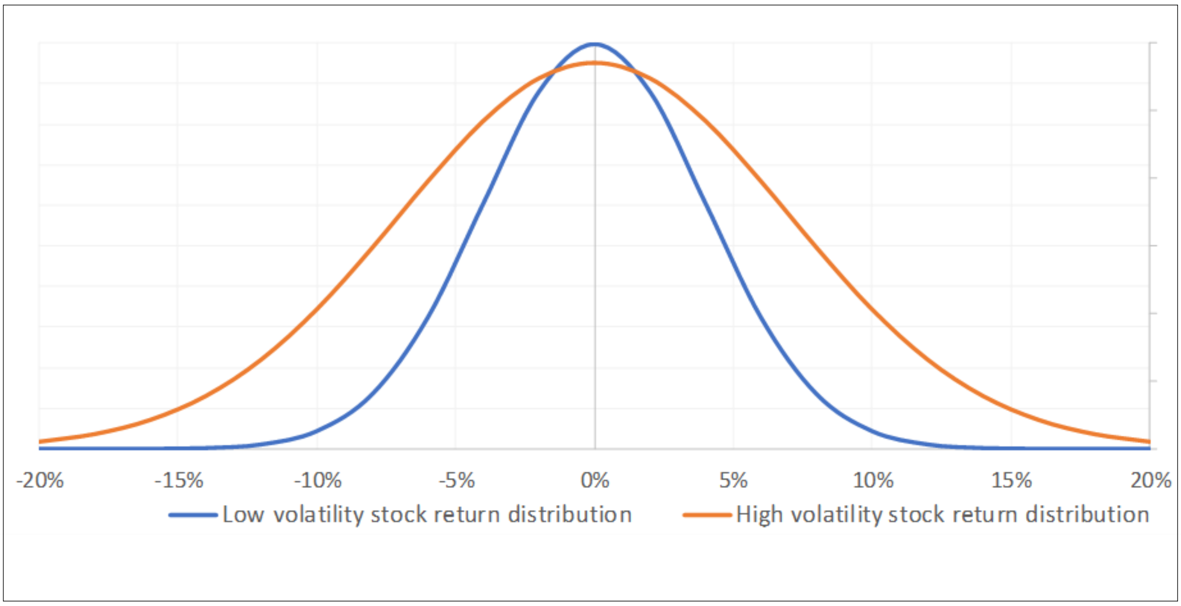
This section discusses the concept of volatility, the role of volatility, stock prices, stock market returns and the role of the risk-return trade-off for investors, and consults prior volatility studies. Volatility is significant economically and statistically. As a result, the relation between the price of a single stock and its volatility has been of great interest to financial researchers (Wu, 2001:1). Volatility is defined as a measure of dispersion of a single stock around the mean for a given security or market index (Tsay, 2010). Volatility is a relative rate at which market returns fluctuate around the expected value. Volatility indicates the magnitude of changes resulting from the upward or downward movement in stock prices, funds or bonds (McCollins, 2017).

A stock price is the price investors are willing to pay for a single stock. Stock prices can be impacted by various factors like volatility in the market, the reputation of a company or current economic conditions (Brailsford & Faff, 1996:423). Stock market returns and the conditional variance of a subsequent period's returns are negatively correlated. This means that when stock market returns increase, the conditional variance of a subsequent period's returns decreases and *vice versa*. The literature of Engle and Ng (1993), Zairian (1994) and Wu and Xiao (1999) refer to this empirical phenomenon as conditional volatility. High market volatility is most visible during stock market collapses; however, volatility is always present in stock markets even during business as usual times. Significant declines in stock prices are associated with increases in market volatility.

The link between stock prices and stock market returns is important because it ties back to why volatility has a great impact on stock returns. When stock prices increase, volatility decreases; this means that there is an inverse relationship amongst underlying prices of assets and volatility (Andrian & Rosenberg, 2008:300). Market parameters such as consumer behaviour, competition in the country and the unemployment level can be observed directly, but volatility is different, as it requires estimation (Pagan & Schwert, 1990:270). The relation between volatility and stock returns is on the basis of a fundamental relationship between risk and return, which suggest that the greater the volatility of a stock, the higher the required return, which is the most desirable outcome for investors with increased risk appetites (Jain & Strobl, 2017:59).

Figure 2.1 shows the relationship between volatility and low and high stock return distribution. As indicated in Figure 2.1, there is a greater demand for stock returns with low volatility than highly volatile stock returns. The demand for stock returns with low volatility would typically be from risk-averse investors − those types of investors that do not have increased risk appetites. Risk-averse investors prefer investing in guaranteed returns or safe haven types of investments like government bonds, index funds or debentures (Kumar, 2017). The demand for stocks with high volatility would typically be from aggressive risk investors. Risk aggressive investors are willing to maximise returns and have increased risk appetites (Hansen, 2018). Risk aggressive investors actively invest in stocks because stocks are generally volatile. These types of investors also consider investing in well-established companies that do not have a history of earnings or dividends (Lightbulb Press, 2016:2).

Figure 2.1: Lognormal stock return distribution

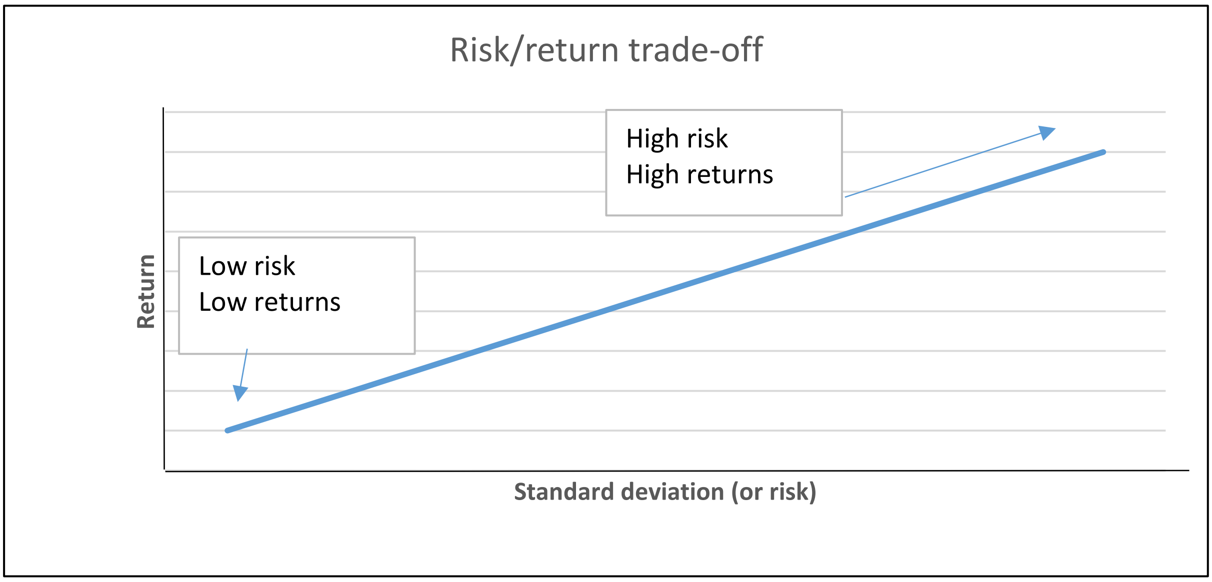


Source: Author compilation

Volatility is associated with uncertainty which makes investors more cautious about holding volatile stocks (Chuang *et al.*, 2007:1052). In turn, investors demand a high-risk premium (compensation for investors to tolerate additional risk) as a form of security against uncertainty due to volatility. As briefly explained in the introduction, a high-risk premium leads to a higher required return, which results in lower private investments (Emenike, 2010). The modelling of volatility advances the importance of intrinsic value (actual value) measurement of assets or securities. In the process, it becomes convenient to raise funds in the market by firms (Brailsford & Faff, 1996:421). The acknowledgement of volatility provides guidance in a more structured way for meaningful investment strategies. It is essential for investors to know how markets behave. Investors should be aware of the usefulness of volatility as a tool or indicator to assist in finding the intrinsic values of investments (Tothova, 2011:22).

Figure 2.2 shows the risk-return phenomenon that most investors tend to believe and follow. The greater the risk, the higher the expected returns, the lower the risk, the lower the expected returns (Reilly & Brown, 2012). What volatility means for returns is that investors tend to believe that the more volatile a sector is, the higher the returns will be. The opposite is true for lower cases of stock volatility, where lower volatility implies lower risk and, hence, lower returns (Blitz, 2010).

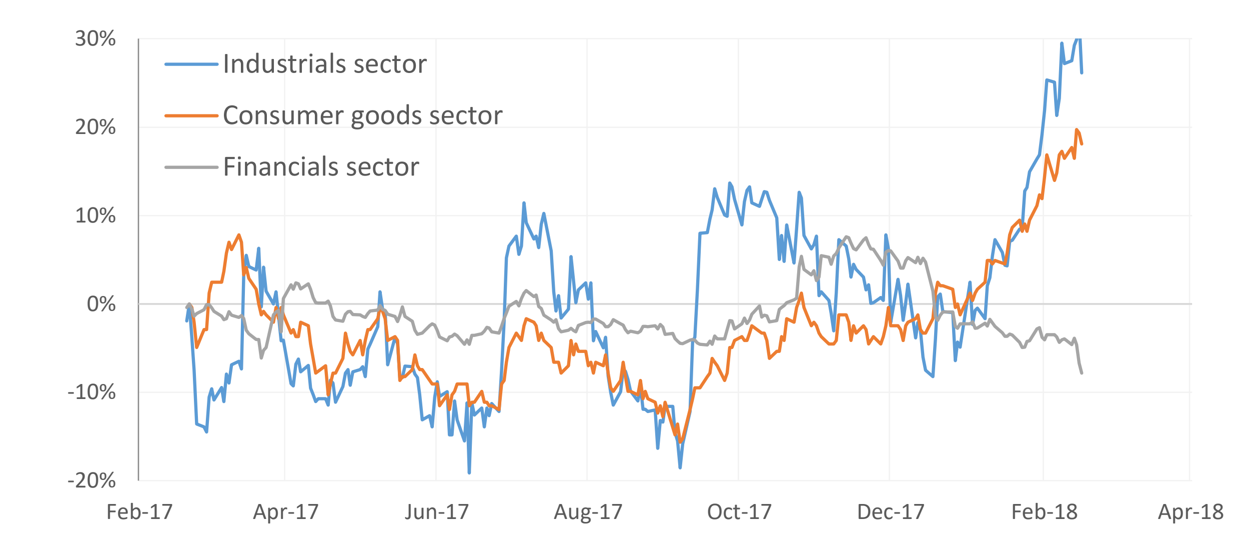
Figure 2.2: Risk-return trade-off graph



Source: Author compilation

French *et al.* (1987:1) provided evidence that unanticipated stock market returns have a negative relationship with unanticipated changes in volatility. This negative relationship implied indirect evidence of a positive relationship between anticipated risk premiums and volatility (Schwert, 1989:98). Figure 2.3 illustrates an example of the sector returns for only three sectors (industrial, consumer goods and financial sectors) from the top five JSE sectors. The industrial sector is the most volatile sector, according to its high returns. Using the risk-return trade-off, it means that this sector bears higher risk as it is the most volatile, therefore, increased returns can be expected from this sector. The financial sector bears the least risk. Therefore, low returns can be expected from this sector. Meanwhile, the risk and volatility in the consumer goods sector are average. Therefore, average returns can be expected.

Figure 2.3: JSE Sector returns



Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

The presence of volatility in the three sectors is not reflected so strongly in opening stock prices at the start of a day compared to the presence of volatility in closing stock prices (Ladokhin, 2009). Therefore, it is more reliable to make use of closing prices in order to predict future returns. In terms of risk and return for investors, it means that increased risk levels are associated with the possibility of higher returns, with no guarantees. Simultaneously, increased risk also means that investors can anticipate high losses on investments and high returns (Makhwiting & Sigauke, 2012:8068). Schwert (1989:1120), researched various variables that may influence volatility such as trading activity, firm profitability, leverage and default risk. According to Schwert (1989), it is challenging to explain movement in aggregate stock market volatility using models that are simple. There is still no consensus on the measurement of, the extent of volatility. Additionally, the persistence of volatility is necessary in defining stock market returns. Previous studies have attempted to separate volatility into components. For example, Campbell *et al*. (2001:34) investigated volatility at market, industry and firm level. The researchers found that volatility at firm level accounts for the greatest share of total firm volatility than market and industry level.

Pindyck's (1984), research indicates that rising volatility leads to a decline in stock prices accompanied by higher risk premiums. Poterba and Summers (1986), discuss the time-series properties of volatility, which cause a decrease in stock prices to increase risk premiums. However, neither study provides a straightforward test of the relationship between risk premiums and volatility. Volatility has the potential to create spill-over effects from one stock to another as well as from one market to another (Bala & Takimoto, 2017:26). Spill-over effect means that economic events from an unrelated context have the potential of affecting stocks and stock markets (Allen *et al.*, 2011:25). Spill-over effects can also exist between stock markets. Spill-over effects can assist investors in determining the relationship between emerging and developed stock markets (Li & Giles, 2015:165). The concept of volatility and the link between the stock market and stock market returns have been explained, and the risk-return trade-off for investors has been discussed in this section and hence, the next section focuses on the characteristics of volatility.

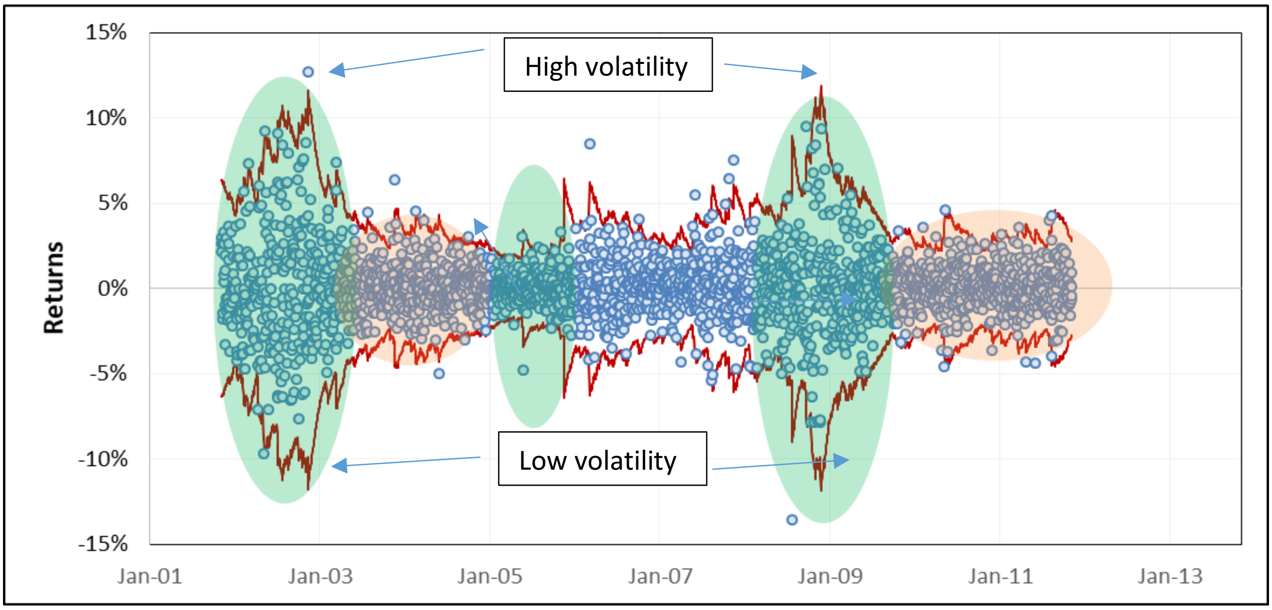
2.3 CHARACTERISTICS OF VOLATILITY

Volatility has specific characteristics that have the potential to increase the accuracy of predicted values (Marra, 2015:1). Section 2.3 focuses on various characteristics of volatility, namely volatility clustering, mean reverting volatility, historical movements and exogenous variables that could affect volatility. Volatility clustering is the trend of substantial movements in prices of financial assets to cluster together, resulting in the continuous magnitude of price changes (Moffatt, 2017). Mean reverting volatility means that both realised and implied volatility will move back or return to average historical levels (Fouque *et al.*, 2000). Historical volatility movements can be used as the sample standard for variable prediction. Various exogenous variables could affect volatility such as political uncertainty which may increase volatility and deterministic occurrences which are like public announcements that may impact volatility (Gustafsson, 2017:11).

2.3.1 Volatility clustering

When there is an interruption of small or large changes in the absolute value of financial returns, these changes tend to revert to mean levels. The magnitude of financial returns consists of latency (Poon & Granger, 2003:5), which means that large movements consequently accompany larger movements in financial returns and in turn, small movements tend to be immediately accompanied by small movements. This phenomenon is known as volatility clustering (Marra, 2015:2). Figure 2.4 illustrates the phenomenon of volatility clustering.

Figure 2.4: Volatility clustering



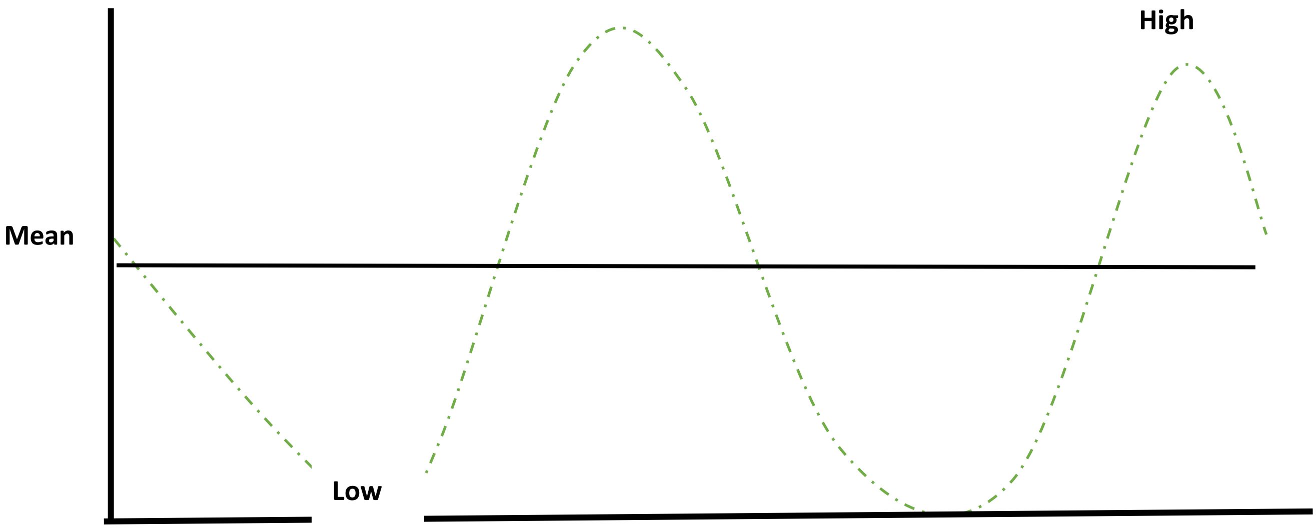
Source: Author compilation

Figure 2.4 displays the clusters of high, moderate and low volatility. The shaded areas do not represent anything specific; the focus is on the red lines, which indicate the level of volatility. The behaviour of volatility clustering explains the dynamics of volatility changes in stock market returns (Asai *et al*., 2012:500). There is a need to model this type of volatility because stock market returns can directly influence the risks of stocks and portfolios (Andersen *et al*., 2007:713). Violent market periods tend to happen more often than tranquil market periods. Estimating future volatility is dependent on recent evidence like daily returns. Most recent returns have a big influence on estimating the variance of periods for future returns, leading volatility to become continuous (Campbell *et al*., 1997:34). Several studies reveal that volatility clustering often happens because of investor inertia (Christensen & Prabhala, 1998:50). Investor inertia is the period when investors are faced with several investment options and are concerned about making the incorrect investment decision (Fleming *et al*., 1995:265). Therefore, it takes a while for these types of investors to participate in the market and action what they think is the correct investment decision, resulting in opposing views when new information is published (Marra, 2015:2).

2.3.2 Mean reversion

Mean reversion is another formalised characteristic of volatility in that stock prices revert to the mean over time. During the times of great volatility, volatility is expected to provide an allowance for normal volatility as periods of declining volatility, ultimately, will be accompanied by increasing periods of volatility (Engle & Patton, 2000:239). Volatility innovations indicate that there are volatility models that imply a hypothesis that restricts volatility from being impacted by constructive and destructive inventions (Engle 1982:987). Mean reversion is based on the foundational notion that what goes up must come down and *vice versa* (Butler, 2016). Figure 2.5 shows the mean reversion of implied volatility when stock prices increase, with time they tend to decline, and when stock prices are relatively low, prices tend to increase again (Shah, 2017). Figure 2.5 does not illustrate the possibility that sometimes stock prices are typically not mean reverting. For example, the price of a particular stock can keep increasing. The stock price does not necessarily have to move back to its average price over a specific period (Hincks, 2016). There are periods when volatility is high (high stock prices), followed by periods when volatility is low (low stock prices). Within these periods, there might be a fluctuation of the stock price, but the volatility can be considered relatively constant until its next principal fluctuation. The minor volatility fluctuations within these periods are relatively insignificant (Fouque *et al.*, 2000:5).

Figure 2.5: Mean reversion of implied volatility



Source: Author compilation

2.3.3 Historical exogenous variables

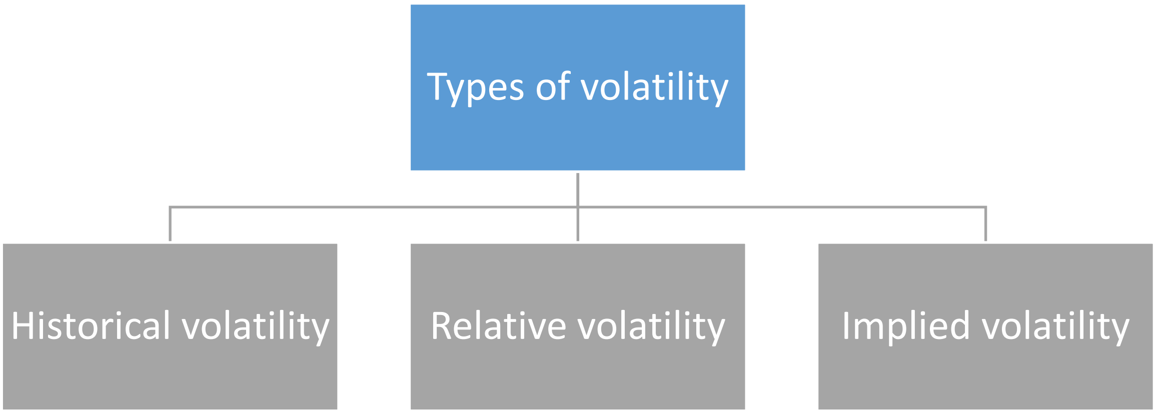
Other than historical movements, exogenous variables can also affect volatility by adding onto the assets that influence volatility. Political uncertainty can impact volatility because it is commonly known that when a political system of any country lacks certainty, this leaves investors in fear of losing accumulated wealth (Hira, 2017:70). This might even result in some investors moving their investments to politically sound countries. Alesina *et al.* (1992) found that the stability of the government would tend to increase the growth of the economy. Barro and Lee (1994) conclude that political instability and economic growth are negatively related. Beaulieu *et al.* (2005) discovered that stock return volatility increases alongside the firm's exposure level towards political risk increases. The results of Hira (2017), indicate a negative relationship between stock prices and political instability. Furthermore, the results implied that political system instability ultimately results in decreasing stock prices. Another exogenous variable is deterministic occurrences. Deterministic occurrences have the potential to influence volatility (Engle & Patton, 2000:240). Deterministic occurrences can be defined as planned announcements to the public and macroeconomic announcements, which have daily effects on volatility (Fleming, 1998:317). All of these occurrences impact processes on volatility because they can influence volatility series (Fleming, 1998:317).

An example of deterministic occurrence that can influence volatility is when the Monetary Policy Committee (MPC) announces a decrease in interest rates, as a result stock prices decrease (volatility decreases). When the MPC announces an increase in interest rates, as a result stock price increase (volatility increases). This suggests a very strong relationship between interest rates and stocks (Alam & Uddin, 2009). It can be concluded that both political uncertainty and deterministic occurrences have a strong relationship with volatility.

2.4 TYPES OF VOLATILITY

There are different types of volatility related to stock returns, namely historical-, relative- and implied volatility, as represented in Figure 2.6. Furthermore, the following sections explain the different types of volatility in depth.

Figure 2.6: Illustration of types of volatility



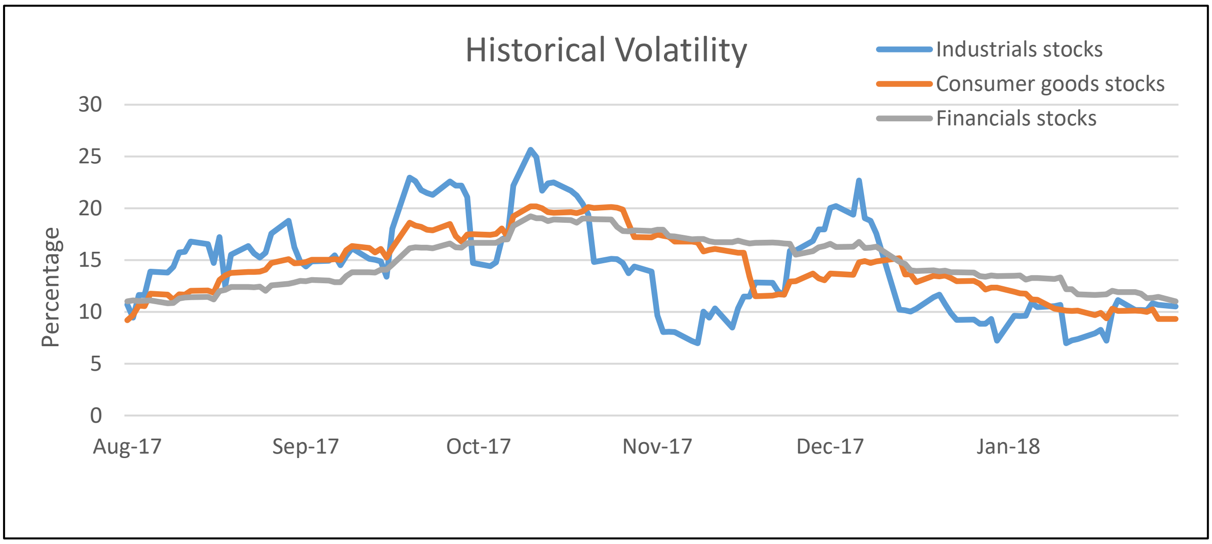
Source: Author compilation

2.4.1 Historical volatility

Historical volatility or realised volatility is the first type of volatility to be discussed. This type of volatility can be noticed and measured by the historical price changes of security (Radtke, 2014:2). Historical volatility looks into the sizes of stock price changes within a year. This type of volatility is often utilised as a comparison of the most recent behaviour of prices amongst two securities (Bliss & Panigirtzoglou, 2002:390). The determined historical volatility, which is the volatility that can be noticed and measured on the basis of historical price changes of a security, is used as a proxy for the estimated; whereas, implied volatility, which is discussed below, is seen as an expression of the market's anticipation of future volatility in stock prices (Kotze & Joseph, 2009:4).

For example, the historical volatility would be an excellent tool to compare the volatility behaviour of two indices, such as the largest industrial stocks to the largest financial stocks. Figure 2.7 illustrates the performance of the industrial, consumer goods and financial stocks. The performance of below stocks is quite volatile (Berman, 2007). All three stocks started on similar returns. The industrial sector picked up and became the most volatile. The industrial sector incurred the lowest (November 2017) and highest returns (December 2017). Towards the end of the period, all three stocks had similar returns, but the financial stocks took the lead.

Figure 2.7: Historical volatility of JSE sectors



Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

2.4.2 Relative volatility

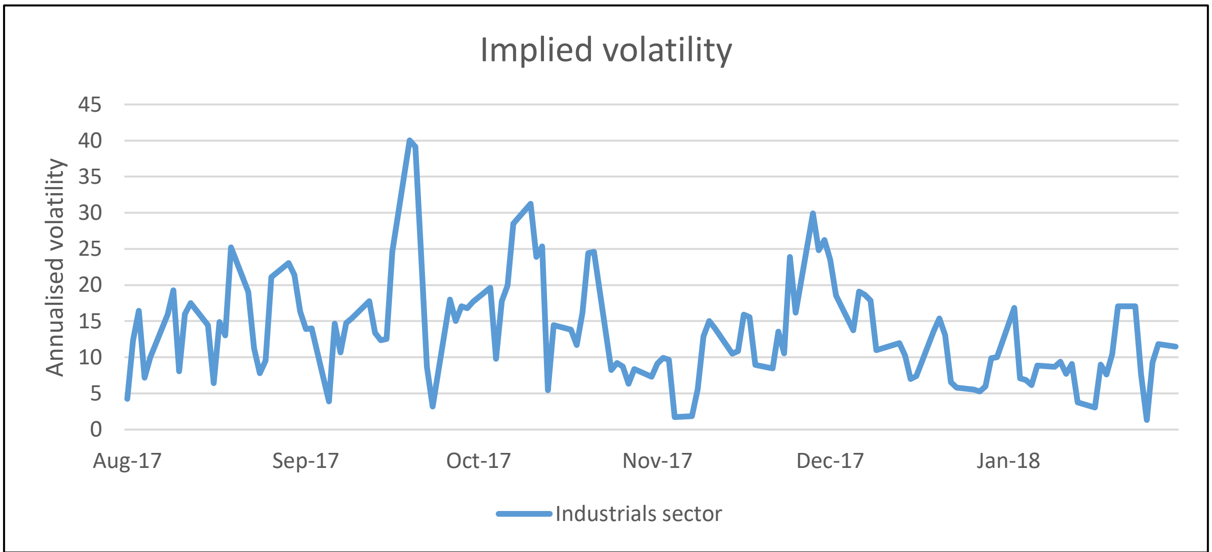
The second type of volatility is relative volatility; this type of volatility is measured by beta. Beta is defined as the correlation coefficient amongst price series greater than one (Radtke, 2014:5). If a value of beta is more than one, this explains that stock is more volatile than the market. In turn, if beta's value is below one this means the stock is less volatile than the market (Britten-Jones & Neuberger, 2000:850). Beta can be considered as a measure of volatility because volatility is an indication of risk and beta measures market risk. Beta is seen as a statistical volatility measure of a stock in comparison to the entire market. Beta can be used as both a measure of systematic risk and a measure of performance (Britten-Jones & Neuberger, 2000:850). For example, if a stock has a beta of 0.6, this shows that the stock has less risk than the market, which has a beta of one.

2.4.3 Implied volatility

The third type of volatility is implied volatility, which is also the primary type of volatility of this study. Implied volatility is a reflection of the market's anticipation of upcoming volatility in prices of stock (Canina & Figlewski, 1993:660). Similar to historical volatility, implied volatility is always annualised, in order to ensure the accuracy of compared values (Christensen & Prabhala, 1998:130). Implied volatility performs better than past volatility estimating future volatility. Therefore, implied volatility is expected to be an effective estimator of future volatility (Ederington & Guan, 2002a:10). Implied volatility is known as an effectual volatility estimator within a broad variety of procedures. Anticipating volatility in the future effectually or not is an empirical plan that can be tested (Ederington & Guan, 2002b:10).

An effectual estimator of upcoming returns on volatility for foreign currency futures is implied volatility (Christensen & Prabhala, 1997:126). Implied volatility has been concluded to be subjective and not efficient because past volatility is made of information regarding future volatility to be greater than the volatility included in implied volatility (Jiang & Tian, 2005:1330). Figure 2.8 shows the implied volatility of the industrial sector. From Figure 2.8, the performance of the industrial stocks is quite volatile. The industrial sector stocks start increasing then decrease until the sector picks up again and at the end of the analysed period the sector further declines. Stocks with higher implied volatilities would be the most effective estimators of future volatility. Therefore, using Figure 2.8 as an example the industrial stocks would be the most effective volatility estimator.

Figure 2.8: Implied volatility of the industrial sector



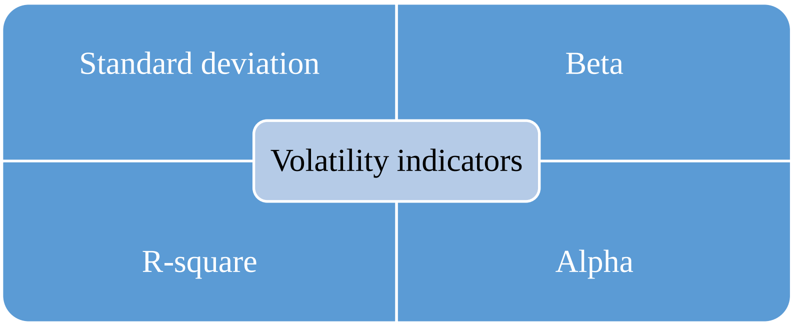
Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

Another interesting finding on implied volatility is that implied volatility has practically no link with future returns on volatility nor does it not include details enclosed in the latest observations of volatility (Jorion, 1995:510). Implied volatility is still effective even though it is subjective in its volatility estimates (Lamoureux & Lastrapes, 1993:300). The various types of volatility are explained and illustrated above, different volatility measures of returns from mutual funds (statistical measures) are explained in the next section.

2.5 INDICATORS OF VOLATILITY

There is a need for indicators of volatility because these indicators are measures of volatility that help investors determine the risk-reward parameters of their investments (Loth, 2018). This study only focuses on the following indicators of volatility including standard deviation, beta, r-squared and alpha. Figure 2.9 is an illustration of the various indicators of volatility, which will be discussed further in Section 2.5.

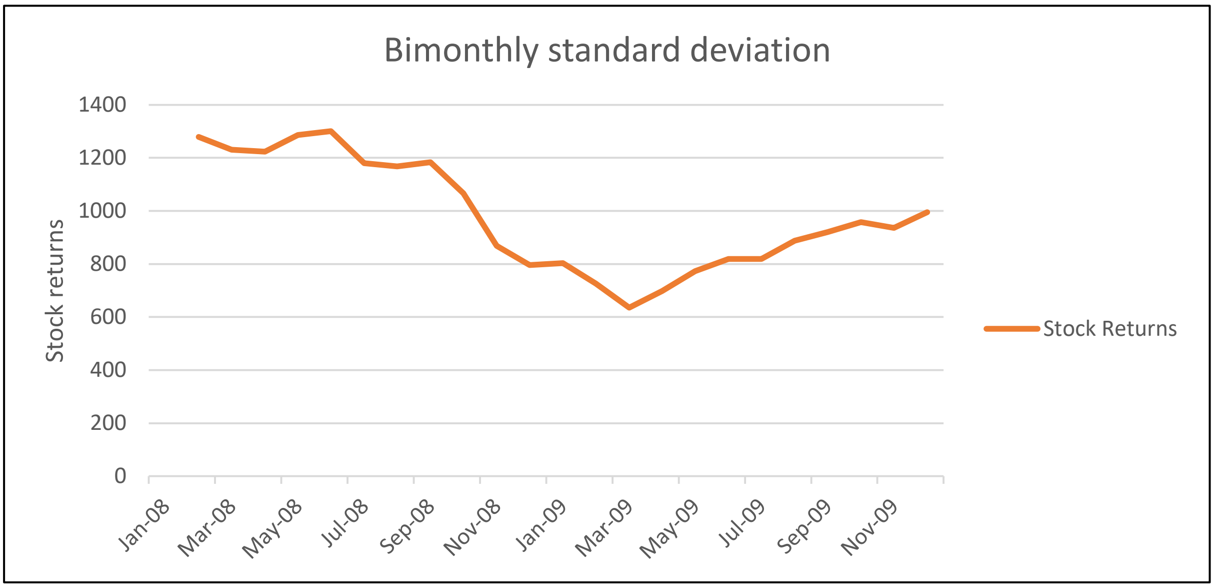
Figure 2.9: Illustration of volatility indicators



Source: Author compilation

The first volatility indicator is standard deviation, which measures how spread out a data set is (deviation from the mean). Price data standard deviations are often used as volatility measures (Kiersz, 2014). Highly volatile stocks are classified as high risk due to their performance in the market, which might change depending on the performance of the stock market (Rothbort, 2007). Standard deviation refers to a statistical measure of volatility; the use of standard deviation comes in to measure this high risk by measuring the extent to which the entire stock market changes (Poon & Granger, 2002). Figure 2.10 is an example of standard deviation as a risk measure.

Figure 2.10: Bimonthly standard deviation of S&P 500 index

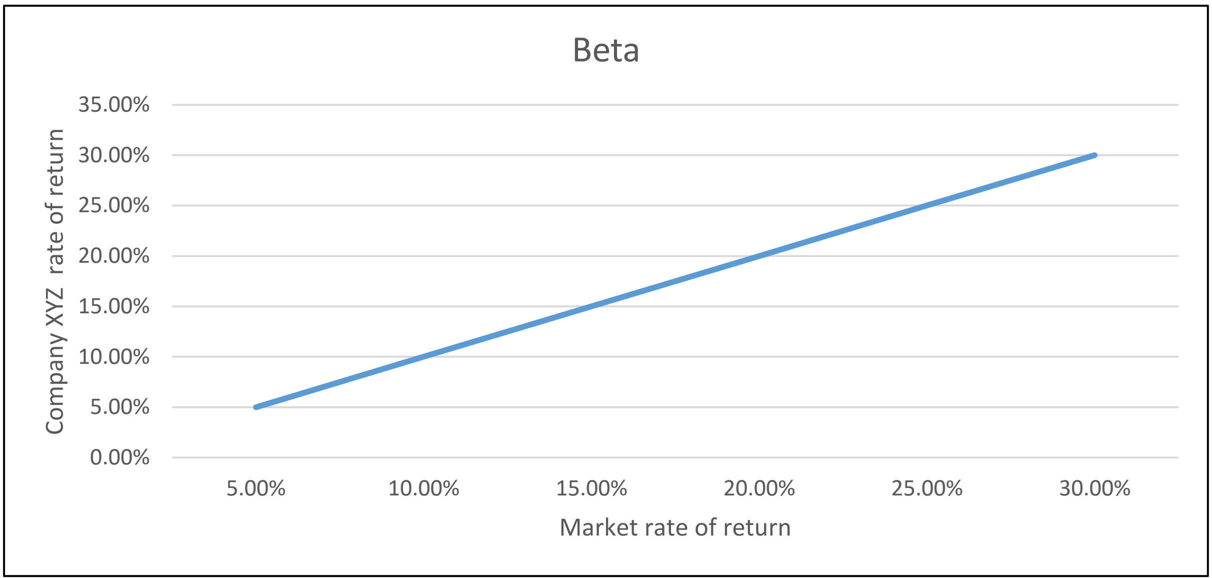


Source: Adapted from McGregor BFA (Pty) Ltd (2015)

Figure 2.10 is an example of the actual S&P 500 index during the 2008/9 financial crisis. The index data is on a bi-monthly basis and obtained from Bloomberg in Figure 2.10; the stock returns are quite volatile. From the early stages of the crisis, there is a continuous decrease, which reaches a trough in early 2009 and signs of improvement towards the end of 2009. Stocks with high returns will have greater standard deviation values. Stocks with low returns will have lower standard deviation values. The higher returns are not a true reflection of increased volatility, but rather a reflection of the actual price (Greenwood & Shleifer, 2013). The value of the standard deviation is displayed in measures that relate directly to the underlying stock.

The second volatility indicator is beta, which measures volatility by regulating the volatility of a stock market compared to that of its index or benchmark over a certain period (Blume, 1975:790). Beta also measures a fund's volatility in comparison to that of a benchmark, which if often the market index. Beta is limited because it is not a perfect measure of volatility. This results in beta being skewed because of variables influencing the stock market's volatility (Camp & Eubank, 1985:55). Figure 2.12 presents a graphical illustration of company XYZ beta value.

Figure 2.11: Beta of company XYZ

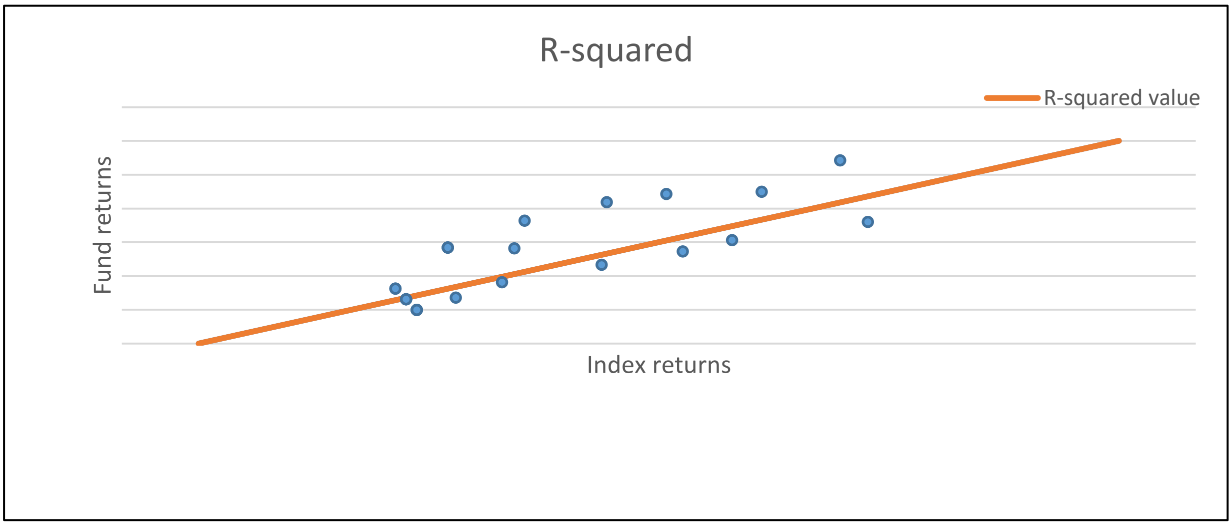


Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

Brigham and Ehrhardt (2002:279) stated the slope in Figure 2.11 is determined by regressing historical returns on stocks, instead of historical returns on the market. On average, five years is normally used for monthly returns by analysts to establish the regression line. Sixty points are often used to determine enough data points along time series to determine any trends and exclude increased random data points (Van Heerden, 2004:12). The third volatility indicator is R-square, which is a statistical measurement representing a certain percentage of a funds' portfolio or movements of security that can be described by changes in a benchmark index (Mitchell, 2018). Figure 2.12 uses the R-square to calculate the estimated fit between a fund's returns and an index's returns. Even with a very low R-square, a portfolio can perform well (Mitchell, 2018). R-square is a correlation measure of a fund's returns to the index's returns. R-square is generally considered as the percentage of a fund or security's changes when it comes to investing, which can be explained by changes in a benchmark index (Carther, 2015).

It is important to note that R-square does not measure the performance of portfolios. A well-diversified portfolio can have a low R-square (Amihud & Goyenko, 2018). What R-square does is that it measures the correlation between the portfolio's returns against the benchmark returns. If an investor is looking for a type of portfolio that moves similar to the benchmark, a high R-square portfolio is recommended. If an investor wants a portfolio that does not move similar to the benchmark at all, then a low R-square is ideal (Loth, 2007).

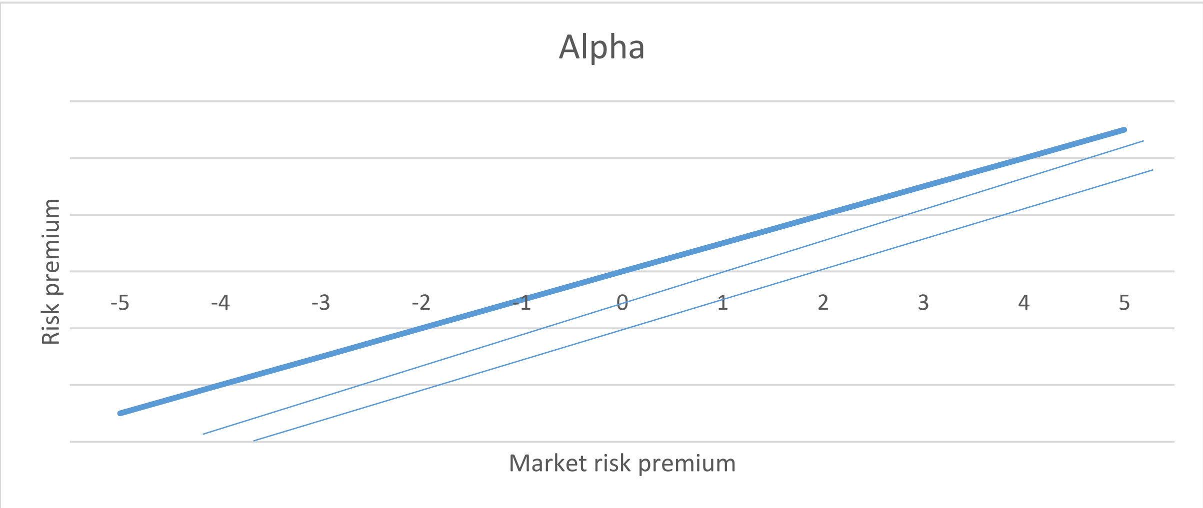
Figure 2.12: A typical example of R-square measure



Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

The last volatility indicator is alpha, a measure of how much risk can assist the stock market to outpace its corresponding benchmark (Hillier, 2000:530). An alpha of one percent indicates that the stock market outperforms the benchmark by one percent and an alpha less than one indicates that the stock market underperforms by one percent. The alpha performance is an indication of the measure of volatility within a particular stock market (Martin & Simin, 2003:60). Figure 2.13 is an illustration of alpha, followed by an example of how investors would typically react according to the performance of the alpha.

Figure 2.13: Alpha as a volatility indicator for investors



Source: Author compilation; McGregor BFA (Pty) Ltd (2015)

Investors can use alpha values to determine the return and volatility of an investment, based on past performance (Loth, 2007). With alpha based at zero, a positive alpha value indicates that investment has generated returns, which have beaten the benchmark (Kane & Marcus, 2005:291). This means that the volatility risk of the assets has performed well. Investors with great risk appetites often prefer a high value, because greater returns can be gained over periods of upside volatility (Kane & Marcus, 2005:294). Figure 2.13 shows that a portfolio with positive additional returns results in a positive alpha and then a portfolio with additional negative returns results in a negative alpha.

From the various indicators of volatility discussed in Section 2.5, each measure has its own characteristics, advantages and disadvantages, which are set out in Table 2.1. From the four indicators of volatility; standard deviation, beta and alpha have more advantages than the R-square. From the four indicators of volatility, standard deviation has more disadvantages.

Table 2.1: Indicators of volatility

Volatility indicator	Features	Advantages	Disadvantages
Standard deviation	• Standard deviation measures the amount of variability or dispersion (the difference between actual and average value) associated with an average. • The standard deviation can be used as an indicator to indicate stocks with very high volatility. • The standard deviation can be used as an expected risk measure and determining the importance of specific stock changes.	• The lower the dispersion, the lower the standard deviation that is more reliable. • Provides more precise idea on the distribution of data. • Extreme values do not impact standard deviation. • Indicates the level of data clustered around the mean value.	• The greater the dispersion, the higher the standard deviation that is less reliable. • Can be challenging to calculate. • Assumption of the normal distribution. • Challenging to calculate. • Full data range is not provided.
Beta	• Beta is a generally used quantity in investment analysis. • Beta is a volatility measure of a given asset relative to market volatility. • Stocks with betas greater than one are more volatile than the market and are known as aggressive stocks. • Stocks with betas less than one are known as defensive stocks.	• Useful measure of an asset's volatility in comparison to the entire stock market. • The beta of a stock can measure the stock's sensitivity to changes in the overall stock market. • Stocks that are more volatile have a beta greater than one.	• Beta fails to consider unsystematic/diversifiable risk. • Beta is based on historical data and may not exactly be a precise predictor of future volatility. • Less volatile stocks have a beta less than one.

Volatility indicator	Features	Advantages	Disadvantages
R-squared	• R-squared represents the percentage of a fund's portfolio or security's changes that can be described by changes in a benchmark index. It can be seen as a percentage from one to 100. • R-squared also measures portfolio performance.	• An increased R-squared will imply a more useful beta figure, which is more relevant to the performance of the portfolio.	• The lower the R-squared, the beta is less relevant to the performance of the portfolio.
Alpha	• Alpha is the excess return that the portfolio generated over what was expected.	• A positive alpha is always favourable for investors. • Alpha differentiates between positive/negative investments over time. • Alpha can help investors determine markets and capitalise on stocks, which match their risk profiles.	• Cannot always anticipate future trends.

Source: Levy (2002); Wilkinson (2013); Sofalof (2015)

2.5.1 Purpose of volatility models

The purpose of volatility models is for more accurate forecast returns for investors to make more accurate investment decisions (Poon & Granger, 2003). Volatility can be estimated through volatility models. Stochastic volatility models can be used to estimate volatility models. The implementation of stochastic volatility models has other model multifractals known as stochastic structural break models, which are implemented based on the unrestricted distributions (Gatheral & Lynch, 2002). Stochastic is a pattern that may be analysed statistically but may not be predicted accurately (Kim & Shephard, 1993:23). The requirement of these models is restructuring the implementation in order to provide estimating associations amongst the models (Kim & Shephard, 1993:23).

Probabilities of unrestricted supplies of returns on assets possess weighty tails. This variable is suggested to be included in models of volatility (Shephard, 1994:190). The variable serves as a link between restricted and unrestricted returns and discloses the basis of the heavy tail probability (Uhlig, 1993:41).

2.5.2 Modelling and forecasting volatility

Understanding volatility, modelling volatility and forecasting volatility to its effects is critical towards understanding accurate volatility behaviour; hence, the necessity of this section to discuss the modelling and forecasting of volatility. Stochastic volatility models are generally associated with the problem that they seem to fail in modelling the aspects of short-term volatility skewness (Ball, 1993:60). The opportunity of applying a stochastic volatility model with correlations is that the stochastic volatility model moves over to the index level, resulting in volatility having to fit suitably into the market volatility twists much better in the short-term (Brown, 1990:520). The problems identified led to the adoption of other volatility capturing models like the autoregressive conditional heteroscedasticity model (ARCH), which further advanced to the generalised autoregressive conditional heteroscedasticity model (GARCH) model (Kotze & Joseph, 2009:8).

In a basic ARCH model, the following period's volatility is only conditional depending on the last period's volatility. As a result, the presence of volatility is not captured fully in a period of crisis (Figlewski, 2004:18). The GARCH model serves the purpose of defining the dependence of the time-varying nature of volatility. GARCH model also captures differences in the error term, changes in volatility and lastly, traces ongoing volatility, as there are changes over the long-term average (Marra, 2015:5).

The ARCH model was extended to GARCH because the GARCH model defines variances by two lag distributions, one on previously squared residuals to capture effects of great frequency and the second one on lagged values of the variance itself, to capture influences in the longer-term (Cumby *et al*., 1993:55). The GARCH model tends to embody a neutral forecasting strategy. This is because the variance anticipated at any random date is a grouping of a long run variance and the previous period expected variance, adjusted to account for the account size of the previous period's observed shock (Fair & Shiller, 1990:150).

GARCH models cater to changes in volatility, resolution of volatility and take responsibility for the non-normality of financial return series (Jorion, 1995:507). The GARCH model, just like any other models, has the limitation of not being able to act upon asymmetrically to decreasing and increasing levels of volatility. For action upon this limitation, several non-linear extensions of GARCH have been discovered (Bollerslev *et al*., 1992:45). However, this study also focuses on asymmetric GARCH models, namely threshold autoregressive conditional heteroscedasticity (TGARCH) and exponential generalised conditional heteroscedasticity (EGARCH). These models are further discussed in Chapter 4 of this study.

It is discovered that the GARCH model performs much better with the use of daily data, when the volatility-forecasting horizon is not long, for example, horizons of up to two years (Theodore & Lewis, 1993:43). It is crucial for volatility to be forecast because there are often changes over time. Once volatility has been forecast there is a need for investors to be aware of the level of volatility in order to make informed investment decisions. The impact of return volatility on investor decisions is explained in Section 2.6.

The various volatility forecasting models have different characteristics, advantages and disadvantages, which are summarised in Table 2.2 and are further discussed and mathematically expressed in chapter 4.

Table 2.2: Summary of volatility forecasting models

Model	Characteristics	Advantages	Disadvantages
ARCH (Autoregressive conditional heteroscedasticity)	• The first model to capture the various change in variance and used estimations of the variance over time.	• Simple and easy to handle • Accountable for errors that are clustered and nonlinearities • Responsible for changes in the ability of the econometrician to forecast.	• Volatility forecasting models like the ARCH model are well known for being complicated. • Volatility is not observed and accurately measured but instead estimated.
GARCH (Generalised autoregressive conditionally heteroscedastic)	• The model was developed for the achievement of a sparing framework. • The model provides an allowance for a conditional variance to be dependent on own previous lags.	• The model encompasses volatility clustering and leptokurtic behaviour. • The model can model the evolution of volatility.	• GARCH models cannot model asymmetries of the volatility due to the sign of the previous shock. • Unsuitability for modelling the regularly observed asymmetric effect.
TGARCH/GJR (Threshold autoregressive conditional heteroscedasticity)	• Asymmetry and negative model returns have more than three times the impact of positive returns on future variances.	• Asymmetric terms that can capture essential occurrence in conditional variance.	• The model does not satisfy the restrictions for eternal marginal variances.
EGARCH (Exponential generalised conditional heteroscedasticity)	• Model is responsible for asymmetric response to shocks.	• Model specification includes positive nature regardless of the estimated parameters as well as asymmetric nature.	• The model has three criticisms: to ensure positivity of the conditional variance all the time, the standard GARCH model does not allow asymmetric responses, and lastly, this model measures persistence difficulty.

Sources: Engle (1982); Bollerslev (1986); Nelson (1991); Glosten *et al*. (1993)

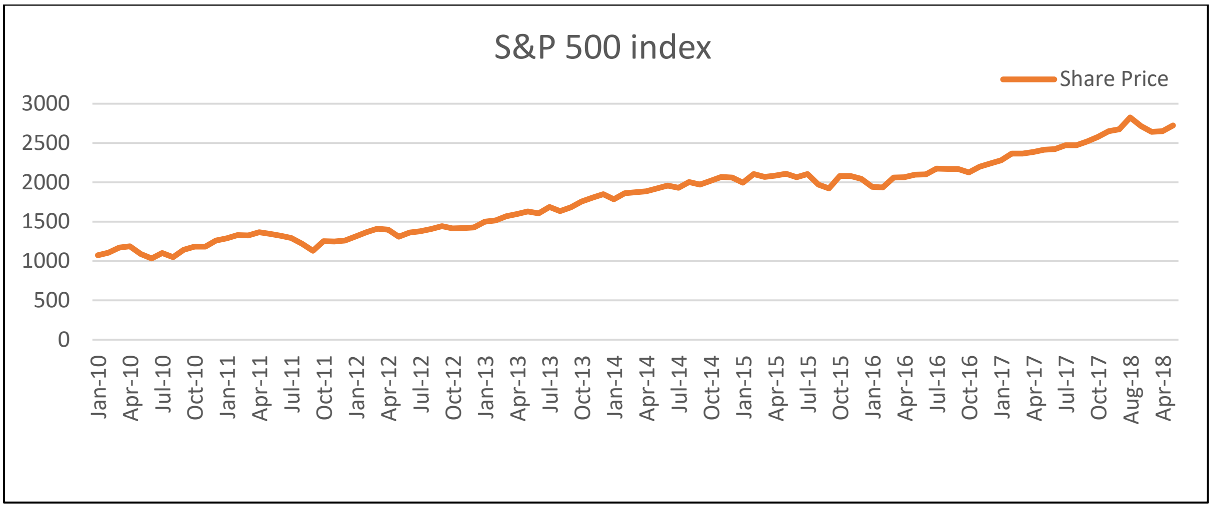
2.6 THE INFLUENCE OF RETURN VOLATILITY ON THE STOCK MARKET AND INVESTMENT DECISIONS

Investors often have a particular investment pattern, which they tend to follow. Investors can invest in various investment products like commodities, money market instrument, bonds or stocks (World Bank, 2013:5). Investors can invest in short-term or long-term investments, depending on the investors risk appetite (Aouadi, 2013:677). Investments that are not long-term usually are seen as hypothetical investments that are typically made up of buying or selling of assets with the intention of taking the opportunity of advantageous exchange rate activities (Sinha, 2018). Long-term investments consist of investors with the intention of possessing assets for a longer period (de Villiers, 2015:20). Risk-aggressive investors (those with high-risk appetites) typically invest in stocks because expected returns from stocks are high. Therefore, stocks operate in a very volatile market (Loh, 2010:1225). Risk-averse investors (those with low-risk appetites) typically invest in bonds because bonds are a safe haven investment operating in a less volatile market (Peress, 2008:17).

Seasholes and Wu (2007:3) state that when a stock maximises its limit, investors focus more on it, therefore, the increasing limit can be a favourable benchmark of gaining investors' attention. Odean (1998:1780) considers turnover rate a benchmark for gaining investors' attention and concludes that increased attention encourages high information efficiency.

Towards individual stocks, the asymmetry between buying and selling makes the attention of investors encourage short-term price increases and results in long-term return reversals (Amal & Teulon, 2013:680). It is important to note that certain factors such as policy, concept and product affect the decision making of the investor. For example, if the majority of investors focus on energy-saving and reducing emission, it can be expected that the energy industry index will go through periods of low and negative returns (Loh, 2010:1230). Figure 2.11 is an example of the relationship between investor focus and the stock market by using the S&P 500 index data.

Figure 2.14: S&P 500 index share price



Sources: Author compilation; Bloomberg (2018)

Figure 2.14 displays periods of low and negative returns as well as high and positive returns. Figure 2.14 is made up of the S&P 500 index and the sample period is 2010-2018, immediately after the financial crisis. Mostly high and positive returns (increasing share price) are seen in Figure 2.14, which means that the S&P 500 index recovered from the negative impact of the financial crisis. Low return periods induce lower returns in the short run (Bloomberg, 2018). High return periods have a major impact on the stock index return because all investors long for this period. Volatility can always increase or decrease in markets and is measured in returns. The majority of investors would rather settle for less volatility instead of taking calculated risks. However, the main concern is that investors tend to focus on shorter than a month investment period instead of longer investment periods (Johnson, 2016). Caballero (1991) concludes that constant returns induce a positive association between volatility and investments, whereas decreasing returns induce a negative association.

Volatility is associated with risk in a sense that volatility provides a possible variation measure or movement in a specific economic variable or some function of the variable like growth rate (Serven, 1998:25). Prospects of growth encourage investors to make greater investments; as a result, volatility is triggered. Macroeconomic uncertainty can influence growth investments (Aizenman & Powell, 2003:98). For a developing country that exports oil, the effects of price increases usually are transmitted through fiscal policy. There is great possibility that the real exchange rate appreciation and volatility can reduce investments in non-oil trading sectors (Aizenman & Pinto, 1990:5).

The study of Figlewski (2004), emphasised the trend of volatility and forecasting volatility. Marra (2015), unpacked the importance of predicting volatility and the different approaches used to forecast volatility. King and Wadhwani (1990), established the transmission of volatility between stock markets. Thus, there is a possible spill-over effect that can be transmitted through the top five JSE sectors; this can only be confirmed through the tests conducted in the study. A positive index has great influence on stock index returns and a positive effect on the stock index volatility (Chemmanur, 2009). A positive outcome drives the investor to invest more. On the other hand, a negative index also has great impact on stock index return and volatility (Grullon & Weston, 2004:440). If there is a negative outcome, the index declines significantly, which discourages investors from investing.

2.7 SUMMARY

The focus of this chapter was to explore what volatility means in the context of the stock market, this objective was achieved through outlining the concept of volatility presented in Section 2.2. Characteristics of volatility were defined and illustrated where relevant in Section 2.3. Section 2,4 discussed the types of volatility and emphasis was placed on the primary type of volatility that is identified in stock markets. Section 2.5 explained the indicators of volatility as well as an illustration of a typical example of the specific volatility indicator. Lastly, Section 2.6 discussed, the impact of return volatility on the stock market on investment decisions. The discussion presented in Section 2.6 further provided detailed guidance for investors in following a particular stock market trend depending on the investor's risk appetite.

The concept of volatility in the context of the stock market has become of massive importance to market participants in the financial markets. Volatility is associated with risk; increased volatility is perceived to have increased risk, triggering market disruption. Characteristics of volatility have the potential to increase the accuracy of predicted values because market variables are not constant. There are various types of volatility, namely historical, relative and implied volatility. These volatility types are associated with the behaviour of each volatility type in the stock market. The need for various indicators of volatility namely standard deviation, beta, R-square and alpha were discussed. These indicators are measures of volatility that help investors determine the risk-reward parameters of their investments. It is important that the ARCH/GARCH volatility models achieve their purpose of being able to model and forecast volatility. The level of the volatility forecasted has an influence on investors' investment decisions. The level of volatility captured has the potential of attracting risk aggressive (high risk appetite) or risk adverse (low risk appetite) investors depending on the investors risk appetite.

Volatility influences investor’s choice whether to buy or sell a stock. This is true because investors tend to make emotional and irrational decisions like selling a stock when volatility increases. When markets are less volatile, investors tend to buy stocks. Investors need to note that with investing it is essential to assess your investments occasionally as this is essential towards accumulating wealth. Although some investors do not analyse prices of stock or funds like mutual fund indicators weekly or monthly, it is critical for investors to completely assess all investments bi-annually or yearly. Throughout the period of reviewing investments, investors should not take irrational decisions of buying or selling. The reason for such assessments is for investors to explore other methods of investments and let go of older investments that no longer grow.

Investors have to be aware of selected constraints of stocks they would like to invest their money towards. If investors are thinking of certain stock like equities, they should be on the lookout for long-term returns and have great risk appetites. Finally, investors should not sit back and wait; it is important to get started, regardless of the size of the investment. Investors are encouraged to start with minimum amounts that will grow, simultaneously learning about the financial markets.

CHAPTER 3: SECTORAL ANALYSIS OF THE SOUTH AFRICAN JSE SECTORS

"What an investor needs are the ability to correctly evaluate selected businesses" Warren Buffet

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3.1 INTRODUCTION

This chapter focuses on the history and trends of the South African stock market. The top five sectors will be unpacked in the sense of how individual investments in each sector are affected by the main macroeconomic factors; real gross domestic product (GDP), inflation and interest rates will be discussed. Lastly, the influence of volatility due to macroeconomic variable changes on investment decisions in the top five JSE will also be discussed. Chapter 3 aims to achieve the following theoretical objectives; conducting a sectoral analysis of the South African JSE sectors, determining the influence of macro-economic factors on the top five JSE sectors and determining the influence of volatility due to macro-economic changes o investment decisions in the top five JSE sectors. Section 3.2 elaborates on the history of the South African stock market, known as the JSE. Section 3.2 outlines the origin and how the operations of the JSE were established. Section 3.2 also makes use of Figure 3.1, which is a graphical illustration of a share's performance traded on the JSE.

3.2 HISTORY OF SOUTH AFRICA'S STOCK MARKET

Typically, when a working day came to an end in the 1880s, individual investors and brokers used to fill up the trading street to trade (Chipkin, 2008:3). The second stock exchange building was completed in 1890. It replaced the first building within two years, showing great industrial growth (Chipkin, 1993:4). A prosperous financial constituency emerged around the stock exchange, featuring banks and mining companies, who wanted to be as near as possible to the financial centre of Johannesburg (Norwich, 1986:4).

A new site for the stock exchange was completed in 1904 on Hollard Street. The catalyst for this building move was the necessity for bigger space and more recent developments (Shorten, 1970:5). It took as long as seven decades before the JSE moved on again after the building change generated the shift of the financial constituency westwards with Hollard Street known as the Wall Street of Johannesburg (Stark, 1956:7). In 1961, the fourth stock exchange building was developed. For the official opening, an influential public relations activity resulted in presidents and chairpersons of well-known stock exchanges, including New York, Frankfort, London and Paris, receiving invitations (Van der Waal, 1987:6). In 1979, on 12 Diagonal Street, the fifth stock exchange opened, which marked the end of the Hollard Street period. This building lasted over 20 years before the relocation to Sandton. The old hall that was used for trading has been kept and is utilised for occasional special functions. In 2000, the JSE moved from 17 Diagonal Street to its current location at 2 Gwen Lane in Sandown, Sandton (Chipkin, 2008:3). The JSE has competed against other African stock exchanges since 1887 (stock market establishments). African stock exchanges have proven to be some of the most lucrative and best-performing platforms (Blainey, 2012:7). However, stock exchanges operate differently because some exchanges operate for capital markets controlled by entities and regulators while others are not controlled by any entity or regulators (Michie, 2012:7). Consensus has not yet been reached on whether a well-performing capitalist economy is sparked by the dynamic trademark of a stock market or not. However, there is advice from the latest research that uncontrolled operations of stock markets might bring about great destruction (Niels & Lensink, 2013:7).

In comparison to other African stock exchanges, the JSE stands out beyond all stock exchanges (Klein, 1948:8). The JSE has been awarded for being Africa's second oldest exchange listing stock in sub-Saharan Africa (Klein, 1948:8). A financial market like the JSE utilises South Africa's colonialism, industrial capital, structural transformation, global economic engagement and financial protectionism (Kubicek, 1979:8). The JSE has connected the natural resource industries of South Africa with international financial and human capital (Stanley, 1971:8). With the history provided on the JSE in Section 3.2, Figure 3.1 is an example of Shoprite holdings' (consumer goods sector producer) share performance in value traded on the JSE.

Figure 3.1: Shoprite holdings share price performance

Source: Adapted from JSE (2018)

Figure 3.1 represents the price movement of Shoprite holdings shares traded on the JSE from 2007 until 2015, which is the most recent year of this study's analysis. The JSE is made up of an index, which includes 150 JSE-listed companies (JSE, 2018). ALSI is the largest index with regards to total value and size (JSE, 2018). Investors can use the JSE financial market platform for insight relating to risk management into the regulatory and trading practices of the markets included in the global and regional indices, which investors track. Figure 3.1 shows the volatile performance of Shoprite holdings shares, starting with an average price in 2007, resulting in a drop in 2009 during the global financial crisis (GFC) when consumers had less spending money. Since 2009, the share price has been increasing. Section 3.2 creates an understanding and an idea of what the JSE is and how it functions as a financial market. Section 3.3.2 outlines macroeconomic factors, which may influence individual investments. There is a need for Section 3.3.2 because when investors make investment decisions, investors need to be well informed of how the macroeconomic factors might affect their investments because markets are volatile.

3.3 DEFINING MACROECONOMIC VARIABLES

The economy of a nation can be split into different sectors to explain the proportion of the population engaged in various activities (Mayer, 2013:4). The classification is an indication of a range from the natural environment. The range begins with primary economic activity, consisting of utilisation of raw materials from the earth, like mining and agriculture. Thereafter, the distance from natural resources increases (Rosenberg, 2018).

3.3.1 Economic sectors in South Africa

As mentioned above, 10 sectors make up the JSE. The sectors include financial, consumer services, industrial, consumer goods, basic materials, health care, oil and gas, technology, telecommunications and utilities (Mayer, 2013:4). This study will be focusing only on the top five JSE sectors according to market capitalisation (Bronkhorst, 2012:13). Less focus is placed on health care, oil and gas, technology, telecommunications and utilities because these sectors are relatively small and the utilities had no companies listed during the sample period.

3.3.2 The influence of macroeconomic variables on investment

It can become challenging for an investor to decide, which sector to invest in when there is limited information. It is important for investors to be informed regarding the performance of each sector should they be interested in investing in economic sectors (Kaplan & Stromberg, 2000:2). The performance of a sector can be impacted by various macroeconomic factors like real GDP, inflation and interest rates (Alam & Uddin, 2009:45). For example, if inflation increases significantly beyond the target bracket of between three and six percent, the monetary standard decreases, therefore, investors can expect low returns and cost of living increases (Alam & Uddin, 2009:45).

Interest rates directly influence individual investments; increased interest rates have the potential of affecting investors in various ways. For example, long-term bond investors lose when interest rates increase because the value of the bond decreases. According to Ghodsi (2015), investors may want to consider a shift in their bond maturities. An average bond of more than 20 years is exposed to 13 percent decrease in price when interest rates increase. However, stock market investors do not have to fear increasing interest rates because some sectors could perform better than others could. In a rising interest rate economy, sectors like energy and banking perform well, while sectors like consumer goods and real estate investment trusts do not perform well (Brecht, 2015).

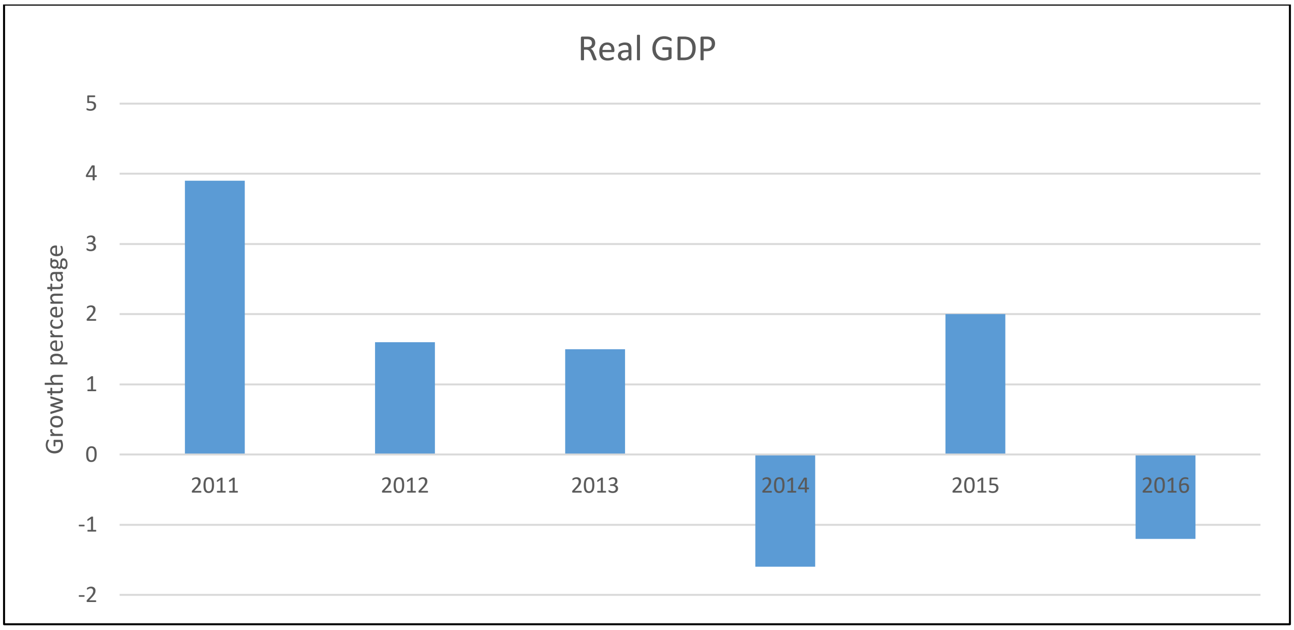
Investors need to take time to regularly analyse their portfolios and consider appropriate changes in an interest rate environment. In South Africa, the South African Reserve Bank (SARB) has a committee called the Monetary Policy Committee (MPC), which regularly meets and decides whether interest rates should increase, decrease or remain unchanged (SARB). The governor of the Reserve Bank makes the announcement. This announcement has a direct impact on both public and individual investors (SARB). The impact of this announcement on individual investors is only discussed in Section 3.4 below due to the fact that public investment is not the focus of this study. Macroeconomic factors influencing investments are discussed below:

3.3.2.1 Real GDP

The real gross domestic product (GDP) is amongst critical indicators in measuring the state of a country's economy. The aggregate value of all goods and services produced over a certain period are presented by real GDP. Standard GDP is a representation of national income and product accounts, produced by virtually every nation in the world (Landefeld *et al*., 2008:1). Real GDP takes into account movements of the price level; therefore, it is more accurate than the standard GDP (Abel *et al*., 2008:27). On the one hand, GDP has an apparent impact on the stock index. On the other hand, the stock index does not act as an indicator of changes in any of the macroeconomic factors. It can be concluded that GDP is proven to have a significant impact on several JSE sectors, which is why GDP is one of the key macroeconomic factors of this study (Putyinceva & Steffe, 2016:4).

Changes in GDP still show changes in the aggregate level of economic activity. When there is anticipated growth in GDP, it is an indication of a growing economy offering the opportunity to companies to increase their sales and profit (Mpofu *et al*., 2013:78). GDP growth, in turn, encourages investment into the local economy because growth attracts investors who are seeking increased returns. A decline in GDP indicates a possible decline in company sales and profits, and then the local economy should export goods if possible. A declining GDP, in turn, discourages investment into the local economy, as no growth is not attractive to investors at all because of low anticipated returns (Abel *et al*., 2008:27). The GDP of a country does not always experience positive growth (Sayed, 2016). Sometimes countries may experience recessions, which, if not appropriately managed using monetary (MPC intervention) and fiscal (government intervention) policy, may result in a depression phase (Pilinkus, 2009). The recession is a decline in real GDP and an increase in unemployment for two or more successive quarters. Depression refers to a decline in real GDP and an increase in unemployment going beyond two consecutive quarters (Mpofu *et al*., 2013:78). Both the depression and recession phases leave investors worse off because of the decline in economic growth, which discourages investment in the country (Pilinkus, 2009). Figure 3.2 displays South Africa's GDP performance from 2011 to 2016, also indicating that the GDP of a country is not always positive.

Figure 3.2: South Africa's Real GDP for period ranging from 2011-2016



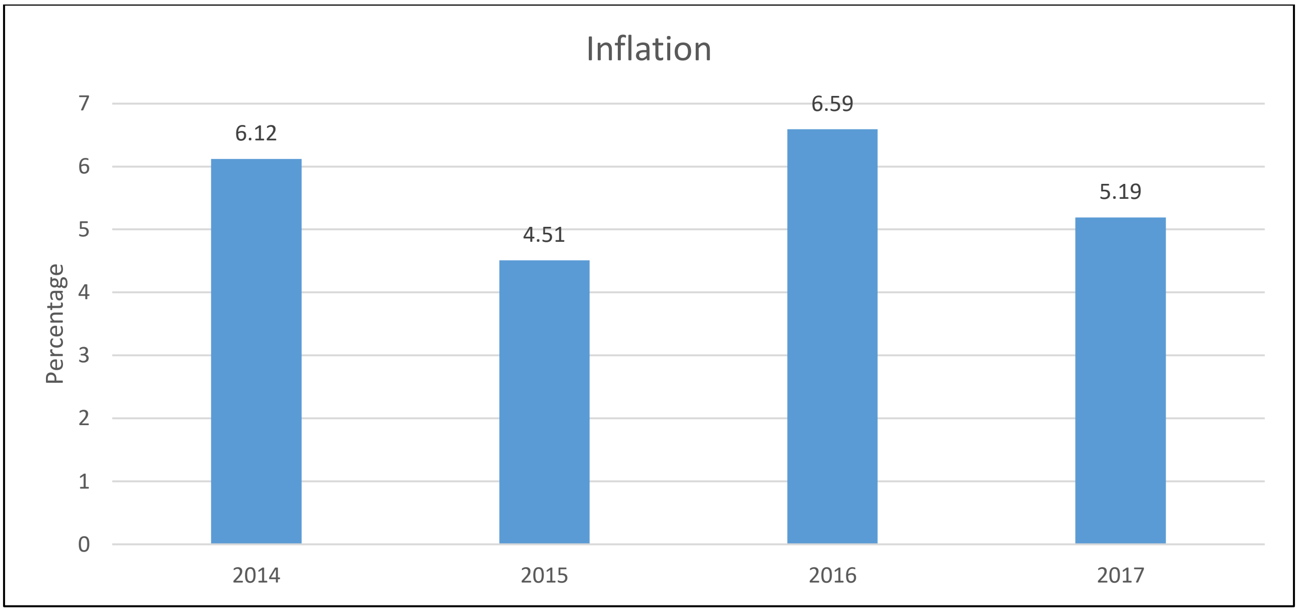
Source: Statistics South Africa (2016)

GDP amounts to the aggregate expenditure for all final goods and services produced in South Africa over a certain period. The trend shows South Africa's GDP declining into negativity, which is due to slow economic growth, increasing unemployment, budget deficit and decreasing purchasing power for consumers (Ndaku, 2010). Positive growth for South Africa's GDP means that economic growth is picking up, resulting in an improved cost of living. Declining GDP negatively impacts investors, business and consumer confidence (Sarfin, 2017). As a result, when income is limited, little or no investments are done, which slows down the overall growth of the economy, resulting in high unemployment and high inflation (Brueckner & Lederman, 2017:2). Increasing GDP results from an expansion in the economy; an increase in savings and investments because consumers' income and wealth improve (Brueckner *et al.*, 2015:156).

3.3.2.2 Inflation

Figure 3.3 displays South Africa's inflation rate from 2014 to 2017. South Africa's targeted inflation rate is between three and six percent (SARB, 2018). It is important for investors to consider inflation because monthly investment premiums are impacted annually by inflation rate and the performance of individual investments (IMF, 2008).

Figure 3.3: South Africa's inflation for period ranging from 2014-2017



Source: SARB (2018)

The SARB is tasked to maintain inflation target within three percent to six percent; when SARB increases interest rates, it is to restrict inflation issues because of a depreciating rand (Sygnia, 2015:10). The period between 2014 and 2016 was not favourable in terms of exceeding the favourable inflation target of between three to six percent, this is a result of a contracting economy. When inflation exceeds the target of six percent, the economy becomes worse off since the cost of living for everyone increases (IMF, 2008). Food and fuel prices increase, and the purchasing power of consumers decreases (IMF, 2008). When the inflation rate remains within the desired target, the cost of living remains manageable.

Inflation undermines the value of money as a unit of account and as a monetary standard (Konieczny, 1994:3). Inflation has the same effect as a tax; it decreases investors' capital returns. When prices increase due to inflation, inflation lowers the purchasing value that a single unit of currency that can be bought. The ultimate result is that profits/ revenues decrease and the economy regresses for a certain period until a recovery phase is achieved (De Villiers, 2015:25). Thus, inflation can be utilised as an indicator towards macroeconomic instability (Muritala, 2011:5).

Inflation has a negative effect on investments that are made up mainly of fixed income from investments. Investment returns can be obtained in either fixed coupons or interest until maturity, meanwhile purchasing power decreases when inflation increases. To some extent, revenue or earnings of companies move simultaneously with the inflation rate (De Villiers, 2015:25). Inflation has the potential of not entertaining foreign investors’ investments choices, due to minimal confidence in the country and overvalued stock returns. Foreign investors often base their investment decisions on upcoming interest rates when it comes to bonds. Anticipated interest rates are equivalent to interest rates in the short-term including risk premiums, which include inflation (Greenwood & Bruce, 1997:165). When future expectations of interest rates and inflation increase, this gives rise to bond risk premiums. Forecasted inflation rates and interest rates increase slow down the current period of additional returns on bonds. In turn, an increased premium of risk decreases the current period’s additional returns on currency for foreign investors (Sturges, 2000:25).

3.3.2.3 Turnover ratio

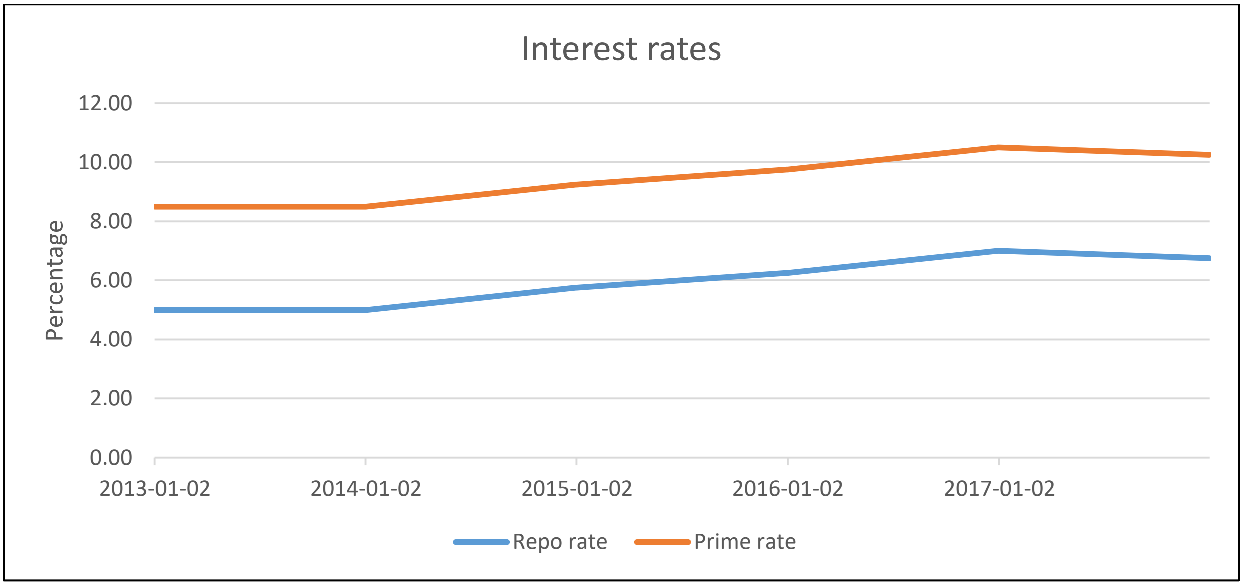
This ratio is a substantial measure of a country’s stock market development. Stock market liquidity is measured by the turnover ratio, which is equivalent to the worth of traded total shares divided by market capitalisation (Pippert, 1991:17). Market capitalisation is accompanied by the turnover ratio in such a way that bigger non-performing markets will have a big market capitalisation and, in turn, a smaller turnover ratio (De Villiers, 2015:26). There is a perception assumed by selected models that countries with minimum capital markets that are liquid will have a lack of encouragement towards investments that are long-term. This often happens due to the difficulty to trade shares within investments (Greenwood & Jovanovic, 1990:1080). Contrary, stock markets that are liquid will lower encouragement towards driving the more efficient allocation of resources and enhance accelerated growth (Levine, 1997:700).

According to Dean *et al*. (2008:1), high trading markets attract foreign investors, which enable investors to trade their assets easily. The turnover ratio is essential when it comes to the quality measure of a country’s market microstructures as well as trading systems of investments. It is important for a country’s security markets to be liquid and effective as efficient trading systems are necessary in inviting domestic and foreign investments (Odhiambo, 2004:50). The turnover ratio can be seen as a liquidity indicator (Lewis, 1995:42). The turnover ratio can measure trading comparative to market size. This would be equal to the sum of shares traded in a country’s stock market over the capitalisation of the stock market (Lewis, 1995:42). As a result, the turnover ratio will be influenced when there are differences in trading frictions (Pippert, 1991:18).

3.3.2.4 Interest rates

Figure 3.4 displays the annual rates of both the repo and prime rates during the first quarter of the respective years. The repo rate is referred to as the rate at which private sector banks can borrow money from the SARB (SARB, 2018). The prime rate is the rate at which individuals lend money from private sector banks (SARB, 2018). South Africa's market is dominated by two primary types of interest rates, namely the repo and prime rate (Research Department, 2007).

Figure 3.4: South African interest rates for period ranging from 2013-2017



Source: SARB (2018)

Figure 3.4 illustrates the 2013-2017 rates for both interest rates. Both rates increased from 2013 until the last quarter of 2017 where the MPC decided to reduce interest by 25 basis points. When interest rates increase, the stock market is not affected directly (Janor *et al*., 2005). The direct effect is that it becomes expensive for private sector banks to borrow money from the SARB. It also becomes expensive for consumers to borrow money from banks because of the increased interest rate (Saac, 2016). This also decreases the purchasing power of consumers. Both the repo and prime rate work together; the MPC cannot leave the repo rate unchanged and the prime rate decreased/increased and vice versa (Saac, 2016).

Interest rates are typically altered to rein in inflation, depending on the performance of an economy (Pape, 2010:2). Numerous factors encourage changes in interest rates. For instance, a weak rand results in imported inflation, meaning that the changes of the United States Federal Reserve on their interest rates will have an impact on South Africa's interest rates. This happens because the United States of America's (USA) dollar is the base currency (Saac, 2016). Although interest rates may increase or decrease, when interest rates increase, it will be slow with minimal increases. Nonetheless, there will not be an impact on all financial markets. The markets that will be affected are bond and equity markets (Nielsen, 2017:2) when bond yields increase, their worth decreases, which is terrible news for bond investors. Equities are usually negatively affected when borrowing rates increase (Patton, 2013:1).

In the USA, investors pull more money back into the United States, seeking higher returns as the Federal Reserve increase interest rates (Imbert, 2016:1). This could end up in withdrawal by investors of some of the capital invested in developing countries like South Africa. Therefore, because of the slow rate increases, a contraction is anticipated in the markets after an initial shock reaction, followed by a recovery phase (Kantor, 2016:26). Increasing interest rate environments can cause difficulty for investors. Only liquid money is attractive when the deposit rate increases (Schwab, 2017:1). Therefore, investors should time their investment according to changes in interest rates. This will be the determining factor in the construction of investment portfolios. Investors need the ability to be disciplined by taking a long-term approach and not to be influenced by short-term market activities. With time, it is expected that equities will out-perform all other asset classes as well as inflation (Kantor, 2016:10). Often investors make the mistake of focusing too much on short-term fluctuations and lose returns when they sell their investments when markets decline and forfeit when the markets recover. Money might seem appealing when rates increase, but investments have to outperform inflation annually before achieving real returns (Smith, 2015:3). The asset class that has out-performed inflation over the long term is equities, even though this asset class comes with great risk and volatility (Luus, 2017:1).

It is always ideal to lower risk exposure if the investment horizon is shorter by being more conservative. Interest rates tend to increase market volatility as well as the uncertainty surrounding what the MPC of the SARB announces to make investors uneasy *(*Sygnia, 2015:10). For investors who will need their money within five years, it is ideal for such investors to consider a balanced portfolio with little exposure to equities and greater offshore exposure that can mitigate against the effects of a depreciating rand (IMF, 2008).

3.3.2.5 Stock of capital

The amount of capital can be affected in two ways; first, most investments replace capital that has depreciated, therefore, there is a likelihood for increased stock of capital to result in increased investment (Xu, 2000:340). As a result, there will be more capital to be replaced that has depreciated. Secondly, the increased stock of capital tends to lower investments. This happens because investments amend capital stock to its favourable level (Rittenburg & Tregarthen, 2017:15). Many investments happen to take over current capital; greater stocks of capital are most probable to increase investment (Xu, 2000:340). However, bigger stocks of capital will lower net investment (Kuznets, 2002:15).

3.3.2.6 Cost of capital goods

Restuccia and Urrutia (1998:26) provide an example stating that some forces move the investment goods demand curve to the right and simultaneously increase capital goods prices as well as the size of investment taken. As a result, this stimulates a favourable relationship amongst rates of investment and capital goods. The prices of capital goods often have an impact towards growth (El-Wassal, 2005). This usually happens where the relation between capital goods, rates of investments and prices of equipment are not positive (Rittenburg & Tregarthen, 2017:12).

3.3.3 Summary of macroeconomic factors influencing investments

There are driving forces determining investment decisions, namely macroeconomic factors. There is an association between the above-mentioned factors impacting investment decisions and the macroeconomic environment (Bailey *et al*., 2011). This association suggests that investment management companies are subjected to analyse factors influencing investment decisions in order to be up to date with the economy. Investment decisions are very important towards the performance of an economy. This is because, from a macroeconomic point of view, in a normal business cycle, investment decisions are accountable for the majority of growth in an economy and their extent serves as a valuable leading indicator of the economic performance (Auret & Golding, 2012:51). Section 3.3.2 looked into the macroeconomic factors influencing investment. Both Sections 3.3.2 and 3.4 are crucial in guiding investors to make well-informed investment decisions.

3.4 THE INFLUENCE OF MACROECONOMIC FACTORS ON THE TOP FIVE JSE SECTORS

The following section discusses how the main macroeconomic factors, namely real GDP, inflation and interest rates, influence the top five JSE sectors. Each sector is impacted differently by an economic variable because each sector functions in a specific way.

3.4.1 Industrial sector

The sections below discuss the influence of volatility due to macroeconomic changes on investment decisions in the industrial sector.

3.4.1.1 The industrial sector and investments

The industrial sector is mainly centred on building and construction, ports, shipping and electronic equipment. This sector is highly likely to be very active because there is a high demand for electronic equipment due to the fast pace of technology (Davies, 2016:5). This sector is also driven by building and construction because of the need for economic growth and development. There is always construction for recreational purposes and construction for the property. There is a great demand for property, in turn, boosting individual investors' confidence (Crampton, 2016).

The industrial development zones are intentionally-built industrial estates connected to international ports and leverage fixed direct investments in value-added and export-orientated manufacturing industries in South Africa. Industrial development zones assist such as free of duty operating environments, expedited customs procedures and quality infrastructure (Moore, 2014). However, various economic factors may cause volatility in the financial market, which may ultimately influence investment decisions within the industrial sector. The sections below explain how the three main factors may affect investment decisions and cause volatility.

3.4.1.2 The influence of real GDP on the industrial sector

The industrial sector can reflect changes in the structure of an economy since it demonstrates the highest amount of volatility in relation to output that is nominal within the business cycle (Zimmermann, 2005:2). There is a strong relationship between the industrial sector and the economic business cycle. The industrial sector does well when the economy is in the boom phase, while during an economic downswing, the industrial sector underperforms (Temple *et al*., 2012).

In South Africa, the industrial sector is made up of physical goods-producing industries making up less than half of the country's economic output. The industrial sector consists of overly volatile components (Xu, 2000:307). Industrial production is regarded as an indicator for future inflation. If this sector is in full capacity due to high GDP, there is the possibility that prices will increase, resulting in chances of inflationary pressures (Wohlner, 2017).

The global industrial sector has been ranked as one of the most positive developments contributing to the JSE industrial sector. Production advancements have led the recovery and improvements during the past decade (2007-2017) in the industrial sector. The more useful and cost-beneficial techniques of manufacturing increased activities and factories reshoring. As a result, cheap manufacturing countries had less competition, which drove the industrial's sector recovery (Wohlner, 2017). Further growth from the industrial sector is expected due to pressure from strong industries like automotive and airlines (Mueller, 2017). GDP growth in the economy as a result of a particular sector's growth from investments or increased activity in the sector has the potential to boost overall investments in the economy.

3.4.1.3 The influence of inflation on the industrial sector

The inflation rate triggers the performance of any sector and thus indicates fluctuations of activity in an economy (Mattingly *et al*., 2014:1). The backdrop of inflation can strongly impact the profitability of certain sectors. It is important to know whether producer prices are increasing much faster than consumer prices. This activity has the potential of negatively affecting profit margins or vice versa (Konchitchki & Landsman, 2010:35). Little or no activity in the industrial sector as a result of inflation has a negative influence on the profitability of the sector, making it less attractive for investors. When inflation increases or is not within the desired bracket of three to six percent, consumers become worse off, and this discourages spending, saving and investment in the economy (Beck *et al*., 2000). This results in less money to save or invest. As soon as inflation is within the desired bracket, the cost of living becomes manageable, which, in turn, improves the overall performance of markets and the economy. However, investors in the investment industry demand higher rates of return for the increased risk due to more volatile performance in the sector (Barro, 1990). After high inflation, MPC adjusts interest rates to curb inflation, which will again influence rates of return and investment.

When growth in the economy stumbles and contracts, sectors that are more economically sensitive are no longer favourable and sectors that are defensively oriented shift to the outperforming line (Bar-Yosef & Lev, 1983:43). On the other hand, economic and interest-rate sensitive sectors like industrials, financials and materials, often underperform against the broader market during the recession phase, which would typically occur when the inflation is outside of the desired target (Beaver, 1979:32).

3.4.1.4 The influence of interest rates on the industrial sector

When interest rates increase, various sectors of the economy tend to behave in certain ways by showing different correlation to the interest rates (Murphy, 2015). Increasing interest rates often indicate robust conditions of the economy and influence sector returns. Higher interest rates are most of the time steady with stronger growth in the economy (Sims, 1980:23). Growth trends can impact performance of the sectors. In terms of correlations, cyclical sectors like industrials, materials and financials demonstrate the most robust correlation to increasing 10-year yields of Treasury (Grossman & Helpman, 1993:22). This makes sense because increasing interest rates tend to come on the top of strong growth in the economy; the same growth economically sensitive sectors gain from (Grossman & Helpman, 1993:22). For individual investors, money is expected to flow where earnings growth is visible. Cyclical sectors tend to be offset by the downswing in industrial production (Barrell *et al*., 2004:25). Investors need to prepare for interest rate hikes or decreases by reviewing their portfolios, most importantly, if investors have been investing mainly for income. When interest rates start to increase, certain stocks tend to become less favourable and are exposed to higher volatility than others are (Clift, 2015).

3.4.2 Consumer goods sector

Consumer goods sector consists of, for example, beverages, clothing and household appliances. The South African textiles, clothing and footwear industry, remain vulnerable to cheap imports (JSE, 2013). This setback decreases job creation and in turn discourages investment into the sector (Krugman & Wells, 2012). However, when the rand depreciates, this causes imports to be expensive, which forces suppliers to buy from local manufacturers, which in turn boosts the local economy (Putyinceva & Steffen, 2016).

3.4.2.1 The consumer goods sector and investments

The sections below discuss the influence of volatility due to macroeconomic changes on investment decisions in the consumer goods sector.

3.4.2.2 The influence of real GDP on the consumer goods sector

The consumer goods sector entails various retail goods bought by consumers ranging from essential food and clothing items to luxurious items like electronics and jewellery (Porter, 1974:420). From the various products, consumers still manage to be loyal to a certain product or brand. Brand loyalty has the potential of driving sales of the respective product or brand. In turn, the growth has an impact on economic growth and real GDP (Putyinceva & Steffen, 2016). The economic performance is expected to be less dependent on individual consumer preferences or the general economic market conditions, but instead on supply related to factors that influence the cost structure of the suppliers (Buyuksalvarci, 2010:408). Producer price index (PPI) has a great influence on the JSE sectors because the pricing for consumer goods sector is mostly independent of consumer preferences or economic conditions (Fedorova & Pankratov, 2010:166). As a result, market participants are able to amend their turnover adequately in order to account for investments. The low magnitude of the factor sensitivity can be viewed as an indicator that price changes have to be made within a reasonable range, or else there might be public criticism (Gan *et al*., 2006:93).

3.4.2.3 The influence of inflation on the consumer goods sector

Various economic factors affect the demand for consumer goods, such as inflation and interest rates (Angeloni & Ehrmann, 2007:16). Prices of goods influenced by the inflation rate naturally influence consumer spending on goods significantly. This results in the producer price index (PPI) and consumer price index (CPI) referred to as the drivers of economic indicators (Andres *et al.*, 2008:853). Increased rates of inflation increase the cost of living for consumers. Increased pricing on consumer goods, in turn, affects spending (Maverick, 2015). According to Schneider (2018), there is a relationship between PPI and CPI. Any change in the rate of increase of the PPI indicates a change in the CPI at a later stage. Due to differences in the variables used in the computation of PPI and CPI, the increase in PPI will not entirely match the increase in CPI (Mpofu *et al*., 2013:79).

Anticipated and unanticipated inflation has an impact on consumers. Negative impacts of inflation are the following (Alam & Uddin, 2009:53): Inflation changes the information delivered by prices; some prices react quickly, while others react slower. Unanticipated inflation changes relative prices including the general price level. Therefore, the impact of inflation affects the investor's investments returns when inflation increases. Lastly, individuals react to increased and variable inflation rates by putting in limited time producing and more time to try to protect themselves from rising inflation. Typically, investors take time in trying to protect their investment returns from inflation increases (Mpofu *et al*., 2013:78).

3.4.2.4 The influence of interest rates on the consumer goods sector

Interest rates have a great influence on the level of spending on consumer goods. Several high-priced consumer goods such as jewellery or automobiles mostly are bought on credit. Increasing interest rates make such purchases significantly more expensive and lead to the deterioration of these purchases (Kiyotaki & Moore, 2015:225). Increased interest rates tighten credit; this makes it very difficult for consumers to be granted the required financing for bigger purchases like new cars. Most consumers usually postpone buying luxury items to a point where more advantageous credit terms are provided (Maverick, 2015).

When consumers rely heavily on credit, it discourages savings and investment (IMF, 2008). South Africa is typically a country that is big on spending rather than saving (Swift, 2011). When the interest rate increases, it is favourable for returns on investments and unfavourable for consumers that dependent on credit because interest charged increases. In turn, when interest rates decrease, returns on investments are low, and consumers applying for credit will have lower interest charged, depending on the type of credit (Wheelock, 2011). Consumers with access to credit benefit from a low-interest environment; this is what drives durable consumption and demand up. This activity is encouraged by creditworthiness of consumers, while, other sources of credit like home equity loans and mortgages stay low (Swift, 2011). Economists continue seeking durable consumption as one direction for the economy (Carroll, 2012:3).

Interest rates impact investors in an expansionary or restrictive monetary policy. An expansionary monetary policy results in lower interest rates, leading to share increases (Auret & Golding, 2012). This is an opportunity for investors interested in purchasing shares to invest in shares. When investors purchase these shares, they expect low risk and improved returns (Kiyotaki & Moore, 2015:228). In restrictive monetary policy, interest rates are higher, and shares decrease. This phase makes it difficult for investors to invest in shares because there are high risks and low returns (Mpofu *et al*., 2013:79).

3.4.3 Financial sector

3.4.3.1 The financial sector and investments

The financial sector is centred on banks, real estate and insurance companies. From the 378 companies listed on the JSE, the financial sector is amongst the sectors most companies belong to (JSE, 2013). This means that there is great activity in this sector, regardless of whether South Africa has an emerging market; South Africa has an advanced financial sector. The financial and real estate sectors have proven to be the support of South Africa's economic growth over the years (Bronkhorst, 2012:13). The financial sector upholds several local and foreign institutions offering an entire variety of services from retail, merchant banking, commercial, mortgage, insurance and lending (Mayer, 2013:4). The banking sector of South Africa is ranked amongst those of developed countries. There have been updates to exchange controls and financial market legislation, which has result in South Africa being an attractive investment hub (Moore, 2014). The sections below discusses the influence of volatility due to macroeconomic changes on investment decisions in the financial sector.

3.4.3.2 The influence of real GDP on the financial sector

When unrecognised real GDP increases and losses are acknowledged over time, then the unrecognised real GDP increases and losses are most likely to assist in anticipating future cash flows for firms (Bloch & Tang, 2003:245). If the stock market does not entirely account for such setbacks for future cash flows, real GDP increases can be associated with future returns of stock (Calderon & Liu, 2003:327). Therefore, it has been revealed that there is a significant interaction between the financial sector and the GDP of an economy.

In South Africa, financial and economic crises affect financial assets, total bank assets grow significantly faster than the GDP (IMF, 2008). In 2009, there was a tendency for deteriorating and decreasing growth rates for GDP due to the 2008/9 GFC (Peetz & Genreith, 2011:41). This led to capital decreasing significantly against the increased return potential of financial markets like hedge funds and equities, which created a situation where too much capital is after minimum investment opportunities (Guryay *et al*., 2007:58). In this context, economists use the term financialisation. Financialisation explains the process where more personal income and corporate earnings are derived from financial transactions instead of real economic growth, for example, increased production and related growth in employment (Huybens & Smith, 1999:297).

South Africa remains an attractive investment hub due to the different investment product opportunities available and the development of the financial sector (Ibrahim & Alagidede, 2016:2). Within the financial sector, investments can vary with regards to doubt from mainly risk-free investment securities such as treasury bills to highly speculative investments, for example, the common stock of small companies that are involved in risky enterprises (Reilly & Brown, 2012:18).

3.4.3.3 The influence of inflation on the financial sector

High inflation patterns often hinder the performance of financial markets. The financial sector stimulates economic activity through activating savings accordingly and the reallocation of resources to projects that are productive (Ibrahim & Alagidede, 2016:2). High inflation rates worsen the financial sectors efficiency through financial market frictions and decelerate economic performance, in turn, discouraging savings and investments (Bittencourt, 2011:93). Inflation often triggers volatility in equity returns and reduces the actual return on savings. During inflationary periods, governments are motivated to enforce an extra tax burden on the financial sector in order to lower the government's budget deficits (Bencivenga & Smith, 1993:105). It has been seen that inflation hinders financial markets' performance by lowering the level of investments in the economy (Wahid *et al*., 2011:145).

Inflation also significantly influences the accumulation of capital and investment, and reduces the distribution of income (Shahbaz *et al.*, 2010:53). Goldsmith (1969:15), McKinnon (1973:3), King and Levine (1993:521), Levine and Zervos (1998:551), Beck *et al*. (2000) and Beck and Levine (2004:430) all believe that the development of finance has a long run positive impact towards growth of the economy. Meanwhile, Bonfiglioli (2006:15), Bittencourt (2007:10) and Shahbaz and Islam (2011) agree that the development of finance seems to lower poverty or income gap through physical capital formation and growth of the economy.

According to Mundell (1963:281) and Tobin (1965:680), portfolio allocations are usually impacted by inflation because of decreasing capital returns, resulting in better investment activities. This promotes growth within the economy. Similarly, English (1999:382) disagrees that increased inflation rates force individuals to replace transactions services that have been bought for balances of money that is not only limited to improve the supply of financial services, but also encourages development of finance.

On the practical side, English (1999:383) provides empirical evidence and concludes that inflation indeed has a positive influence on the development of finance. On the contrary, Haslag and Koo (1999:2) and Boyd *et al*., (2001:230) concluded that increased inflation rates unfavourably influence the development of finance as theoretically anticipated. A case study of Brazil by Bittencourt (2011:93) using time series and panel data concluded that increased inflation has a favourable influence on the development of finance because of limited macroeconomic performance. In the case of Zimbabwe, Murombedzi (2008:41) reports that increased inflation negatively impacts the development of financial institutions through troubling channels. The above-mentioned studies also discovered a non-linear relationship between inflation and financial development and implied a specific benchmark of 15 percent annually. Khan *et al*. (2006:170) vary with previous benchmark levels by proposing a new benchmark point with the debate that the benchmark level of inflation is three to six percent. Beyond the benchmark, inflation has a robust adverse influence on the development of the financial sector and in turn encouraging investments. When the anticipated inflation rate changes, the change affects the nominal risk-free rate of the economy, which affects all investments, regardless of the level of risk (Reilly & Brown, 2012:49).

3.4.3.4 The influence of interest rates on the financial sector

Empirical researchers of finance are often surprised by their inability to find significant evidence of a substantial relationship between the stock returns of non-financial firms and foreign exchange rate changes (Joseph, 2001:306). This happens because economic theory suggests that movements in foreign exchange rates can have a significant influence on the value of firms through exchange rates influences on cash flows, profitability and investments (Choi & Prasad, 1995:81). Economic theory also features similar and related effects to movements in interest rates. However, when interest rates increase, less money is injected into the financial sector because consumers are discouraged from borrowing (Ali, 2014:64). In turn, when interest rates decline, more money is injected into the financial sector because consumers are charged reasonable interest and start to purchase more, benefiting companies and growing the financial sector (Auret & Golding, 2012:41).

The majority of investors seek increased return rates on investments if they realise that there is no clarity regarding the anticipated return rate. This is an indicator that investors raise their required return rates as soon as perceived risk (uncertainty) increases (Reilly & Brown, 2012:21). Typically, investors would choose investments that are aligned with interest rate outlook. When interest rates are perceived to increase, investors will consider high-risk investments, on the other hand when interest rates are perceived to decrease; investors would consider low-risk investments (Masoud, 2013:791).

3.4.4 Consumer services

3.4.4.1 The consumer services sector and investments

The consumer services sector is made up of restaurants, media agencies, hotels and airlines (Putyinceva & Steffen, 2016). From a general observation perspective, the consumer services sector is growing tremendously. For example, there is an increased demand for accommodation bookings for business and personal reasons all year round. The majority of consumers are keen on eating out and trying new restaurants, while work-related functions contribute and word-of-mouth is powerful in spreading the word about recommended places to try out. Booking of flights for both work and leisure occur throughout the year. The consumer services sector has great activity; monetary injection into this sector boosts not only the sector but also economic growth and the tourism industry to a great extent (GICS, 2006). This sector is one of the significant sectors that keeps South Africa functioning and contributes to the tourism industry (Swift, 2011). The sections below discuss the influence of volatility due to macroeconomic changes on investment decisions in the consumer services sector.

3.4.4.2 The influence of real GDP on the consumer services sector

It is evident that consumer services have become significantly globalised in recent years. In 1992 and 2005, the share price of services exports in GDP nearly doubled (Allen, 2005:35). The sector followed a slightly negative trend during the Dot-Com-Bubble in the early 21st century (Geier, 2015) as well as during the GFC (Swift, 2011); this indicates the possibility of the cyclicality of the consumer services sector. The sector shows great dependence on earnings per capita and GDP. The positive correlation with EPC could be an indication of a behavioural effect of wealth, resulting in a general increase in individual living standards and increased expenditure on non-essential goods. The positive correlation with GDP supports the expectation of cyclicality and dependency on general market conditions of the consumer services sector (Putyinceva & Steffen, 2016:19).

The growth of a sector like consumer services depends on how attractive the services provided within the sector are to investors and investments in the sector as well as the return rate earned on investing in the consumer services sector (JSE, 2013). The more investors invest in the consumer services sector, the more it will boost the overall economic growth. The sector will grow faster and offer higher return rates on shares investors purchase (Reilly & Brown, 2012:293). Higher growth rates also attract more investment because of increased anticipated returns, and in turn, lower growth rates do not attract investment at all because of low anticipated returns. Therefore, high growth rates attract risk-aggressive investors because these investors have increased risk appetites and seek high returns. However, low growth rates attract risk-averse investors because these investors have minimum risk appetites (Maio & Philip, 2013).

3.4.4.3 The influence of inflation on the consumer services sector

Great movement leaning towards consumer services sector output is usually in the practice of producer services. Prices of the services sector seem to be rising at the same rate as prices of consumer goods (Diewert, 2005:60). This is likely to happen because end consumers make use of consumer goods and consumer services daily. Also, middle income consumers spend a greater portion of their income on services, even on those services that start becoming more expensive because of increased demand (Duguay, 2006:2). Continuous spending from end consumers is due to loyalty or increased competition in the market where the consumer has the option of choosing from a cheaper supplier. However, services like these can still add value towards income, profits and capital returns and payout limited amounts to their intermediate and final consumers (Lane & Schmidt, 2006:7).

A particular trend may constitute a movement in the relative consumer goods price and services while the overall price change refers to inflation. Debates have been held over relative price changes for overall inflation (Malley *et al*., 2003:92). Relative price changes for total inflation has been one of the critical issues that have been part of consultations regarding how monetary authorities should react to the increase in energy prices, which also results in a relative change in price (Marrano & Haskel, 2006:21). The tendency of consumer services prices to be in the front line of consumer goods price has been observed. This does not suggest an inflationary bias in terms of structural change from the production of services to goods (Oulton, 2004:6). Consumer price index (CPI) changes are dependent on the balance of demand and supply factors in the entire economy. The strength of the service sector is relevant to rulings about the strength of the South African economy (Tily & Jenkinson, 2006:47).

Investors anticipate the price level to increase (increase in the inflation rate) during investment periods (Bahadur & Neupane, 2006). As a result, the rate of return can include compensation for the anticipated rate of inflation. For example, if an investor requires a four percent real rate of return on a risk-free investment but anticipates price increases by three percent, in such a situation, an investor should increase their anticipated return rate by the expected inflation rate to roughly about seven percent (Reilly & Brown, 2012:17).

3.4.4.4 The influence of interest rates on the consumer services sector

When interest rates change, great emphasis should be placed toward the real economy as well as the disadvantages of structural changes in South Africa's economy for economic prosperity. Setting the interest rate policy to reach the inflation target is a great concern for the MPC. To do so effectively, the underlying forces that lie behind patterns of change within the South African economy need to be understood, and this should be used to formulate decisions of where inflation is headed in the medium term (Ndako, 2010). The large trends that have been described above form part of the background against which interest rate policy is determined (Paramati & Gupta, 2011). When the MPC decides to raise interest rates, consumer services become less attractive because consumers can no longer afford these services due to the cost of living increasing (Reilly & Brown, 2012:18). In turn, when interest rates are decreased, consumers have extra money to spend and generally spend the money on consumer services (Reilly & Brown, 2012:18). This results in an injection into the consumer services sector and investors being open to investing in the sector as investors see growth prospects in the respective sectors (Peia & Roszbach, 2013:17).

3.4.5 Basic materials sector

3.4.5.1 The basic materials sector and investments

The basic materials sector is made up of companies involved in gold, paper, metals, minerals and diamonds; most companies listed on the JSE belong to this sector. In 2013, basic materials sector had the most market capitalisation of 26 percent (Mayer, 2013). The basic materials sector market capitalisation grew significantly and increased its share price (Putyinceva & Steffen, 2016:40).

In 2014, South Africa was the biggest producer of steel in Africa with more than half of the total crude steel production of the continent. However, the steel industry changed drastically, resulting in several steel companies closing down and protectionism increasing (Putyinceva & Steffen, 2016:40). Mining companies dominated in the global industry, contributing 4.9 percent towards GDP in 2013. South Africa was the world's biggest producer of gold, platinum and one of the leading producers of base metals and coal in 2013 (Niyitegeka & Tewari, 2013:622). Due to South Africa's growth of secondary and tertiary industries, including a decrease in the production of gold, the contribution of mining to South Africa's GDP has decreased over the years (Niyitegeka & Tewari, 2013:622). This may be triggered by an increase in the downstream or beneficiated minerals industry (Samouilhan & Shannon, 2008:21). South Africa's mining industry continues to expand and adapt to world conditions changing locally and internationally. The mining industry continues to be the foundation of the economy, producing a substantial contribution towards the creation of jobs, foreign exchange earnings and economic activity (Smith & Jefferis, 2005:61). From the historical performance of this sector, it makes sense that the basic materials sector holds the greatest sector value contribution amongst all other JSE sectors and investment injection into the sector due to the growth of the sector (Mayer, 2013).

The section below discusses the influence of volatility due to macroeconomic changes on investment decisions in the basic materials sector.

3.4.5.2 The influence of real GDP on the basic materials sector

The basic materials sector is in the mature phase in the industry growth stages. There is slower revenue and earnings growth in this sector. Growth of the overall economy rate creates higher dividend yields with margin pressure (Lewis & Meredith, 2013:9). Gains in productivity have been reached in recent years. Regardless of continuous growth in relation to the volume of materials consumed nationwide and in Organisation for Economic Co-operation & Development (OECD) countries, there is the presence of environmental degradation decreasing while there is economic growth (Alfarano & Lux, 2001:21). The global economy produces 50 percent more economic value with only one ton of raw materials than it did in the 1980s (Chinzara, 2008:15).

Environmental degradation decrease while the economy is growing occurred in industrial minerals, construction minerals and wood. The decline in consumption occurred between 2000 and 2008 (Hourvouliades, 2007:23). The lowest gains in productivity were in metal ores, where extraction remained relatively strong linked to economic growth. This type of trend is not solely for OECD countries; extraction of metal is rising worldwide and is growing rapidly in Brazil, Russia, India, China, South Africa (BRICS) countries (Jacobsen & Dannenburg, 2003:482).

Progress in material productivity can be credited to policy measures and changes in technology, including structural changes. This includes the replacement of resource-intensive domestic production by imported goods (Samouilhan, 2007:101). OECD economies have shifted towards being service-based; their reliance on imports is increasing with resource-intensive production mostly being shifted over to non-OECD economies (Yamamoto, 2011:50). Imports make up 25 percent of materials inputs in the OECD area and only 5 percent in BRICS economies.

Surprisingly positive performance by the mining industry was experienced in quarter three of 2017, amounting to a third of the quarters' GDP performance (Menon, 2017). Mining production increased by 6.9 percent annually in August 2017, having expanded by 0.9 percent annually in June 2017. The most significant contributors to the mining sector were iron ore, gold and diamonds (Menon, 2017). Mining is the leading sector in the South African economy because when the mining sector outperforms the other sectors, it also uplifts the other sectors that supply inputs into the industry. In turn, through substantial export revenue, it brings back into the economy (Mgojo, 2017). Therefore, investors with large risk appetites who are willing to take the risk can invest in the mining sector because this sector is referred to as a difficult operating environment. This means that with great risk, investors can anticipate great returns (Reilly & Brown, 2012:18).

3.4.5.3 The influence of inflation on the basic materials sector

When interest rates increase this is an indication of stronger economic conditions and can influence sector returns. Increased interest rates are mostly stable with stronger economic growth and inflationary pressures (Murphy, 2015). The performance of a sector can be impacted by trends in both inflation and growth (McMillan & Ruiz, 2009:231). Decreasing growth in gold production and mining contribution has led to the low performance of this sector. The deaths that have occurred in the South African mines due to poor safety conditions have contributed to the low performance of the basic materials sector.

It is up to the investor to establish a mechanism for benefiting from sector exposure. When looking into a sector rotation strategy, investors should be looking at realistic methodologies, capable of capturing trends and able to manage and mitigate risks (McMillan & Ruiz, 2009:231). Due to the low performance of the mining sector from quarter one of 2018 resulting from a decrease in gold production and poor safety conditions in the mining sectors, investing in this sector has been a challenge for investors (Writer, 2018).

3.4.5.4 The influence of interest rates on the basic materials sector

In South Africa, as soon as interest rates start to increase, different sectors of the economy will react in various ways because the sectors show various correlations to rates (Magnusson & Wydick, 2002:98). For sector-focused investors, this means a changing investment opportunity set in a rising interest rate environment (Murphy, 2015). Looking into correlations to interest rates, materials, industrials and financials sectors show the most robust correlation to increasing 10-year treasury yields. Health, consumer staples and utility sectors show a weaker correlation (Yartey & Adjasi, 2007:11). This is understandable given that inflationary pressures and increased interest rates often come on the peak of strong economic growth. This same growth benefits economically sensitive sectors (Starica & Granger, 2005:32). When an economy is positive, it is likely to boost capital expenditure.

Increased interest rates tend to be consistent with stronger economic growth, resulting in a stable environment with improved profitability of cyclical shares (Hearn & Piesse, 2009:41). A positive relationship exists between growth in industrial production and the direction of the 10-year yield. Higher interest rates are likely to indicate an increase in production growth and improvement in profitability towards cyclical sectors (Amihud, 2002:42). However, stocks usually perform well through much of the interest rate increase cycle. The beginning and end phases can be riskier (Bloomberg, 2006). This means that investors are encouraged to invest more in an increasing interest rate environment in order to gain increased returns, instead of a decreasing interest rate environment due to lower returns. Understandably, interest rates affect investment decisions. For example, if fixed deposit rates decrease to 3.5 percent from 4 percent, investors are most likely to find other investment options that outperform fixed deposits (Business News, 2003). Investors should make a comparison link between economic indicators and the stock market's performance over a long time horizon. Institutional investors tend to capitalise on this relationship. This type of comparison will assist investors in determining how the economy influences the stock market at the end (Barnes, 2018).

The stock market acts as a leading indicator of the economy's performance. Understanding the macroeconomic environment and the leading economic indicators will assist the retail investor in identifying companies in potentially high growth areas (Sayed, 2016:3). This will encourage the investors to capitalise on future growth prospects. These can be seen as long-term asset allocation decisions that retail investors can benefit from to build up value in their investment portfolios. It is ideal for retail investors to be on the lookout for companies that are best able to integrate technology, markets and services. This will ultimately benefit their long-term performance (Ajit & Wang, 2013:98).

Section 3.4 contributes towards in-depth understanding on how the top five JSE sectors are impacted by the three main macroeconomic variables real GDP, inflation and interest rates. Each sector is influenced differently by the variables because the functions of the sectors are different. This section will further guide investors on how each sector is likely to perform due to the discussion on the influence of a particular sector on investments.

3.5 SUMMARY

Chapter three achieved the following theoretical objectives, conducting a sectoral analysis of the South African JSE sectors in Section 3.4 and determining the influence of macro-economic factors on the top five JSE sectors in Section 3.3.2. In conclusion, the purpose of this chapter was to provide a history of the JSE, analysis between macroeconomic factors and investments as well as the relationship between real GDP, inflation and interest rates with the top five JSE sectors. Investors can choose to invest in several sectors; the performance and expected returns of a sector are the key drivers for investors to make the decision of which sector to invest in. There is no clear evidence as to which sector provides the highest return, however, this study has provided insight for investors based on the results achieved from using the ARCH/GARCH models, which are the best volatility capturing models. As a result, the most volatile sector provides the highest return, which is exactly the investment intention of most investors.

The next chapter, is the methodology of the study. This chapter focuses on the process of data collection and providing a detailed explanation of the models used in this study. Chapter 4 first explains the top five sectors selected, alongside motivation as to why the five sectors were selected and the data collection type. The chapter continues to discuss each model type that will be used to analyse the level of volatility for each sector and lastly, a summary of the chapter is provided.

CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

"*When you can measure what you are talking about and express it in numbers, you know something about it*" *W Thompson*

4.1 INTRODUCTION

The focus of this chapter is on the data collection process and provides a thorough explanation of the models used in this study. It first explains the five sectors chosen, alongside motivation for why the five sectors were selected and data collection type. The chapter continues with a discussion of each model used to analyse the level of volatility for each JSE sector and concludes with a summary of the content covered.

4.2 RESEARCH APPROACH

There are specifically two main types of research approaches, the qualitative and quantitative approaches. The qualitative approach focuses on customer sentiment using surveys or testimonial feedback with less focus on numbers. The quantitative approach focuses on secondary data and models to reach an answer to a research question (Leonard, 2018). A quantitative approach was followed by this study with the use of secondary time series data. This approach supports the aim of this study, which is to model the most volatile JSE sector.

4.3 DATA DESCRIPTION

This study used daily secondary data for each sector. The data were obtained from the Johannesburg Stock Exchange, South African Reserve Bank and McGregor BFA (Pty) Ltd, which is a financial data feed and online analysis tool. McGregor offers data from the JSE, including company information, such as financial statements/ annual reports or global share prices.

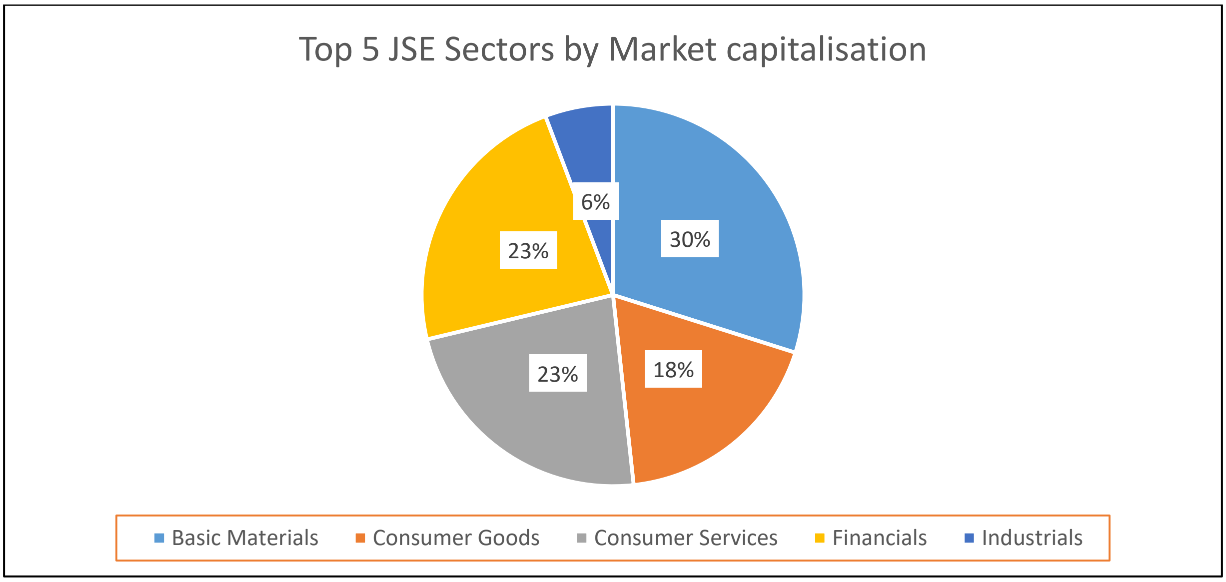
4.4 SAMPLE DESCRIPTION

There is a need to analyse different sectors because the JSE is made up of 10 sectors; financial, consumer services, industrial, consumer goods, basic materials, health care, oil and gas, technology, telecommunications and utility sectors. However, this study only includes data from the top five sectors according to market capitalisation and not all 10 sectors listed on the JSE. The selected sectors represent the JSE through their market capitalisation, which is 87 percent of the total market capitalisation of the JSE (Sharenet, 2013). The top five sectors, according to market capitalisation in 2015, were industrials, consumer goods, financials, basic materials and consumer services. However, in March 2018 the JSE Indices Department released communication regarding South Africa's sector indices. As of 1 January 2019, consumer services will be referred to as consumer discretionary and consumer goods will be referred to as consumer staples (Sharenet, 2013). In addition to the current ten sectors, real estate, as an industry, will be included in the sectors.

A cross-sector analysis of the top five sectors of the JSE was conducted for this study. The industrial sector is made up of companies comprising of construction and building materials, industrial transportation, industrial engineering and support services (ValuePenguin, 2018:1). The consumer goods sector is made up of companies producing cars and selling car parts, clothing, beverages or stationery (Statistics South Africa, 2014:6). The financial sector consists of companies focused on banking, financial services, investments or insurance (GICS, 2006). The basic materials sector is made up of companies involved in the trading of chemicals, various types of mining, industrial metals, forestry and paper (JSE, 2014). The consumer services sector consists of companies that offer services like restaurants, travel and leisure companies, media companies and hair salons (Bosiu *et al*., 2017).

Out of about 378 companies listed on the JSE, the majority of the companies belong either to financial, basic material or industrial sectors (Bosiu *et al*., 2017). The pie chart in Figure 4.1 illustrates the top five sectors of the JSE in terms of the valuable contribution of each sector or market capitalisation in the year 2015.

Figure 4.1: Market capitalisation of the top five JSE sector in the year 2015

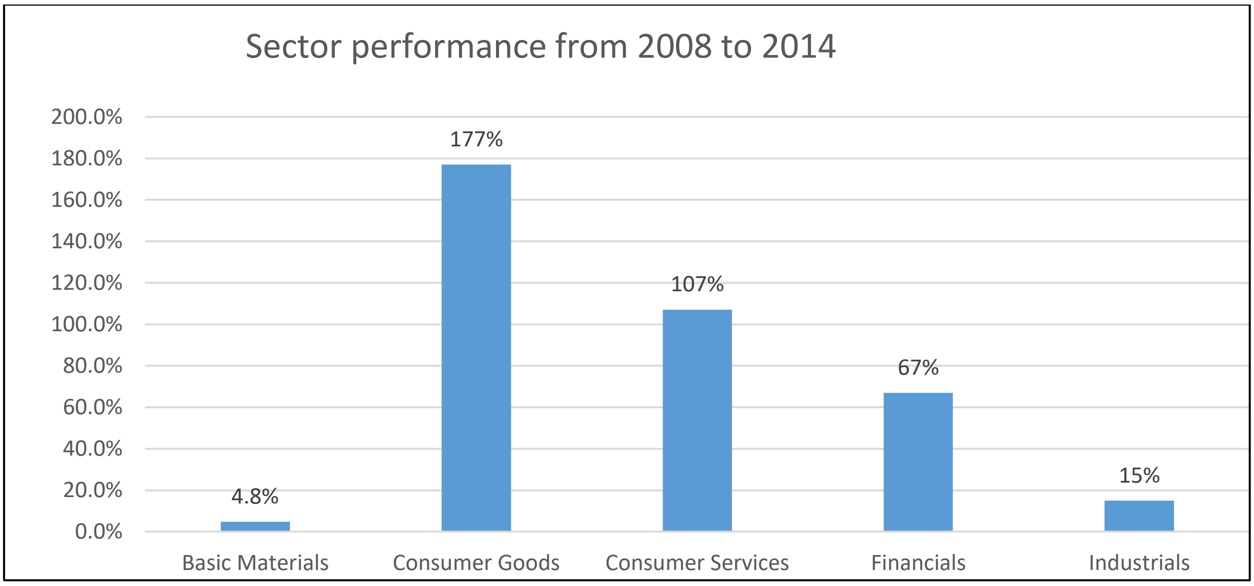


Source: Author compilation; JSE (2014)

Figure 4.1 represents the value contribution of each sector. The biggest contributor of the top five JSE sector by market capitalisation in 2015 was the basic material sector, followed by consumer goods, consumer services, financials and lastly, the industrial sector. This means that there was great demand for either trade chemicals, various mining types, industrial metals, forestry and paper and less demand for either construction, building materials, support services, industrial engineering or industrial transportation.

According to Tregenna (2014), about 30 percent of the aggregate value of all companies listed on the JSE is contributed by basic materials sector, which amounts to roughly R2 trillion. In 2015, the basic materials sector was the biggest sector of the JSE, given South Africa's abundance of natural resources. The second biggest sector was the consumer services sector, which was worth about R1.6 trillion (Johnson & Soenen, 2014:365). In third place was the financial sector, contributing about R1.5 trillion, making up around 20 percent of the aggregate value of companies listed on the JSE (Tregenna, 2014). Figure 4.2 illustrates average growth in market capitalisation by sector from January 2008 to January 2014.

Figure 4.2: Growth in market capitalisation by sector



Source: Author compilation; JSE (2013)

The size of a sector is not entirely related to its return rate. Besides basic materials being the biggest sector, the sector only managed to achieve a 4.8 percent growth rate since January 2008 (Tregenna, 2014). Over the period 2008-2014, in terms of increased market capitalisation, the consumer goods sector achieved the highest growth rate of 177 percent. In second place was the consumer services sector, which achieved 107 percent increase and financials sector was third with 67 percent increase. These sector value increases could have been contributed by a growing economy where consumers had more spending more to purchase goods and services and still have left over money to invest in financial institutions. Sector value contribution and sector performance analysis are important because the higher the volatility of a sector the higher the risk level; thus, higher returns for investors. There is a need for the application of the ARCH/ GARCH models because these models are well known for being the best volatility-capturing models (Engle & Patton, 2001).

The sample period followed by this study includes a full period of investment analysis entailing a bull market − prices are expected to increase in this market − and a bear market − prices are expected to decrease in this market (Eben, 2016:1). The sample period of this study covers the strong bull-run market; prices were expected to increase due to the global financial crisis. This study includes the bullish and bearish markets in the sample period because of the emphasis of the study on the financial markets, which tend to fluctuate. The fluctuation of financial markets is best described using the bull and bear market concepts.

4.5 STATISTICAL ANALYSIS

4.5.1 Index returns

The top five JSE sector indexes were used in this study to calculate returns for each sector. These returns were calculated by taking the current day's closing index value minus the previous day's closing value of the return divided by the previous day's closing value. The value obtained is then the return for the specific sector index. Returns were calculated for each top five sectors and these returns were then used to run various tests achieved in Chapter 5 of this study. The returns of each sector were calculated using Equation 4.1:

$$\mathrm{R_t} = \frac{\mathrm{P_t} - P_{t-1}}{P_{t-1}} \tag{4.1}$$

Where:

- $R_t$is the sector return of each sector *i* on day *t*
- P_t is the sector closing price for the sector on day *t*
- P_t is the sector closing price for the sector on day *t* – 1

4.6 MODEL SPECIFICATION

Different volatility models can be used to capture the level of volatility; the choice of model depends on what the study aims to achieve. For example, the study of Amskold (2011:11) aimed to investigate and evaluate volatility models on how well the models fitted implied volatility. The models used in this study were historical volatility models, GARCH volatility and a model where the implied volatility for an index is scaled using a scaling factor connected to the historical stock-return or index. With regard to this study, the results obtained from each volatility model were used to determine which sector is most volatile and compare the level of volatility across the top five JSE sectors.

Various volatility models can be used to capture volatility, but this study only uses the ARCH and GARCH models and their extensions. ARCH/GARCH models are well known for their simplicity and accuracy in capturing volatility (Bollerslev *et al*., 1994). The ARCH/GARCH models formulate the conditional variance directly as a function of observables. The other volatility models formulate models of volatility, which are not functions of observables. These models might be referred to as misleading stochastic volatility models (Joubert & Vencatasawmy, 2005). Such models are usually challenging to estimate and forecast.

The model specification section comprises of full discussions of the volatility models: the ARCH, GARCH, TGARCH/ GJR and EGARCH models to determine the most volatile JSE sector. This is followed by each model's advantages and disadvantages because each model functions differently and the econometric expression of each model. The application of the models is to run several tests executed in chapter five of this study. The tests conducted in Chapter 5 are summarised into descriptive statistics, unit root testing, ARCH effect and, lastly, the dynamic conditional correlation (DCC) test. Each model in this study was used to determine the most volatile JSE sector; the quality of the results is a reflection of the selected model's characteristic to understand the relationship between the exogenous and endogenous variables (Baillie & Bollerslev, 1992:100). The model with the lowest Akaike information criterion (AIC) and Schwarz information criterion (SIC) values will be identified as the best model (Matei, 2009:2).

For further background on volatility models, there are two main types of volatility models, namely the GARCH or stochastic volatility models. The GARCH models are structured in terms of conditional moments. On the other hand, stochastic volatility models are structured in terms of underlying variables, which make it convenient to determine conditional moments.

Meanwhile, multifractals or stochastic structural break models are structured in terms of unconditional distributions. These models often need reformulation to provide forecasts (Caims & Rosas, 2003). This study uses the GARCH type of models because GARCH models are well known for their volatility expression and reaction to returns, which is exactly what this study aims to achieve through the top five JSE sectors. Despite the developers of the ARCH/GARCH models, other studies support the use of GARCH models. Studies like Perrelli (2001), Masinga (2015) and Campbell *et al*. (2017) make use of GARCH models in their respective studies for conducting robustness tests.

In this study, the GARCH models assisted in conducting the following tests:

- Descriptive statistics of the data − which presents the data in a structured manner
- Correlation analysis − the degree to how changes in one sector are associated with changes in another sector (McDaniel & Gates, 2002:560)
- Unit root testing − because it is essential to test for unit root in all series and check for ARCH effects in all mean equations before estimating and selecting the best GARCH model
- Diagnostic checking − which is to test the best model for serial correlation, ARCH effect and normality (Gujarati & Porter, 2009)
- Estimating the risk premium for each sector − by estimating the best model in mean
- The spill-over test using the DCC model – which is used to test the correlation amongst the sectors (Lee *et al*., 2006)

The results of the above-mentioned tests are further explained in Chapter 5 of this study.

This study follows the broad class of models for conditional volatility. The first volatility model is the autoregressive conditionally heteroscedastic (ARCH) class of models introduced by Engle (1982). The ARCH model was extended to generalised autoregressive conditionally heteroscedastic (GARCH) by Bollerslev (1986). Glosten *et al*. (1993) and Zakoian (1994) proposed the threshold autoregressive conditionally heteroscedastic (TGARCH) and were encouraged by the exponential generalised autoregressive conditionally heteroscedastic (EGARCH) model of Nelson (1991). These models are discussed further in the sections to follow.

4.6.1 ARCH MODEL

The ARCH model is one of the simplest models; the model explains inflationary uncertainty in the United Kingdom during the progress of standard linear time series models stemming from using a conditional versus an unconditional mean (Bollerslev, 2009:3). The significant understanding that can be gained from the ARCH model is in the difference between the conditional variances and covariances, often dependent on historical states of the world (Bollerslev *et al*., 1994:2961). The ARCH model is made up of autoregressive (AR) and conditional volatility. AR originates from the element that the ARCH model is an autoregressive model in squared returns. The conditional volatility is rooted in the element that this model's following volatility period is conditional during the information period. Heteroscedasticity means volatility is not constant (Reider, 2009:3).

Bachelier (1900) was the first person to conduct a detailed study of the pattern of prices that are speculative. The study of the pattern of prices that are speculative, time series properties of asset prices and change in prices all lead to the development of the ARCH model. The development of the ARCH model was not immediately successful because ARCH models provide tools that are new for risk measurement and impact on returns (Engle, 2006:2). The first model to capture the various change in variance and use estimates of the variance over time was the ARCH model (Bera & Higgins, 1993:306). ARCH models have also been developed to measure price risk (Engle, 2006:2). The ARCH model is advantageous, not only because it captures some stylised facts, but also due to its numerous applications to diverse areas (Bollerslev *et al*., 1992:16).

An interesting finding on ARCH models is that ARCH models assume that error term variance is constant and this variable is known as homoscedasticity, implying that the volatility dispersion is constant (Bauwens *et al*., 2006:81). The simple least squares model version assumes that the expected value of all error terms, when squared, will be the same at all times. This assumption is known as homoscedasticity, and this assumption is the main focus of ARCH models (Engle, 2001:2). This model contains the conditional variance σ_t^2 (as the dependent variable), which is described as a linear function of lagged squared residuals ε_t (Hamadu, 2010:108).

The mean process is expressed as:

$$r_t = c + \mathcal{E}_{t,}\ \mathcal{E}_t = z_t\ \sigma_{t\ ,\ and}\, \sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4.2}$$

Where: $z\_t \sim WN(0, \sigma\_t^2)$

The mean equation is an estimate of the conditional mean of the variable and distributed random variables with zero mean (Sjo, 2011:3). Before estimating the ARCH/ GARCH model, it is essential to get the mean equation correctly specified. The mean equation essentially can be modelled as an AR process. AR in combination with other explanatory variables, similar to a function of other explanatory variables. The mean equation is essential because if it is incorrectly specifying variables, the variance estimate will not be positive either (Sjo, 2011:5). The mean equation describes the expected value of the stochastic process $\{\gamma t\}$. As a result, the mean equation can be an AR, an autoregressive-moving-average model (ARMA) or a structural econometric model (Mondal *et al.*, 2014:15). However, the mean equation expressed in 4.1 does not have an AR process; the results of this study are also not estimated with an AR term.

The ARCH model is further expressed as:

$\sigma t^2 = \sigma + \beta 1 \in (t-1)^2 + \beta 2 \ \in (t-2)^2 + \ldots + \beta_p \ \in (t-p)^2$ .... (4.3)

Where: σ_t^2 is unconditional variance;

$\alpha + \beta$ is the rate of convergence of conditional volatility;

ϵ_t^2 is the residual term or deviation of the return from the estimated mean return at time t

From this formula:

$\sigma\_t^2 = \alpha + \alpha\_0 + \alpha\_1 \ U\_(t-1)^2$ .... (4.4)

The non-negativity condition would be:

$\alpha\_0 \geq 0$ and $\alpha\_1 \geq 0$ .... (4.5)

On a general perspective, for an ARCH (q) model, non-negative constraints are required for all coefficients: $\alpha\_i \geq 0$ A i = 0, 1, 2, …….q. This is adequate but not an important non-negativity condition for conditional variance (it is a slightly stronger condition than is necessary) (Brooks, 2014:425).

ARCH models are popular because they are a common and simpler to handle, ARCH models take care of clustered errors, consider nonlinearities and, lastly, are responsible for changes in the econometrician's forecasting ability (Perrelli, 2001:5). The main problem with forecasting is that it becomes difficult to make observations, which makes it challenging to the actual model's performance (Tsay, 2005:942). However, ARCH models have been characterised as essential tools in time series and can assist econometricians in forecasting and analysing volatility. With results obtained from tests, econometricians can conclude on the size of the errors and clustered errors found in the models (Engle, 2001:1). Econometricians can also conclude that variance data of error terms are different, due to error terms being anticipated to be greater for certain points or data ranges, then the remaining data points are said to undergo heteroscedasticity (Schwert, 1989:1120). The existence of heteroscedasticity is a basic warning that for an ordinary least squares regression, regression coefficients are still balanced. However, the standard errors and confidence intervals estimated by conservative processes will be too contracted, resulting in incorrect forecasting and analysis (Newey & West, 1987:705).

An advantage of the ARCH model is that even if heteroscedasticity is present, ARCH models consider heteroscedasticity as a variance to be modelled rather than treating heteroscedasticity as a concern needing attention (Christoffersen & Diebold, 1997). Ordinary least squares have deficiencies that need to be corrected, but also anticipation is captured for the variance of each error term (Engle, 2002:2). From the success of the ARCH model, researchers might be tempted to model higher order moments in a more systematic way (Bera & Higgins, 1993:359). Several ARCH models serve as reliable filters for the similar processes as well as efficiency issues, which may be important to the design of an ARCH model, which needs to extend the model to solve efficiency concerns (Bollerslev *et al.*, 1994:2987). One of the disadvantages of the ARCH model is that ARCH models have distinct issues, which are not present in modelling the conditional mean. (Grek, 2014:7). Below are the limitations of the ARCH model:

4.6.2 Limitations of ARCH models

ARCH models have a framework for the analysis and development of time series volatility models. ARCH models have hardly been used since they have certain challenges:

- The model decision limited to the q value, the number of the squared lags residual in the model? A possible approach to this situation would be using the likelihood ratio test. However, there is no defined approach.

- The q value, the lag numbers of the squared error required to capture all the dependence in the conditional variance, may be extremely large that could result in a large conditional variance model that was not limiting.
- There is a possibility for non-negativity constraints to be violated. Everything else remains the same, the greater the parameters in the conditional variance equation, the more chances there are that one or more of the parameters will have negative estimated values (Brooks, 2014:428). A natural ARCH (q) model extension, which achieved some of the above-listed limitations, is the GARCH model. The GARCH model is further explained in Section 4.6.3.

4.6.3 GARCH MODEL

Bollerslev (1986) and Taylor (1986) developed the GARCH model. The GARCH model is attributed mainly to Bollerslev (1986) who revealed the unobserved character of volatility. The unobserved volatility character changes the estimation of volatility and forecasting issue into a filtering problem where accurate volatility cannot be determined but instead extracted to some degree of error (Matei, 2009:44).

The properties of GARCH models are not easy to determine, as the GARCH model is a development of the ARCH model. Stochastic volatility models have been examined mostly in discrete time, however, with modern easy access to large quantities of very high-frequency data, there is a greater demand for continuous-time models (Muller *et al*., 2007:3).

The GARCH model addresses the limitations of ARCH models, as addressed above in Section 4.6.2. Trying to design a continuous-time GARCH model goes as far back as to Nelson (1990) who took maximum discrete time GARCH processes, formulated by a bivariate diffusion lead by two Brownian motions that are independent. The discrete time GARCH model includes only one element of uncertainty (Muller *et al.,* 2007:3). Nelson's continuous time limit process results in higher volatility, which is a unique feature of the discrete time GARCH process (Muller *et al.*, 2007:3). However, the diffusion limits do not have heavy trailed return distribution required for realistic modelling of returns in high-frequency financial data (Bollerslev, 2009:47).

The GARCH model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \ldots + \alpha_p \epsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + .. + .. \beta_q \sigma_{t-q}^2 \ldots\ldots (4.6)$$

Where: σ_t^2 is unconditional variance

α +β are GARCH parameters that suggest that volatility is finite and that conditional standard deviation increases.

ϵ_t^2 is the residual term or deviation of the return from the estimated mean return at time "t".

Non-negativity constraint would be:

$\alpha_0 \geq 0$ and $\alpha_1 \geq 0$.

For ARCH (q) model

$\alpha_i \geq 0$ ∀ ≥ i = 0, 1, 2,……,.q).

The ARCH (q) non-negativity constraint is adequate but not an essential condition for non-negativity of the conditional variance. This is a slightly more robust condition than is required.

Important model limitations of ARCH/ GARCH models are the non-negativity constraints, which confirm positive conditional variances (Terasvirta, 2006:4). GARCH models assume that the impact of updates on the conditional volatility is dependent on the magnitude only, but not on the innovation sign (Hamadu, 2010:108). The conditional variance of the GARCH (q,p) model can be described as a weighted function of a long-term average value dependent on α_0, of the information that is associated to the volatility and variance during the previous period (Bauwens *et al*., 2006:82). A GARCH (1, 1) model is equal to an ARCH (1) model, where the lags of the models are for one lag. GARCH (q,p) model is equal to an ARCH (q+p) model (Gujarati, 2004:862). This study refers to GARCH (q,p) because the lags are not specific as they will be determined using the information criteria.

For portfolio risk to first be analysed a model that is non-linear is estimated with the potential to capture the growth of portfolio volatility over a specified period and the model frequently used in financial applications of this kind is GARCH (1, 1) (Predescu & Stancu, 2011: 80). Before the GARCH (1, 1) model can be estimated, ARCH effects had to be detected in the portfolio return series. Thereafter, the existence of ARCH effects can be determined (Predescu & Stancu, 2011: 80). GARCH models are an effective way of investigating how a function of past returns, in a specific financial series, should be structured and mapped (Audrino & Buhlmann, 2001:730). When GARCH models are estimated, a particular kind of computer-based software has to be used (Nasstrom, 2003:6). The entire estimation procedure for GARCH (1, 1) model is based on the symmetric standard GARCH with a normal distribution. GARCH

(1, 1) represents a number of GARCH coefficients and number of ARCH coefficients (Carnero *et al*., 2004:325). GARCH models innovated seizing the possessions of volatility that is time-varying (Attanasio, 1991:485). During the development of the ARCH model, there was a need for many parameters, which led to the extension of the GARCH model (Baillie & Bollerslev, 1990:315). The GARCH model then expanded its broad approval and was utilised for stochastic modelling volatility risk found in financial time series (Bollerslev *et al*., 1992:16).

Time-dependent estimated coefficients could be a sign that the stock market behaves differently due to volatility during different periods (Chu, 1995:252). A suggestion could be that one GARCH model should be used when the stock market is expected to increase and then the other GARCH model should be used when the stock market is expected to decrease (Nasstrom, 2003:6). A perception has been created that no ARCH effects exist in the GARCH (1, 1) model; this model was also ranked as the best model amongst ARCH, EGARCH and TGARCH (Nasstrom, 2003:6).

Below are the advantages and limitations of the GARCH model:

4.6.4 Advantages of the GARCH model

Between the ARCH and GARCH models, the GARCH model is used better and more widely than the ARCH model. This is because the GARCH model is more limiting and evades overfitting. Regarding breaching non-negativity constraints, the GARCH model is less likely to breach (Brooks, 2014:429). In comparison to the ARCH model, GARCH is the ideal model to use in evaluating the returns volatility of group stocks with large observation numbers (Albu, 2003:198). The suitability of the GARCH model can be determined through a view of the volatility forecast quality provided by GARCH when compared to the ARCH model. The prestige of GARCH over ARCH is argued only on a theoretical basis. Enhancements refine each forecasting volatility model and, as a result, GARCH models show improvements that each refining has targeted to (Hansen & Lunde, 2001:23).

4.6.5 Limitations of GARCH

Just like every other model with problems, one of the disadvantages to the standard GARCH model is that GARCH models fail in modelling asymmetries of the volatility with respect to the sign of previous shocks (Brooks *et al*., 2001:51). Therefore, GARCH models influence the level, however, not on the sign (Klaasen, 2002:374). The main disadvantage of the GARCH model is that it is not suitable for modelling the regularly observed asymmetric effect when robust volatility is recorded systematically in the case of positive or negative news (Gazda & Vyrost, 2003:18). Another implication of the GARCH model is that it promotes fair results of positive and negative fluctuations (Brooks, 2014:440).

The limitation of the GARCH (1, 1) model is its inability to provide decent forecasts to accurately specify the actual volatility measure against which the forecasting performance can be measured (Matei, 2009:43). On the limitations of the GARCH model, various studies have found different findings. Marcucci (2005:75) discovered that the GARCH model performs better than complicated models like the Markov Regime-Switching (MRS-GARCH) only in long horizons. The MRS-GARCH model performs much better than the GARCH model in a shorter period. Marcucci (2005) means that, because of the properties of the GARCH model, the MRS-GARCH model implies to smooth out high volatility forecasts. On the other hand, Ederington and Guan (2004:982), discovered that the financial market had extended memory than explained by the GARCH (1, 1) model with minimum impact on the ability to forecast greater volatility. Awartani and Corradi (2005:173), examined the forecasting ability of various GARCH (1, 1) models against asymmetric GARCH models and discovered that the asymmetric models perform much better than the GARCH (1, 1) model. Therefore, GARCH (1, 1) models are outperformed by models that allow for asymmetry.

Asymmetric models assist in estimating stock market volatility. Conditional variance forecasting with asymmetric GARCH models has been broadly studied by Pagan and Schwert (1990:173), Brailsford and Faff (1996:75) and Loudon *et al.* (2000:54). Asymmetry is important for this model since the last term would be zero; returns that are negative in this model have more than three times the impact of positive returns towards future variances (Gonzalez-Rivera, 1998:171). The GARCH model's extension is inclusive of asymmetric terms that can capture an essential occurrence in the conditional variance of equities in order for the tendency of the volatility to increase subsequentially to greater negative shocks instead of large positive shocks, referred to as the leverage effect (Figlewski & Wang, 2000:2). When the GARCH model fails in clarifying the leverage effects, which are identified in the financial time series, leverage effects characterise the trend of change in stock prices to be correlated negatively with stock volatility changes (Matei, 2009:52). This means that the shock impact upon the volatility is asymmetric; therefore, the effect results in positively lagged residuals and negatively lagged residuals.

However, the GARCH model has the limitation of non-negativity constraint, which led to the development of other models such as the TGARCH and EGARCH models to be discussed in sections 4.6.6 and 4.6.8.

4.6.6 GJR/ GARCH/ TGARCH MODEL

The need for the development of another model rooted from the limitations of the GARCH model in capturing movements of negative shocks, because these negative shocks have greater influence on volatility instead of positive shocks (Tsay, 2005:130). In order for changes to be noticed, the GARCH model allows the conditional standard deviation to be determined by the signs of the earlier lagged values (Bollerslev, 2009). Glosten *et al*. (1993) introduced an asymmetric volatility model named GJR/GARCH or TGARCH for threshold GARCH. The GJR/GARCH model was named after well-known authors, Glosten, Jagannathan and Runkle (1993), who presented and introduced the model. Threshold GARCH was introduced by Zakoian (1994). The TGARCH and GJR GARCH are the same but were introduced differently. The establishment of the TGARCH model was to deal with the remaining effect of leverage, which GARCH models were not able to seize due to the effect of leverage on stock returns.

When the price of the fundamental asset declines, volatility raises more, which is referred to as leverage (Tsay, 2005:97). In terms of the news of asymmetric effects, the EGARCH model is not the only model that is responsible. TGARCH is a similar model. However, the leverage effect is expressed in a quadratic manner, where EGARCH is expressed in the exponential form. The TGARCH model has several outcomes on the conditional variance (Nelson & Foster, 1994:17). The influence of the news is asymmetric and the leverage effects do exist. The TGARCH model takes the form of a standard GARCH model (Nijman & Palm, 1993:35).

The conditional variance is given by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{4.7}$$

Where d_t = 1 if ϵ_t < 0 and d_t = 0. Desirable results would be when ϵ_t < 0 and undesirable results when ϵ_t > 0, which have various effects on the conditional variance. Results that are favourable also have an impact on α and negative results have an impact on α + y (Hamadu, 2010:108). For effects like leverage, γ > 0 would be clear. The condition for desirable results would be expressed as $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, $\alpha_1 + \gamma \geq 0$, meaning that the model is not rejected, although $\gamma < 0$, given that $\alpha_1 + \gamma \geq 0$ (Brooks, 2008:440).

The threshold autoregressive conditional heteroscedasticity (TGARCH) model tends to make essential alterations to the GJR/ GARCH model (Taylor, 1986:429). Instead of modelling the variance directly by using squared innovations, a TGARCH model parameterises the conditional standard deviation as a function of the lagged absolute value of the shocks (Zakoian, 1994:429).

TGARCH model can be defined as:

$$\sigma t^t = w + \alpha \cdot (YN_{t-1})\alpha_{t-1}^2 \; + \beta\, \alpha_{t-1}^2 \text{ .... } (4.8)$$

Where α and β are positive parameters, which have similar properties to the GARCH models' parameters. The difference between the GARCH and TGARCH is because of γi >0 and if α_{t-1} is negative then α_{t-1}^2 has a bigger impact on σ^2t (Tsay, 2005:130).

Conditional standard deviation models regularly outperform models that directly parameterise the conditional variance. The gains come up because absolute shocks are less responsive when shocks are squared, which is an empirically relevant feature (Davidson, 2004:21). Below are the advantages and disadvantages of the GJR/ GARCH or TGARCH model:

4.6.7 Advantages of GJR/ GARCH/ TGARCH model

The GJR/ TGARCH model is an extension of the standard GARCH (1,1) model. The main function of this model is that it entails asymmetric terms that capture an essential phenomenon found in the conditional variance of equities (Gourieroux, 1996:56). According to Haas *et al*. (2004:501), this is also known as the tendency for the volatility to rise following large shocks that are negative instead of large shocks that are positive (leverage effect). This model also can parameterise the conditional standard deviation as a function of the lagged complete value of these shocks (Hagerud, 1997:21).

The TGARCH model also has an advantage of reverting to the normal GARCH if there is no leverage effect. The ARCH models have different features, which makes the accuracy of forecasting better. The TGARCH model is designed to capture the negative changes in volatility that are usually greater than positive movements (Ramasamy & Munisamy, 2012:81).

The ARCH parameter of the TGARCH model is statistically significant. The more complicated models like the TGARCH perform better. It was discovered that the TARCH (2, 2) model is the best in modelling and forecasting volatility. However, it is favourable for one day ahead forecasts as it often over predicts one week ahead of forecasts (Abdalla & Winker, 2012:175). Another asymmetric model that explains the leverage effect is the EGARCH model, which is further explained in Section 4.3.4.

4.6.8 EGARCH MODEL

The GARCH model does not define leverage effects, which are often analysed in the financial time series (Nelson, 1991). As discussed above, the leverage effect is the capacity for volatility to increase greater negative shocks instead of positive shocks. Black (1976) was the first to observe the leverage effects, which is a representation of the tendency of variation in stock prices to be negatively correlated with movements in the stock volatility (Matei, 2009:52). The EGARCH model is responsible for asymmetric response to shocks. The impact of a shock upon the volatility is asymmetric; this means that the influence of positive and negative lagged residuals varies (Matei, 2009:52). The reason for this is that volatility is given allowance to react more accurately to reductions in negatively lagged residuals instead of consistent increases in positively lagged residuals (Nelson, 1992:73). The EGARCH model equals changes in the negative and positive effects (Hamadu, 2010:107).

Nelson introduced the EGARCH model and stated that the model overcame specifically three criticisms of the standard GARCH model (He *et al*., 2002:871) through three main parameters that the EGARCH model can outperform. The first parameter limitations are expected to ensure conditional variance positivity all the time, the second parameter is that the standard GARCH model should prohibit asymmetric response to shocks and the last parameter is if the model is an integrated GARCH (IGARCH) model, which measures determination difficulty since this model is strong, instead of weakly stationary (Terasvirta, 2006:20). The IGARCH model is estimated when the series is not stationary or has a unit root; however, the IGARCH is not discussed in this study.

Most of the models discussed above have had symmetric underlying distributions. Nelson noticed that some financial sets of data contain the leverage effect (Nelson, 1991:4). The leverage effect is when variance (volatility) becomes greater than a return and is not positive in comparison to when a return is not negative (LaBarr, 2014:4). This refers back to the typical market conditions that investors tend to become risk-averse and will tend to react differently to negative returns than positive ones (LaBarr, 2014:4).

EGARCH model's equation can be expressed as:

$$\text{Ln } (\sigma_t^2) = \omega + \beta \ln (\sigma_{t-1}^2) + \gamma \; \mu_{t-1} / \sqrt{\sigma_{t-1}^2} + \alpha \; [\text{ I } u_{t-1} / \sqrt{\sigma_{t-1}^2} \text{ - } \sqrt{\;} 2 / \pi \;] \tag{4.9}$$

Where: Ln (σ_t^2) is the log of conditional variance

σ_t^2 is conditional variance

The constraints w > 0 and αi ≥ o (for all i=1), βj ≥0 (for all i=1). Nelson (1991) suggests the EGARCH model does not require non-negativity constraints. Since it is the log of conditional variance (Ln (σ_t^2) regardless of the parameters being negative the conditional variance (σ_t^2) remains positive, that is why there is a need to artificially suggest non-negativity constraints. When it comes to modelling (Ln (σ_t^2) the leverage effect is exponential in comparison to quadratic and validating that conditional variance will be non-negative (Emenik & Aleke, 2012:54). The EGARCH model caters for the asymmetric effect of news or shocks on the conditional volatility. γ is the asymmetry coefficient. If γ < 0 and statistically significant, shocks that are negative impose a greater period of conditional variance than shocks that are positive of the same magnitude, this is where the EGARCH model is responsible for asymmetric influences (Brooks, 2008).

The process of EGARCH is specified in terms of the conditional variance log, which means that σ_t^2 is always positive and automatically there are no limitations on restrictions regarding the sign model parameters. The effect of the leverage is exponential instead of being quadratic; the predictions can be tested by the hypothesis y < 0. This model has many advantages in relation to the GARCH model. Due to the log(σ_t^2) being displayed, even if there were negative limitations, σ_t^2 will be positive. It is not necessary to show falsely positive results in the model's limitations. Asymmetries are provided in the EGARCH formulation, because if it happens the link amongst volatility and returns reveals negativity, it means that γ will also be negative, however, the EGARCH model performs exceptionally well in capturing asymmetry (Brooks, 2008: 441).

The EGARCH model is not the only model development using the natural logarithm of volatility rather than volatility itself. However, the model also makes use of a rather general distribution instead of normal distribution proposed by Engle (Engle, 1982:4). Nelson tends to make use of the generalised error distribution instead (Nelson, 1991). The EGARCH model has further been expended to protect the asymmetric influence or leverage effect returns on volatility and long memory property in the volatility (Gabriel, 2012: 1007).

The concept of the EGARCH model is to loosen positivity constraints from the basic GARCH model and maintain the non-negativity constraint on the volatility towards the conditional variance (Nasstrom, 2003:24). Each model has its distinct strengths and weaknesses; the challenge arises because all of the models are structured to fulfil the same scope. Hence, it is crucial to differentiate accurately between the different models discussed above in order to determine which model provides the most precise forecasts (Matei, 2009:43). This study identified the most accurate model by using different information criteria, namely the AIC, BIC and SC as mentioned above under Section 4.6 (Model specification).

Another model, which is not discussed in depth in this study, is the mean GARCH (GARCH-M) model (Tsay, 2005:123). This model adds a heteroscedasticity term into the mean equation. GARCH-M model is used mostly to estimate risk premiums. The classical GARCH-M in its modelling can capture two stylised facts of financial data: leptokurtosis (big tails) as well as volatility clustering (Bentes & Menezes, 2012). The main disadvantage of GARCH-M is that it is symmetric and cannot account the asymmetric feature of financial data. This asymmetric feature is referred to as leverage effects (Magnus & Fosu, 2006:2043). The leverage effect studied in financial data has been shown in different empirical studies; it is the trend for negative news to have a more pronounced influence on the volatility of asset prices instead of positive news. Therefore, the volatility increases because of a price decrease is usually greater than that of a price increase of the same magnitude (Samouilhan & Shannon, 2008:23).

4.6.9 Advantages of EGARCH model

The first advantage of the EGARCH model is that the model specifications ensure, although parameters are negative, the conditional variance always remains positive since it is expressed as a function of the logarithm (Su, 2010:7). The second advantage is that asymmetries, which are the leverage effects, are allowed since the relation between the volatility and returns is negative.

Advantages of the EGARCH model specification are positive, regardless of the estimated parameters as well as the asymmetric nature of innovations influence (Malmsten, 2004:250). A shock that is positive will have a different influence on volatility instead of a shock that is negative by representing findings within an equity market research about the effect of negative and positive volatility news within the market (Baum, 2014:9). EGARCH models tend to provide a favourable match when compared to general GARCH models (Terasvirta & Zhao, 2006:71). The existence of the asymmetric term is mostly responsible for the favourable match because several returns of asset series have been discovered to have the leverage effect and utilise the standardised shocks in the development of the log-variance, often lowering the impact of large shocks (Silvennoinen & Terasvirta, 2007:41).

4.6.10 Summary of GARCH volatility models

Various volatility models were discussed in Section 4.6.1 to 4.6.8 and a specific criterion was followed in selecting the best model. The results from the diagnostic tests for ARCH models regarding different specifications reveal the model with the lowest AIC and SIC values in each sector will then be categorised as the best volatility model. Diagnostic checking test is done to determine if the best model successfully meets the requirements of being the best volatility-capturing model. This is achieved when there is no ARCH effect, no serial correlation and there is a normal distribution. The presence of the volatility risk premium is important for indicating a continuous link between two distributions; the GARCH model is fully accountable in doing so (Carr & Wu, 2009:1322). The estimation approach does not only drastically lower the bias but also enhances the efficiency of the joint maximum likelihood estimator, specifically for the parameters of the volatility process. As a result, this can be essential for the option-valuation performance of GARCH models (Chernov, 2007:421).

4.6.11 DYNAMIC CONDITIONAL CORRELATION (DCC)

The dynamic conditional correlation (DCC) is used to test if there is a volatility spill-over across the top five JSE sectors. The need for DCC is to identify the co-movement between the different JSE sectors (an indication of spill-over effect). Engle (2002) developed the DCC model, which is a nonlinear model but can be matched with univariate (one variable) or two-step-based methods on the probability function (univariate GARCH series and estimating correlation). Engle (2002) discovered that the bivariate (relationship between two variables) DCC model provides an excellent approximation to different time-varying correlation processes (Peng & Deng, 2010:5).

Correlations change dynamically. Therefore, the DCC model can be expressed as:

$H_t = D_t R_t D_t,$

$D_t = \text{diag}\ (h_{11,} t^{0.5},\ \ h_{mm,}\ t^{0.5}$

$Q_t = (1 - \alpha - \beta)\ \text{R} + \alpha \in_{t-1} \in_{t-1} + \beta Q_{t-1},$

$$R_t = (\text{diagQ}_{t)}^{-0.5} Q_t (\text{diagQ}_{t)}^{-0.5}, \quad (4.10)$$

Where:

H_t, is the conditional variance matrix

$h_{11,t}$, is a univariate GARCH equation

Q_t, evolution of correlation in a standard DCC model

D_t, the m x m diagonal matrix of time-varying standard deviations from univariate GARCH models with $h_{ii,t^{0.5}}$ on the diagonal.

R is the m x m unconditional correlational matrix of $\in_t$ while α and β are positive scalar parameters sustaining α and β < 1 (Engle *et al*., 2005).

DCC models are flexible around univariate GARCH models together with limiting parametric models for the correlations (Peng & Deng, 2010:5). A greater understanding of the nature of the spill-over effect can assist investors in taking calculated risks when making investment decisions and diversifying their portfolios. Volatility modelling and forecasting, as well as correlations, are core focusses in financial econometrics. Correct volatility estimates and correlations are vital in risk management, hedging strategies, derivative pricing and portfolio optimisation (Peters, 2008:4).

This study used bivariate DCC to model the time-varying volatility (conditional heteroscedasticity) in the JSE top five sectors and estimate bivariate correlation. Parameter numbers to be estimated for conditional correlations are not dependent on the number of variables in the model. The computational burden can be eliminated, while still obtaining large-dimensional correlations. The simple structure of the DCC-GARCH parameters can come across as a weakness due to the entire correlation processes that are assumed to have the same dynamic behaviour (Engle, 2002).

4.6.12 Correlation analysis

Correlation is known as a statistical process that is used to determine whether two variables are associated with each other (Leedy & Ormrod, 2010:273). Correlation analysis is a measurement of the strength and direction of a relationship between two variables that are quantitative (Remler & Van Ryzin, 2011:261). Different correlation measures can be used, for example either the Spearman's rho, point-biserial correlation coefficient or the Pearson's product-moment correlation coefficient, denoted by *r*, originally proposed by Karl Pearson (Struwig & Stead, 2010:140). The Pearson correlation coefficient is ideal to be utilised with metric data and ranges from -1, reflecting a perfect negative correlation, to +1, indicating a perfect positive correlation. Furthermore, if *r* is equal to zero, there is no relationship between the two variables (McDaniel & Gates, 2007:530). This study applied the Pearson correlation analysis to determine the relationship between the returns of the top five JSE sectors. Table 5.2 indicates that each variable correlates perfectly with itself, which is denoted by $r = 1$ (Field, 2009:178). When looking at the correlation between all of the variables, the Pearson correlation was significant at 0.05 level of significance. The results indicate a positive linear association between all the JSE top five sectors. A discussion follows Table 5.2 on the relationship between the variables. Results were presented using a two-tailed significance level at 0.05 ($p<0.05$).

P-values add onto the significance of the correlation between the sectors using the significance level of 0.05 as a benchmark. P-values greater than 0.05 indicate that a correlation coefficient is not statically significant at the 0.05 level of significance and P-values less than 0.05, indicating a correlation coefficient is statically significant at the 0.05 level of significance. All the p-values were found to be less than 0.05, which means that the correlation coefficients between the JSE sectors are statistically significant at the 0.05 level of significance. The p-value results show that there is a high correlation between the sectors (significant correlations) because the p-values are all less than the 0.05 level of significance. When there is a correlation between the JSE sectors, diversification has the potential of being eliminated (Korkis, 2013:3). High correlation eliminates diversification due to the size of the correlations whereas low correlations imply diversification.

However, the correlation between the financial and basic materials sectors of 0.024 is very low, which implies diversification between the two sectors. Negative/ low correlation maximises investor's returns per unit of risk assumed, hence the opportunity for diversification and positive/ high correlation minimises investor's returns per unit of risk assumed; therefore, there is little opportunity for diversification (Research Desk, 2017).

4.6.13 Diagnostic tests

Once the model selection has been done, diagnostic tests follow in Chapter 5 of the study. The purpose of the diagnostic tests was to determine whether the selected GARCH models do not violate any econometric assumptions, such as serial correlation, heteroscedasticity and normality test. Diagnostic checking test is done to determine if the best model successfully meets the requirements of being the best volatility capturing models. This is achieved when there is no ARCH effect, no serial correlation and there is a normal distribution. However, residuals that are not normally distributed are not a problem in GARCH models because GARCH models are not sensitive to normality therefore non-normally distributed residuals can be acceptable in GARCH models. However, some models are robust to normality and can be used to conduct tests such as equal variances (Ogee & Ellis, 2018).

The ARCH test was implemented in the usual Box-Ljung Q statistic test for auto-correlations in the series (McLeod & Li, 1983). The second test that can detect the ARCH effect in the time series returns is the Lagrange multiplier (LM) test of Engle (1983). The Jarque-Bera test is used for testing normality in the time series data; the goodness-of-fit to determine whether the residuals have the skewness that matches a normal distribution. The results of this study in Chapter 5 indicate that residuals are not normally distributed for all five JSE sectors. This study followed the LM test, and all five sectors have ARCH effects, which is not a desirable outcome within the criteria of a good GARCH (1, 1) model when residuals have an ARCH effect. There is serial correlation in all five JSE sectors. Overall, the GARCH (1, 1) model does not meet the criteria for being the best volatility-capturing model. However, the model extensions TGARCH and EGARCH successfully meet the criteria of being the best volatility-capturing models. Chapter 5 elaborates further on the tests and results of the study.

Another important test that will be conducted in chapter five is the unit root testing (stationarity test). This test is essential because stationarity in a series is robust and can help determine whether there are shocks in a series or not. When using the ARCH models to test for stationarity, stationarity can be found at level, first or second difference. The results of chapter five will reveal whether the series of this study has stationarity or not.

4.6.14 SUMMARY

This chapter explained how the data were collected and provided a description of the top five sectors according to market capitalisation. Furthermore, the study explained the origin, characteristics, advantages, disadvantages and expression of each of the ARCH family models.

Chapter 4 focused on the original ARCH to the extensions of the GARCH, TGARCH/ GJR and EGARCH models. The ARCH and GARCH models focus on issues like the variance of error terms, heteroscedasticity and volatility clustering. These models are used on a large scale towards handling time series heteroscedastic models. The main aim of these models is to deliver a volatility measure, for example, the standard deviation. The volatility measure can then be used in financial decision making affecting the analysis of risk and selection of portfolios for investors. ARCH/ GARCH models have been discovered to be very useful, especially when the goal of this study is to analyse or forecast volatility, just as this study forecasted the level of volatility of each of the top five JSE sectors.

CHAPTER 5: EMPIRICAL RESULTS AND DISCUSSION

5.1 INTRODUCTION

Chapter five intends to achieve the following empirical objectives:

- identify the best model for modelling volatility in each of the top five sectors of the JSE;
- estimate the most volatile sector between the top five sectors of the JSE;
- compare the level of volatility across the top five sectors of the JSE; and
- determine the spill-over effect across the JSE sectors.

Each empirical objective achieved will be linked to the respective test result.

5.2 EMPRICAL RESULTS AND DISCUSSION

The various volatility capturing models have created great debates in the past, with various theories opposing, which model is the best volatility capturing model. The application of the GARCH models mentioned in Section 4.6.1 to 4.6.8 of the methodology is presented in this chapter. This study aims to determine, which JSE sector is the most volatile using the GARCH models. Several tests were conducted in each sector to determine the most volatile sector; unit root testing, application of ARCH, GARCH, TGARCH and EGARCH models. The best model was selected through the use of different information criteria, namely the Akaike information criterion (AIC), Bayesian information criterion (BIC), also known as the Schwarz information criterion (SIC) and Hannan-Quinn (HQ). The model with the lowest AIC, SC and HQ values in each sector was classified as the best model. The model selection also provides detail on how lags in each model were selected. Lastly, the dynamic conditional correlation (DCC) results for the co-movement between the sectors are discussed.

This chapter is presented in different sections. Section 5.4 introduces the descriptive statistics of the data in a more meaningful way. Section 5.5 gives a comparison of correlation results of the sectors. Section 5.6 is the preliminary investigation, which displays brief analysis of how volatile each sector was between 2002 and 2015. Section 5.7 covers unit root testing and Section 5.8 determines the ARCH effects in all mean equations before estimating and selecting GARCH models in Section 5.9. Section 5.10 is the volatility determination section, which determines the most volatile sector as per the econometrics equation criterion (Brooks, 2014).

Section 5.11 covers the diagnostic checking to confirm if the estimated models are robust. Section 5.12 is to estimate the risk premium for each sector by estimating the best model in the mean. The last section, Section 5.13, tests for spill-over effects using the DCC model, which is used to test the movement amongst the sectors.

5.3 HYPOTHESIS TESTING

Failing to reject the null hypothesis is not the end; there is still the need to investigate the possibility of nonlinear transformations of the variables and of outliers, which may be sceptical of the relationship. There may be insufficient data to show a real effect, which is why it is important to know when to fail to reject the null hypothesis rather than accept the null hypothesis. It would be incorrect to conclude that no real relationship exists. When the null hypothesis is rejected, this does not imply that the alternative model is the best model. It is unknown whether all the predictors are required to predict the response or just some of them. Other predictors might also be added, or existing predictors transformed or recombined (Faraway, 2005:27).

The null (H_{01}) and alternative (H_1) hypotheses of this study are formulated as follows:

For probability (p-value): If the p<0.05, the null hypothesis can be rejected at 0.05 level of significance (Faraway, 2005:27).
H_{01}: Residuals are normally distributed
$H_{a1:}$ Residuals are not normally distributed
H_{02}: Series contains a unit root
H_{a2}: Series is stationary
$H_{03:}$ No ARCH effect
H_{a3}: ARCH effect
H_{04}: There is no serial correlation
H_{a4}: There is serial correlation

5.4 DESCRIPTIVE ANALYSIS

Descriptive statistics are important because they present data in a more meaningful and structured way. Descriptive statistics do not allow conclusions to be made beyond the data presented. Table 5.2 presents a summary of each sector's descriptive statistics and elaboration on what the outcome of the descriptive statistics means for each sector.

Table 5.1: Descriptive statistics summary

Sectors	Mean	Std.Dev.	Min.	Max.	Skewness	Kurtosis	Jarque-Bera	p-value
Industrials	-3.15	0.010	-0.05	0.07	-0.09	5.55	960.09	0.000
Consumer goods	-9.67	0.015	-0.07	0.15	0.44	9.04	5447.35	0.000
Financials	8.52	0.012	-0.06	0.08	0.23	6.75	2091.99	0.000
Basic materials	3.37	0.012	-0.08	0.07	-0.03	6.56	1852.43	0.000
Consumer services	1.98	0.012	-0.05	0.07	0.021	5.24	738.21	0.000

Source: Own estimate

Table 5.1 reveals that the JSE consumer goods sector has greater standard deviation than the JSE industrials, financials, basic materials and consumer services sectors, which means that consumer goods sector is more volatile than the other four sectors; as standard deviation is an effective measure of volatility and a total measure of risk (Faraway, 2005:2). The preliminary investigation of the different sectors in Section 5.6 also revealed the consumer goods sector as the most volatile sector. Therefore, the consumer goods sector is indeed a volatile sector and matches the needs of high-risk investors seeking high returns. The results achieved meet the empirical objective of estimating the most volatile sector between the top five JSE sectors and using standard deviation as a measure of comparing the level of volatility across the top five JSE sectors.

When the kurtosis is greater than three, data are skewed to the right and from the above output; the kurtosis values for all JSE sectors are greater than three, meaning that the data are skewed to the right. The Jarque-Bera test would be an indication of the distribution's deviation of zero, skewness and kurtosis if it was an accurate normal distribution (Stephanie, 2017). The general belief behind the Jarque-Bera test is that the normal distribution with any mean or variance with a skewness coefficient of zero and a kurtosis coefficient of three. The test aligns the skewness and kurtosis of the data set to see if it meets a normal distribution. The data could be in various forms like time series data, data in a vector or errors in a regression model (Zikmund & Babin, 2013:257). According to Struwig and Stead (2010:159), skewness is referred to as the degree of deviation from symmetry. Results can have a symmetrical distribution or positive skewness and negative skewness. Malhotra (2010:488) describes kurtosis as a measurement of the respective peak or flatness of the curve as indicated by the frequency distribution. As mentioned by Struwig and Stead (2010:159), a kurtosis is made up of three main classifications, namely a normally distributed kurtosis, known as mesokurtic, a peaked kurtosis, usually known as a leptokurtic and kurtosis that is not often flat, alternatively known as platykurtic.

The industrials sector has a mean value of -3.15, the standard deviation value of 0.010 and returns value of 0.05. There is great chance of high volatility in this sector because of the returns deviation from the mean. The negatively skewed distribution is represented by the skewness value of -0.09. The negatively skewed distribution is sharper than the normal distribution as indicated by the kurtosis value of 5.55, a Jarque-Bera value of 960.09 and a probability value of 0.000.

The consumer goods sector returns are the most volatile in comparison to other sectors analysed in this study. This is supported by the highest standard deviation value of 0.015. The distribution of the consumer goods sector is positively skewed, indicated by the skewness of 0.44 and a kurtosis value of 9.04. This is stressed by the Jarque-Bera value of 5447.35 and a probability value of 0.000. The maximum value of 0.15 and a minimum value of -0.07 implies that outliers do exist in the distribution. The high volatility of the consumer goods sector is supported by the preliminary investigation of the consumer goods sector in Figure 5.2. The financial sector returns seem to be less volatile towards returns that do not deviate significantly from the mean. This is indicated by the mean value of 8.52 and standard deviation value of 0.012. The financial sector returns distribution is positively skewed as indicated by the skewness value of 0.23 and the kurtosis value of 6.75. This also implies that the distribution is also sharper than the normal distribution. This is supported by the Jarque-Bera value of 2091.99 and probability value of 0.000.

The basic materials sector returns have a mean value of 3.37 with a standard deviation value of 0.012; this shows that basic materials sector returns are volatile as they deviate from the mean just like with the industrial sector. Distribution for this sector is also sharper than normal distribution, and it is supported by the Jarque-Bera value of 1852.43 and probability value of 0.000. Outliers exist in the distribution as indicated by the maximum value of 0.07 and a minimum value of -0.08. The returns distribution is negatively skewed as indicated by the skewness value of -0.03. The consumer services sector returns have a mean value of 1.98 and a standard deviation value of 0.012. This shows that the consumer services sector returns sometimes deviate from the mean; the sector returns are not entirely volatile but are still around 0.00. There is positively skewed distribution that is sharper than the normal distribution with great values to the right as shown by the skewness value of 0.021 and a 5.24 kurtosis value.

The Jarque-Bera value of 738.21 and probability value of 0.000 support the positively skewed distribution.

5.5 CORRELATION ANALYSIS

TABLE 5.2: CORRELATION RESULTS

	Basic materials	Consumer goods	Consumer services	Financial	Industrial
Basic materials	1				
Consumer goods	0.516***	1			
Consumer services	0.654***	0.393***	1		
Financial	0.024***	0.975***	0.877***	1	
Industrial	0.724***	0.445***	0.656***	0.938***	1
***** Correlation is significant at 0.05 level (2-tailed)**					

Source: Own estimate

The correlation between consumer goods and basic materials (*r* = 0.516) indicates a high positive correlation between the two sectors. Consumer goods was significant at 0.05 significance level (p=0.000<0.05). The correlation between consumer services and basic materials (*r* = 0.654) indicates a high positive correlation between the two sectors. Consumer services was significant at 0.05 significance level (p=0.000<0.05). The correlation between consumer services and consumer goods (*r* = 0.393) indicates a high positive correlation between the two sectors. Consumer services was significant at 0.05 significance level (p=0.000<0.05). The correlation between financial and basic materials (*r* = 0.024) indicates a high positive correlation between the two sectors. Financial was significant at 0.05 significance level (p=0.000<0.05). The correlation between financial and consumer good (*r* = 0.975) indicates a high positive correlation between the two sectors. Financial was significant at 0.05 significance level (p=0.000<0.05). The correlation between financial and consumer services (*r* = 0.877) indicates a high positive correlation between the two sectors. Financial was significant at 0.05 significance level (p=0.000<0.05). The correlation between industrial and basic materials (*r* = 0.724) indicates a perfect correlation between the two sectors. Industrial was significant at 0.05 significance level (p=0.000<0.05). The correlation between industrial and consumer goods (r = 0.445) indicates a high positive correlation between the two sectors. Industrial was significant at 0.05 significant level ($p=0.000<0.05$). The correlation between industrial and consumer services (r = 0.656) indicates a high positive correlation between the two sectors. Industrial was significant at 0.05 significant level ($p=0.000<0.05$). The correlation between industrial and financial (r = 0.938) indicates a high positive correlation between the two sectors. Industrial was significant at 0.05 significance level ($p=0.000<0.05$).

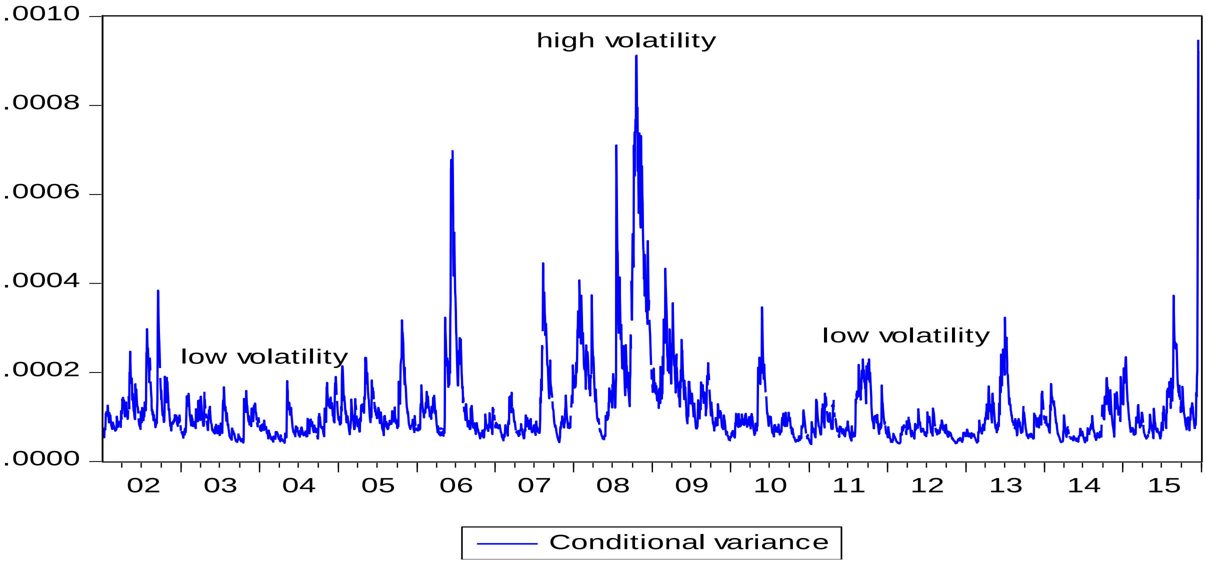
Some studies have found similar results even though these studies correlate the JSE sectors to other variables instead of correlating the JSE sectors amongst each other as in this study. The study of Putyinceva and Steffen (2016:29) found the consumer services sector to have a positive correlation to earnings per capita (EPC). This could be an indication for a behavioural effect of wealth resulting in a general increase in individual living standards and increased spending on non-essential goods. The consumer goods sector showed neither positive nor negative correlation. The financial sector showed a strong positive correlation towards EPC and a negative correlation with the unemployment rate, meaning that in times of low unemployment, the financial sector performs well. The industrial sector showed a significant positive correlation with EPC and the oil price. The positive correlation with EPC shows the behavioural aspect of increasing wealth mentioned above. The basic materials sector showed a positive correlation towards earnings per capita signals and anticyclical supply management within the sector.

The study of Manolis *et al*. (2002) found significant positive and negative correlation between the top 10 sectors. A possible reason could be that the effects of inflation on the health and consumer sectors are already captured by the demand-driven factors such as EPC, CPI (consumer price index) and private consumption, resulting in inflation being insignificant.

5.6 PRELIMINARY INVESTIGATION

The primary aim of the preliminary investigation is to analyse the return volatility of each sector before any tests are conducted. This investigation is to provide a premature analysis of the performance of each sector. The preliminary investigation is presented in figures 5.1 to 5.5. This is only a preliminary investigation; therefore, the results of each sector are most likely to change with time.

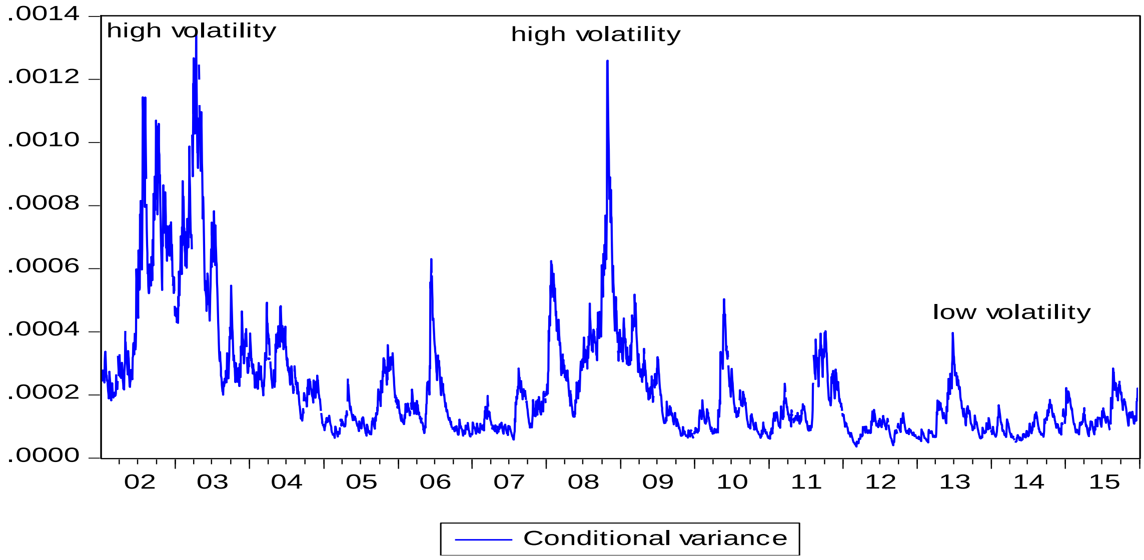
Figure 5.1: Preliminary volatility analysis of the industrial sector



Source: Own estimate; McGregor BFA (Pty) Ltd

Figure 5.1 is a preliminary investigation of the industrial sector's daily returns. The industrial sector seems to be volatile because there is either low or high volatility. The volatility could be due to performance in the scope of work in construction and building materials, industrial engineering and industrial transportation. The industrial sector started on below-average volatility in 2002 and maintained downward to upward volatility for a sustained period until 2008. There was high volatility in 2008/9; a possible cause being the GFC, which had a negative impact on the South African economy (Wachter, 2013). During the GFC period, there was a low-interest rate environment and increasing inflation pressures. As a result, the entire economy was negatively affected. After the GFC, the sector maintained low volatility until 2015. The performance of the industrial sector showed downward and upward volatility during the 2002-2015 period. Therefore, this sector would attract risk-aggressive investors; those investors that have increased risk appetite and are willing to take on risk.

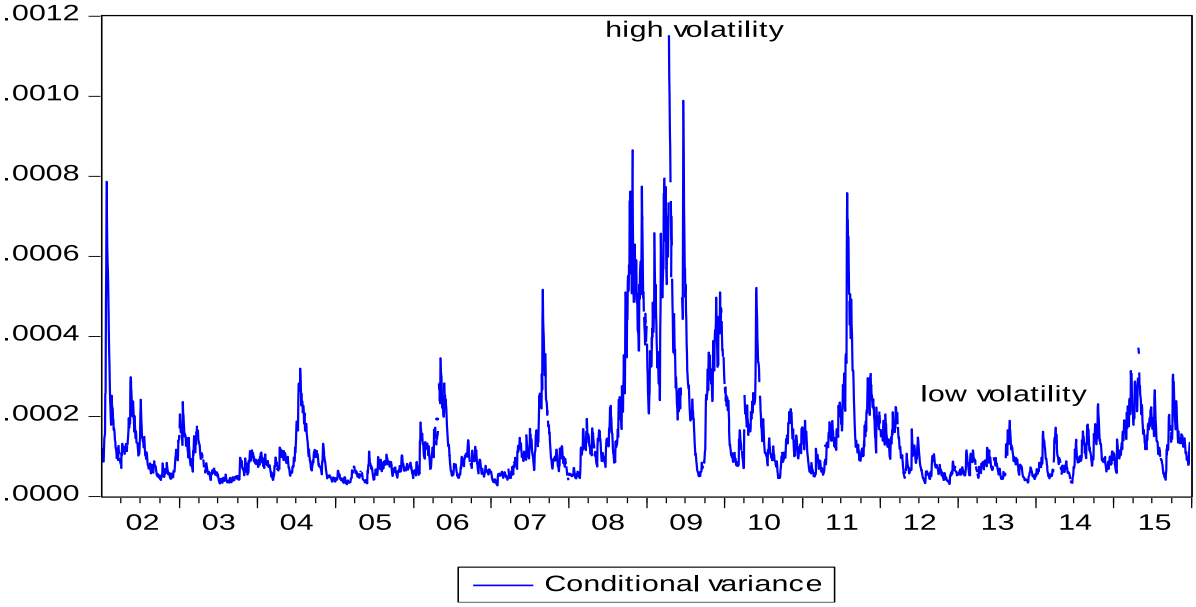
Figure 5.2: Preliminary volatility analysis of the consumer goods sector



Source: Own estimate; McGregor BFA (Pty) Ltd

Figure 5.2 is a preliminary investigation of the consumer goods sector's daily returns. There is great volatility in the consumer goods sector; this could be a result of positive results from sales and increased sales in food and leisure. In 2002, this sector had low volatility, which rapidly increased within the next year and started to decline until 2008/9 where the sector reached peak levels of volatility. The peak levels could be a result of the GFC impact followed by low volatility levels until 2015. Low returns in this sector are driven by the increased cost of living, inflation increases, increasing unemployment and low economic growth. All these factors have a negative impact on the consumer goods sector because consumers have less spending money. A sector having the capacity of reaching such high results would be favourable for investors because of the high returns investors would gain. However, such a sector poses a high risk as well because just after the high returns the sector reached its lowest returns, which is unfavourable for investors (Reilly & Brown, 2012). The performance of this sector is ideal for investors willing to take calculated risks and have an increased risk appetite.

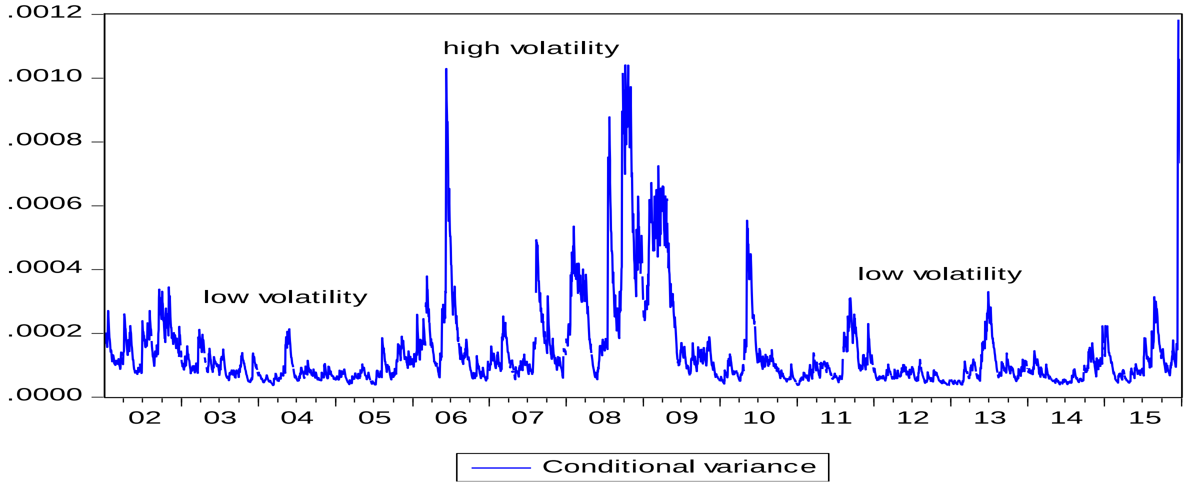
Figure 5.3: Preliminary volatility analysis of the financial sector



Source: Own estimate; McGregor BFA (Pty) Ltd

Figure 5.3 is a preliminary investigation of the financial sector's daily returns. The financial sector started on high volatility levels and maintained low volatility levels from 2003 until 2008/9. The peak levels of volatility in 2008/9 were probable impacts of the GFC. Thereafter, the sector-maintained average to low volatility levels. Increased returns in the financial sector are a result of increases in the insurance industry and financial services (BIS, 2017). Low returns are the result of declining investments and reduce overall business confidence (Domanski *et al*., 2011). The sector returns are moderate and stable. However, the financial sector is for investors with large risk appetites because interest rates are constantly changing and have a great influence on investments in the financial industry.

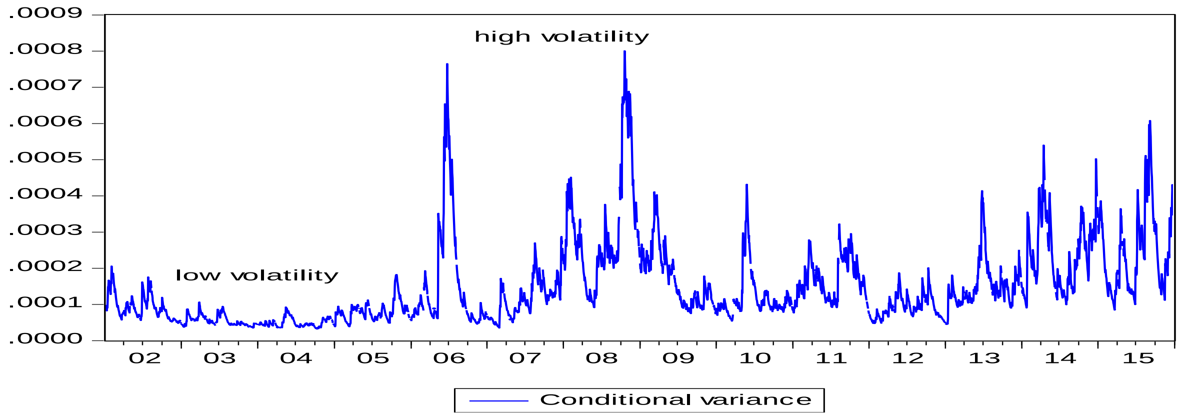
Figure 5.4: Preliminary volatility analysis of the basic materials sector



Source: Own estimate; McGregor BFA (Pty) Ltd

Figure 5.4 is a preliminary investigation of the basic material's sector daily returns. The basic materials sector maintained low levels of volatility between 2002-2005 and 2011-2014. Low volatility levels could result in a decline in the performance of the mining, forestry or paper industries (Sithole, 2018). This, in turn, affects the overall growth of the economy. High levels of volatility are seen in 2006, 2008-2009 and 2015. The basic materials sector increases are boosted by mining, forestry and paper. Increases in this sector improve the cost of living and encourage economic growth (Sithole, 2018). Overall, the sector performance is average, not too volatile and not too constant. This type of sector would attract investors with moderate risk appetite seeking average returns.

Figure 5.5: Preliminary volatility analysis of the consumer services sector



Source: Own estimate; McGregor BFA (Pty) Ltd

Figure 5.5 is a preliminary investigation of the consumer services sector daily returns. The consumer services sector maintained low volatility levels in 2002-2005, 2007 and average returns in 2008, 2009-2015. Low returns in the consumer services sector is a result of the low interest rate environment and increased inflationary pressures because consumers have less money to save or invest, as well as the overall cost of living increases (Research Desk, 2017). This, in turn, has a negative impact on economic growth. The sector experienced high volatility levels in 2006 and 2008. Food and clothing retailers and travel and leisure companies boost increases in the consumer services sector. Overall, the sector performance is stable and not too volatile. This sector is ideal for less aggressive investors who are seeking average returns (JSE, 2013).

5.6.1 Summary of preliminary investigation

The outputs from the figures under Section 5.1 of the volatility of JSE sectors express anticipation of low to high future volatility. Implied volatility is an effective estimator of volatility. Looking into the outputs, consumer goods, financial and basic materials sectors are indeed more volatile than the industrial and consumer services sectors. Consumer goods, financial and basic materials sectors are volatile, therefore, ideal for risk-aggressive investors. Risk-aggressive investors are those who have an appetite for risk exposure. Whereas, the industrials and consumer goods sectors are ideal for conservative investors. Conservative investors are those types of investors that are not willing to take on risk and are satisfied with minimum to average returns.

As referred to in the literature, there is an influence of return volatility on the stock market on investment decisions. The results from the sectors' volatility influences investor decisions; for example, the most volatile sectors would attract investors with a high-risk appetite. Less volatile sectors would attract investors with low-risk appetite because these types of investors are willing to take the limited risk.

5.7 UNIT ROOT TESTING

Unit root testing is a stationarity test because stationarity in a series is robust and can help determine whether there are shocks in a series or not. When using the ARCH models to test for stationarity, stationarity can be found in levels, first or second difference. Once stationarity is found in levels, there is no need to continue testing for stationarity at first or second difference. Table 5.3 presents the ADF unit root test results of the JSE sectors.

Table 5.3: ADF unit root testing (stationarity test) at level

Sector	Test statistic	P-value
Industrial	42.98	0.0000
Consumer goods	60.10	0.0000
Financial	43.50	0.0000
Basic materials	43.59	0.0000
Consumer services	56.43	0.0000

Source: Own estimate

If $p=0.000<0.05$, the null hypothesis (series contains unit root) is rejected.

If p-value=0.000>0.05, alternative hypothesis (series is stationary).

Unit root testing is a stationarity test; the above tests were conducted because the stationarity of a series can greatly influence the behaviour and properties of a series, which can result in continuous shocks that will be endless for non-stationary series (Priestley & Rao, 2013:3). Results of this study found stationarity in levels for all sectors; therefore, it was not necessary to proceed to either first or second difference because test statistics are greater than the critical values at 0.01 and 0.05 significance level. Therefore, JSE sectors' series are stationary in levels, I (0) and do not have a unit root. The unit root test is for stationarity of variables because non-stationarity variables produce spurious results.

The purpose of unit root testing was to analyse the autocorrelation function of the series on hand. Unit root process shocks will remain; however, the autocorrelation for a unit root process is most of the time seen to deteriorate away very slowly approaching zero. It is impossible to use autocorrelation or partial autocorrelation to determine whether a series has a unit root or not. The biggest criticism that has been identified for unit root tests is that the power of unit root tests is low if the process is stationary but with a root close enough to the non-stationary boundary (Brooks, 2014:364).

The study of May (2015:75) tested for a unit root in the returns series by applying the augmented Dickey-Fuller (ADF), the Phillips-Perron test (PP), Kwiatkowski Phillips Schmidt and Shin (KPSS) and Dickey-Fuller generalised least squares (DF-GLS). The results of the study reported unit root results for the rand returns. All the return series variables were stationary at 0.01 significance level, indicating the series is likely to be stationary at level I (0), this study also found stationary in levels, I (0).

Ideally, investors would invest in returns that do not have spurious results, for example, invest in sectors that have variables that are stationary. Spurious results would give investors false information regarding the performance of a sector, resulting in investor frustration and seeking other investment opportunities. Stationary results provide investors with a true reflection of a sector's performance (Ayat & Burridge, 2000:82).

5.8 TESTING FOR ARCH EFFECT

The need for the ARCH effect test is to confirm if the GARCH model is relevant for the estimation of the results. To test for the ARCH effect, a 0.05 significance level is used. If a p-value is less than 0.05, the null hypothesis (no ARCH effects) is rejected. However, if the p-value is greater than 0.05, then the null hypothesis of no ARCH effects is not rejected, indicating that there is no ARCH effect.

Table 5.4: Results of ARCH effect

Sector	P-value
Industrial	0.0000
Consumer goods	0.0000
Financial	0.0000
Basic materials	0.0000
Consumer services	0.0000

Source: Own estimate

The ARCH effect aims to test the GARCH models for different mis-specifications (Wooldridge, 2003:7). The determination of GARCH model mis-specifications is important because the results assist in the confirmation on whether the GARCH model is relevant for the estimation of the results. For all JSE sectors, p-values are 0.0000, which is less than the significance level of 0.05 ($p=0.000<0.05$), meaning that the null hypothesis is rejected as there are ARCH effects. Therefore, all JSE sectors have ARCH effects. For the first estimation, it is ideal to have ARCH effects so that the GARCH models can be used.

5.9 SELECTION OF THE BEST MODEL

With the model selection test, which is the main test of the study, the model with the lowest AIC and SC values in each sector is classified as the best model. The lag selection is determined according to the AIC and SC selection criterion. Lag selection varies for each model; for the ARCH model, five lags were selected in order to achieve low AIC values. For the GARCH (1, 1), TGARCH/GJR (1, 1) and EGARCH (1,1) models, only one lag was selected in each model.

The GARCH model described in Table 5.5 is the GARCH 1, 1 model. The 1, 1 is a standard notation in which the first number is an indication of how many autoregressive lags or ARCH terms exist in the equation. The second number is an indication of how many moving average lags are specified or the number of GARCH terms. Sometimes, models with more than one lag are required to determine favourable variance forecasts (Engle, 2000:8). However, in this chapter, only one lag was required to find good variance forecasts and compare to other models. Using one lag is motivated from the main finding of Hansan and Lunde (2005) that there was no material evidence showing that other models outperformed the GARCH (1, 1) model. Samouilhan and Shannon (2008) found that for their out-of-sample results, the GARCH (1, 1) model specification produced the best forecast of all asymmetric models in comparison to GARCH (1, 2), (2, 1) and (2, 2) models.

Table 5.5: Model selection

Sector	**GARCH (1, 1)**		**TGARCH/GJR**	**EGARCH**
Industrials	AIC	-6.366	-6.377	-6.373
	SC	-6.358	-6.368	-6.368
Consumer goods	AIC	-5.799	-5.814	-5.814
	SC	-5.792	-5.805	-5.805
	HQ	-5.797	-5.811	-5.811
Financial sector	AIC	-6.227	-6.279	-6.281
	SC	-6.266	-6.271	-6.272
Basic materials sector	AIC	-6.266	-6.279	-6.278
	SC	-6.259	-6.270	-6.269
Consumer services	AIC	-6.192	-6.198	-6.196
	SC	-6.185	-6.189	-6.187

Source: Own estimate

The best fit model from Table 5.5 is selected based on the criteria of having the lowest AIC and SIC values. From Table 5.5, it can be observed that each sector has the best fit model according to the lowest AIC and SIC values:

- In the industrials sector- the TGARCH model was the best fit model.
- In the consumer goods sector- the EGARCH model was the best fit model.
- In the financial sector- the EGARCH model was the best fit model.
- In the basic materials sector- the TGARCH model was the best fit model.
- In the consumer services sector- the TGARCH model was the best fit model.

For confirmation of the best model in case of conflicting results, another minimising criterion can be used, which is the Hannan-Quinn (HQ) criteria, which confirms that the best model is between the TGARCH and EGARCH model, as both models resulted in the lowest AIC and SIC value. The empirical objective of identifying the best model for modelling volatility in each of the top five JSE sectors was successfully met. TGARCH and EGARCH models are known as asymmetric models that can deal with leverage effects. Leverage effects are the tendency for volatility to increase followed by a large price decrease then followed by a price increase of the same degree (Brooks, 2014:416). Fischer Black was the first researcher who studied the relationship between equity and volatility. Fisher observed that implied volatility and historical volatility of individual stocks increase when stock prices decrease (Black, 1976:179). This study was conducted using large time intervals and found that the effect was very significant. Fisher then observed the relationship of the leverage effect (Bouchaud *et al*., 2001:2287). Therefore, the TGARCH and EGARCH models are best known for considering the leverage effect.

Some studies have compared GARCH models and reported similar volatility capturing models to this study as their best fit models. The study of Zamani (2015) showed that the JSE ALSH and all other indices were best modelled by GARCH (1, 1) and out-of-sample for JSE ALSH proved to be best for GARCH (1, 1). In forecasting out-of-sample, EGARCH proved to outperform other forecasting models based on different procedures for JSE ALSH. The GJR/ GARCH model was the best model for Resources 20 and the industrial data suggested PGARCH. Meanwhile, the study of Kgosietsile, (2014) discovered that the EGARCH model outperformed all other GARCH models in modelling and forecasting volatility. The study found that the explanatory power of the EGARCH model on out-of-sample realised volatility is enhanced when its predictions are combined with predictions from the South African Volatility Index (SAVI).

Section 5.10 tests the models volatility levels and which sector is the most volatile. Section 5.10 determines whether the TGARCH and EGARCH models successfully meet the requirements of being the best volatility models. Diagnostic checking is done in Table 5.6. If any of the models fail the diagnostic test, the distribution can be changed. For example, instead of using the Gaussian, the student distribution can be used, and if this does not address the problem, then the next best model is considered (Pollard, 1998).

5.10 VOLATILITY DETERMINATION

A volatility determination test is done to determine which sector is the most volatile according to the equation criterion. The equation criterion was applied for each sector, and the results are in Table 5.6 and are further discussed below.

Table 5.6: Volatility determination

	Industrials	Consumer goods	Financial	Basic materials	Consumer services
Ꞷ	4.10E-06***	2.02E-06***	3.10E-06***	2.55E-06***	1.32E-06***
α	0.107661***	0.068439***	0.109770***	0.099145***	0.077335***
β	0.858319***	0.923489***	0.868455***	0.883965***	0.915833***
Ø	-	-	-	-	-
α + β	0.9659	0.9919	0.9782	0.9831	0.9931

Source: Own estimate

In Table 5.5, under model selection, for the industrial sector, the best model is TGARCH, for the consumer goods sector, the best model is EGARCH, for the financial sector, the best model is EGARCH, for the basic materials sector, the best model is TGARCH and for consumer services sector, the best model is TGARCH.

The leverage effect is present in each sector. The leverage effect (α + β) in the consumer good and consumer services sectors are significant and less significant in the industrial, basic materials and financial sectors. This means that when the returns of a sector decrease, volatility increases and *vice-versa*. For example, if the returns in the consumer goods decrease, volatility increases. The sum of the coefficients (α + β) in Table 5.6 is greater than zero, which is very significant, signalling that positive news provides more positive returns than negative news of the same extent.

The level of volatility can be determined through:

var $(\mu_t) = \alpha_0 / 1 - (\alpha_1 + \beta)$

$\alpha_1 + \beta < 1$, needs to be maintained if $\alpha_1 + \beta > 1$, the model cannot be proceeded with and the model is explosive.

Both TGARCH and EGARCH models can be proceeded within all the top five JSE sectors because the models are too explosive and are all <1.

The results of this study reveal that JSE consumer goods is the most volatile sector compared to the JSE financials, industrials, basic materials and consumer services sectors. Great volatility exists within consumer goods and consumer services sectors due to growing demand from consumers for goods and as demand increases so does the consumer goods sector because, in reality, these two sectors are utilised daily by end consumers, which results in high volatility periods in these sectors. Volatility periods are seasonal, for example, the consumer goods sector can be volatile during the festive season, which is when most consumers get bonuses and 13th cheques and consumer demand for goods increases (Niels & Lensink, 2013). The more money consumers have at their disposal; the more consumers tend to spend on luxury items like going on holiday (consumer services) and buying clothing and food (consumer goods) while on holiday. This goes back to the point that these two sectors complement each other.

5.11 DIAGNOSTIC CHECKING OF THE SELECTED MODELS

Diagnostic tests aim to test the ARCH models for different mis-specifications, for example, the ARCH effect, serial correlation and normality test. A diagnostic checking test is done to determine if the TGARCH and EGARCH models successfully meet the requirements of being the best volatility capturing models. This is achieved when there is no ARCH effect, no serial correlation and there is normal distribution. The null hypotheses of these tests are as follows:
If ($p<0.05$) the null hypothesis (no ARCH effects) is rejected.
If ($p<0.05$) the null hypothesis (no serial correlation) is rejected.
If ($p<0.05$) the null hypothesis (residuals are normally distributed) is rejected.

Table 5.7: Diagnostic checking: EGARCH and TGARCH model

Sector	**Industrials**	**Consumer goods**	**Financials**	**Basic materials**	**Consumer services**
Model	TGARCH	EGARCH	EGARCH	TGARCH	TGARCH
ARCH effect	p-value: 0.7036	p-value: 0.4060	p-value: 0.4060	p-value: 0.7036	p-value: 0.7036
Serial correlation	p-value: 0.00	p-value: 0.00	p-value: 0.00	p-value: 0.00	p-value: 0.00
Normality	p-value: 0.00	p-value: 0.00	p-value: 0.00	p-value: 0.00	p-value: 0.00

Source: Own estimate

For the ARCH effect, each sector has its own volatility model to determine whether the models have ARCH effects or not. As a result, all p-values in each sector are >0.05. Therefore, there are no ARCH effects. TGARCH and EGARCH models do not have ARCH effects.

For serial correlation, all p-values are $0.000<0.05$; this means that the null hypothesis is rejected and there is serial correlation in each sector. For the normality test in each sector ($p=0.000<0.05$) reject the null hypothesis at 0.05 level of significance. Therefore, residuals are not normally distributed in each sector. Residuals that are not normally distributed are not a problem in GARCH models because GARCH models are not sensitive to normality; therefore, non-normally distributed residuals can be acceptable in GARCH models. However, there are models that are robust to normality to conduct tests such as equal variances (Ogee & Ellis, 2018). In conclusion, both the EGARCH and TGARCH models have ARCH effects. Results indicate that there is serial correlation and the residuals are not normally distributed in the sectors. The study of Gao *et al*. (2012:1971) declared results where the series did not have normal distribution and only considered the use of a different GARCH model to dispose of the leptokurtosis and fat-tail distributions. Normal distributions are not common, they have been tried on stock returns, but did not work well (Aksakal, 2015). It is not mandatory to have normally distributed residuals in GARCH models (White, 2016). The preferred outcome is when a model has no ARCH effects, no serial correlation and residuals are normally distributed. However, even when the model does not meet the desired outcome, as in this study, the model can still be used to conduct further tests.

5.12 RISK PREMIUM

The GARCH-M models assist in understanding the risk premium, which is denoted by δ in the specification of conditional mean in the methodology. The extent of the risk premium is important as the sign of it in the model; this includes standard deviation or the square root of GARCH in mean equation (GARCH-M). If the coefficient is positive and statistically significant ($p<0.05$), this means that the increased risk stemming from an increase in the conditional mean provides an increase in mean return. This means that investors are being compensated for a higher risk taken (Appiah-Kusi & Menyah, 2003:250). If the coefficient is negative and statistically insignificant ($p>0.05$) this means that investors are not being compensated for assuming more risk. Results that follow indicate whether a sector has a risk premium or not. The risk premium term in the conditional mean equation helps to determine the statistical significance of a coefficient.

Table 5.8: Summary of risk premium coefficients

Sector	Risk premium coefficient	P-value
Industrial	0.1007310	0.9147
Financial	0.313967	0.0000
Consumer goods	0.029624	0.5894
Basic materials	0.044268	0.4375
Consumer services	0.017966	0.7405

Source: Own estimate

p>0.05- coefficient is insignificant

p<0.05- coefficient is significant

In the industrial sector, the p-value is 0.9147, meaning that there is no risk premium in the returns. The risk premium term (SQRT GARCH) in the conditional mean equation is insignificant. This means that investors are not being compensated for assuming more risk. In the financial sector, the p-value is 0.0000, meaning that there is a risk premium in the returns. The risk premium term (SQRT GARCH) in the conditional mean equation is significant. This means that investors are being compensated for a higher risk taken. In the consumer goods sector, the p-value is 0.5894, meaning that there is no risk premium in the returns. The risk premium term (SQRT GARCH) in the conditional mean equation is insignificant. This means that investors are not being compensated for assuming more risk. In the basic materials sector, the p-value is 0.4375, meaning that there is no risk premium in the returns. The risk premium term (SQRT GARCH) in the conditional mean equation is insignificant. This means that investors are not being compensated for assuming more risk. In the consumer services sector, the p-value is 0.7405, meaning that there is no risk premium in the returns. The risk premium term (SQRT GARCH) in the conditional mean equation is insignificant. This means that investors are not being compensated for assuming more risk.

The study of Mahieu (2007) and Ichiue and Koyama (2008) main findings was that risk premium is significant in most countries. Including the risk premium in the uncovered interest parity (UIP) condition improves on the original model, as the coefficient is much more significant with a risk premium included in the model than in the basic ordinary least squares (OLS) model , although UIP still does not hold in many countries. UIP implies that the interest rate differential should be equal to the exchange rate change.

This result implies that risk is an important part of modelling the exchange rate and needs to be considered in both empirical and theoretical models. The study also finds that in general emerging countries work better in terms of UIP and the inclusion of the risk premium than developed countries. The coefficients in emerging countries like South Africa, Brazil and Thailand are positive and close to unity. In conclusion the CGARCH-M (component generalised autoregressive conditional heteroscedasticity in mean) model works better with UIP, in terms of modelling the risk premium as it considers both the long-run and short-run volatility components. Risk premium findings of Mahieu (2007) and Ichiue & Koyama (2008) was applied to exchange rate changes using GARCH-M and CGARCH-M models where else this study applied risk premium to the top five JSE sectors using the ARCH/GARCH models.

5.13 SPILL-OVER TEST USING DCC

The dynamic conditional correlation (DCC) is used to test if there is a volatility spill-over across the top five JSE sectors. The need for DCC is to identify the co-movement between the different JSE sectors (an indication of spill-over effect).

Results from Section 5.13 are obtained from a Two-Step Asymmetric DCC (1, 1) model with univariate GARCH fitted model. Dynamic conditional correlation with correlation targeting is determined between the JSE sectors. The stability condition between the sectors is met because the coefficients are less than one. If the coefficients were greater than one that would indicate that there is no co-movement between the sectors. As a result, the empirical objective of determining spill-over effect across the JSE sectors has been identified. Table 5.9 is an output of the basic materials correlated to the consumer goods, consumer services, financial and industrial sectors to identify co-movement between the sectors.

Table 5.9: Basic materials sector output (dependent variable)

	Basic materials to consumer goods sector	**Basic materials to consumer services sector**	**Basic materials to financial sector**	**Basic materials to industrial sector**
C (1) = μ **Coefficient** **Sig.**	0.1000 0.000	0.1000 0.000	0.1000 0.000	0.1000 0.000
C (2) = β **Coefficient** **Sig.**	0.850 0.000	0.850 0.000	0.850 0.000	0.850 0.000
C (3) = α **Coefficient** **Sig.**	0.000 0.000	0.000 0.000	0.000 0.000	0.000 0.000

Source: Own estimate

The correlation coefficients are below one and the p-values are 0.000. P-values add to the significance of the correlation between the sectors. Using the significance level of 0.05 as a benchmark, $p>0.05$ indicates no correlation coefficient significance and $p<0.05$ indicates correlation coefficient significance. Therefore, there is a correlation coefficient significance between the sectors. When there is correlation coefficient significance between the sectors, it creates possible causes of volatility spill-over between the sectors. This simply means that volatility in one sector can influence the other sector to have volatility as well. This is a result of correlation between the sectors. Coefficients of 0.1000 and 0.850 are high, therefore, eliminating diversification opportunity; coefficients of 0.000 are low, therefore, presenting diversification opportunity.

Table 5.10: Consumer goods sector output (dependent variable)

	Consumer goods to basic materials sector	**Consumer goods to consumer services sector**	**Consumer goods to financial sector**	**Consumer goods to industrial sector**
C (1) = μ **Coefficient** **Sig.**	0.1000 0.000	0.1000 0.000	0.1000 0.000	0.1000 0.000
C (2) = β **Coefficient** **Sig.**	0.850 0.000	0.850 0.000	0.850 0.000	0.850 0.000
C (3) = α **Coefficient** **Sig.**	0.000 0.000	0.000 0.000	0.000 0.000	0.000 0.000

Source: Own estimate

Table 5.10 is an output of the consumer goods sector correlated to the basic materials, consumer services, financial and industrial sectors to identify co-movement between the sectors. The correlation coefficients are below one, and the p-values are 0.000. P-values add to the significance of the correlation between the sectors. Using the significance level of 0.05 as a benchmark, $p>0.05$ indicates no correlation coefficient significance, $p<0.05$ indicates correlation coefficient significance. Therefore, there is correlation coefficient significance between the sectors. When there is correlation coefficient significance between the sectors, it creates possible causes of volatility spill-over between the sectors. This simply means that volatility in one sector can affect the other sector. Coefficients of 0.1000 and 0.850 are high, therefore, eliminating diversification opportunity; coefficients of 0.000 are low, therefore, presenting diversification opportunity.

Table 5.11: Consumer services sector output (dependent variable)

	Consumer services to basic materials sector	Consumer services to consumer goods sector	Consumer services to financial sector	Consumer services to industrial sector
C (1) = μ Coefficient Sig.	0.1000 0.000	0.1000 0.000	0.1000 0.000	0.1000 0.000
C (2) = β Coefficient Sig.	0.850 0.000	0.850 0.000	0.850 0.000	0.850 0.000
C (3) = α Coefficient Sig.	0.000 0.000	0.000 0.000	0.000 0.000	0.000 0.000

Source: Own estimate

Table 5.11 is an output of the consumer services sector correlated to the basic materials, consumer goods, financial and industrial sectors to identify co-movement between the sectors. The correlation coefficients are below one and the p-values are 0.000. P-values add onto the significance of correlation between the sectors. Using the significance level of 0.05 as a benchmark, $p>0.05$ indicates no correlation coefficient significance, $p<0.05$ indicates correlation coefficient significance. When there is correlation coefficient significance between the sectors, it creates possible causes of volatility spill-over between the sectors. This simply means that volatility in one sector can affect the other sector. Coefficients of 0.1000 and 0.850 are high, therefore eliminating diversification opportunity; coefficients of 0.000 are low, therefore, presenting diversification opportunity.

Table 5.12: Financial sector output (dependent variable)

	Financial to basic materials sector	Financial to consumer goods sector	Financial to consumer services	Financial to industrial sector
C (1) = μ Coefficient Sig.	0.1000 0.000	0.1000 0.000	0.1000 0.000	0.1000 0.000
C (2) = β Coefficient Sig.	0.850 0.000	0.850 0.000	0.850 0.000	0.850 0.000
C (3) = α	0.000	0.000	0.000	0.000

Coefficient Sig.	0.000	0.000	0.000	0.000

Source: Own estimate

Table 5.12 is an output of the financial sector correlated to the basic materials, consumer goods, financial and industrial sectors to identify co-movement between the sectors. The correlation coefficients are below one and the p-values are 0.000. P-values add onto the significance of the correlation between the sectors. Using the significance level of 0.05 as a benchmark, p>0.05 indicates no correlation coefficient significance, p<0.05 indicates correlation coefficient significance. Therefore, there is correlation coefficient significance between the sectors. When there is correlation coefficient significance between the sectors, it creates possible causes of volatility spill-over between the sectors. This simply means that volatility in one sector can affect the other sector. Coefficients of 0.1000 and 0.850 are high, therefore, eliminating diversification opportunity; coefficients of 0.000 are low, therefore, presenting diversification opportunity.

Table 5.13: Industrial sector output (dependent variable)

	Industrial to basic materials sector	**Industrial to consumer goods sector**	**Industrial to consumer services**	**Industrial to financial**
C (1) = μ Coefficient Sig.	0.1000 0.000	0.1000 0.000	0.1000 0.000	0.1000 0.000
C (2) = β Coefficient Sig.	0.850 0.000	0.850 0.000	0.850 0.000	0.850 0.000
C (3) = α Coefficient Sig.	0.000 0.000	0.000 0.000	0.000 0.000	0.000 0.000

Source: Own estimate

Table 5.13 is an output of the industrial sector correlated to the basic materials, consumer goods, consumer services and industrial sectors to identify co-movement between the sectors. The correlation coefficients are below one and the p-values are 0.000. P-values add onto the significance of the correlation between the sectors. Using the significance level of 0.05 as a benchmark, p>0.05 indicates no correlation coefficient significance, p<0.05 indicates correlation coefficient significance. In summarising the co-movement between the sectors, some sectors are highly correlated and those that are less correlated (Evans & McMillan, 2006).

Highly correlated sectors eliminate diversification opportunity because investor returns are minimised. Therefore, the investor's portfolio is not large enough to be diversified. Less correlated sectors encourage diversification opportunity because investor returns are maximised. Therefore, the investment portfolio is large enough to be diversified (Lioudis, 2018). When there is correlation coefficient significance between the sectors, it creates possible causes of volatility spill-over between the sectors. This simply means that volatility in one sector can affect the other sector. Coefficients of 0.1000 and 0.850 are high, therefore, eliminating diversification opportunity; Coefficients of 0.000 are low, therefore, presenting diversification opportunity.

In conclusion to the dynamic conditional correlation among the JSE sectors, three model specifications were examined: the asymmetric GARCH specification, the asymmetric GARCH model with volatility risk premium and the asymmetric parametrisation for the GARCH model (Papantonis, 2016:12). It can be estimated that the three model specifications with the univariate GARCH model can be viewed in two ways: first, the likelihood components can be considered of the returns and uncorrelated volatility and, secondly, provision for contemporaneous correlation between the sectors returns (Carr & Wu, 2009:1320). The results in Section 5.11 are a result of a two-step estimation approach that disregards the theoretical parameterisation of the underlying pricing. The two-step estimation process provides a more practical idea of the two processes by recovering the physical and risk-neutral parameters of the GARCH model constructively.

5.14 SUMMARY

Chapter five aimed to illustrate and discuss the empirical results determined in the study. The primary aim of this chapter was to determine, which top five JSE sectors are the most volatile using the ARCH/GARCH volatility models. Furthermore, the study used various volatility testing methods to get the most volatile sector and the most favourable model. This chapter aimed at addressing the following empirical objectives:

- Identify the model best fit for modelling volatility in each of the top five sectors of the JSE;
- Estimate the level of volatility in each of the top five sectors of the JSE
- Compare the level of volatility across the top five sectors of the JSE;
- Determine stationarity across the JSE sectors; and
- Determine the correlation of dynamic conditional correlation among the JSE sectors.

The chapter provided a preliminary analysis of the returns of each JSE sectors. The results vary from sector to sector because different tests were conducted. From the preliminary analysis, the consumer goods sector was the most volatile sector. This type of sector is most suitable for aggressive risk investors, seeking greater returns and willing to take the risk of a volatile sector.

The model selection was to identify the best fit model for modelling volatility in each of the top five JSE sectors. From the model criteria of having the lowest AIC and SC values, the EGARCH and TGARCH models proved to be the best volatility models in either one of the sectors. The diagnostic checking test is done to determine if the TGARCH and EGARCH models successfully meet the requirements of being the best volatility models. Descriptive statistics describe each sector mean, standard deviation, minimum value, maximum value, skewness, kurtosis, Jarque-Bera and p-value. The outcome for each sector was different and thoroughly explained. Descriptive statistics do not allow conclusions to be made beyond the data presented; this prevents assumptions on results presented.

In this study stationarity (unit root) was found in levels. Therefore, it was not necessary to continue to first or second difference to find stationarity. This means that the results of this study are not spurious because non-stationarity variables produce spurious results. The volatility determination test also revealed that JSE consumer goods are the most volatile sector compared to the JSE financials, industrials, basic materials and consumer services sectors. The volatility determination test revealed the level of volatility of each model and its explosiveness. The more explosive a model is, the higher the risk of proceeding with the model. The DCC is used to test if there is a volatility spill-over across the top five JSE sectors. The need for DCC is to identify the co-movement between the different JSE sectors. Results of this chapter regarding the best volatility model indicated two models as the best volatility capturing models for the top five JSE sectors. The results established in this chapter indicate that the EGARCH and TGARCH models are the best volatility capturing models. In conclusion, the JSE consumer goods sector is the most volatile sector due to its standard deviation value and the deviation of this sector’s returns to its mean value; standard deviation is the most accurate measure of volatility.

The implication of the results in this chapter comes from the model selection. Instead of one main best fit model, there are two best fit volatility models, namely the TGARCH and EGARCH models. This is not conflicting because both models are asymmetric models and are extensions of the GARCH models.

A similar study by Masinga (2015) modelled and forecasted stock return volatility in the JSE. Using daily returns on the JSE All Share Index (ALSH), Industrial 25 Index, Resource 10 Index and Top 40 Index in the model selection, results revealed that for the JSE ALSH GARCH (1, 1) model performed best in modelling volatility. AIC, SBIC and HQ suggested EGARCH for ALSH and Top40 indices. Resources 20 Index suggested that GJR/ TGARCH was the best model and Industrial 25 data suggested PGARCH.

CHAPTER 6: SUMMARY, CONCLUSION AND RECOMMENDATIONS

6.1 INTRODUCTION

Volatility plays a vital role in different financial applications, such as hedging, economics and calculating measures of risk. Volatility is seen as the relative rate at which market prices fluctuate around the expected value. Stock market volatility is a topic of great interest for investors, practitioners and researchers.

Volatility tends to make investors more cautious, causing them to hold onto stocks. As a result, for protection against uncertainty, investors demand a higher risk premium. Increased risk premium leads to an increased cost of capital, which in turn results in lower individual investment. Therefore, modelling and forecasting volatility progresses the importance of measuring the fundamental value of securities. In this process, it becomes convenient for money to be raised in the market by companies. Identifying volatility guides an enhanced way to take strategic investment strategies. It is ideal for investors to have an idea of how the stock market performs and use volatility as a tool or indicator for guidance.

The theoretical framework for modelling volatility goes as far back as when the original ARCH model was developed, which captured the variability of time variance returns by suggesting an autoregressive structure on the conditional moment of returns. The GARCH model is an extension of the ARCH model. The GARCH model further extended the ARCH model by including lagged conditional variance terms as additional regressors. In this study, various univariate GARCH models were estimated, including ARCH, GARCH (1, 1), EGARCH and GJR/ TGARCH models. The purpose of these estimated models was to reveal that volatility clustering and leverage effects characterise the JSE stock market returns. This chapter aims to highlight the theoretical and empirical objectives achieved in each chapter.

6.2 SUMMARY AND REALISATION OF OBJECTIVES

The study aimed to determine the level of volatility within each JSE sector. The study went on to review previous studies on volatility. The study then tested the volatility level of each JSE sector in order to determine the most volatile sector. In order to test the volatility level, the study utilised the univariate GARCH models. The JSE sectors were compared against each other; as a result, the most volatile sector can be used as a benchmark to guide investors for investment decisions. The best model was selected through the use of different information criteria, namely the Akaike information criterion (AIC), Bayesian information criterion (BIC), also known as the Schwarz information criterion (SIC) and Hannan–Quinn (HQ). The model with the lowest AIC, SIC and HQ values in each sector was classified as the best model.

Chapter 1 introduced the study and reasoning for researching the problem statement. A link was established between volatility and sector returns. For the primary objective to be achieved of modelling and determining the most volatile sector in the top five JSE sectors, the volatility models were utilised in order to determine the volatility level of each sector.

Chapter 2 discussed the concept of volatility, characteristics of volatility, types of volatility, indicators of volatility, the purpose of volatility and, lastly, the influence of return volatility on the stock market on investment decisions. The chapter also discussed how a highly volatile sector triggers higher expected return. This chapter met the theoretical objectives of analysing the concept, characteristics, types, indicators and purpose of volatility as well as determining the influence of return volatility in the stock market on investment decisions.

The concept of volatility in the context of the stock market has become of massive importance to market participants in the financial markets. Volatility is associated with risk; increased volatility is perceived to have increased risk, triggering market disruption. Characteristics of volatility have the potential to increase the accuracy of predicted values because market variables are not constant. There are various types of volatility, namely historical, relative and implied volatility. These volatility types are associated with the behaviour of each volatility type in the stock market. The need for various indicators of volatility, namely standard deviation, beta, R-square and alpha were discussed. These indicators are measures of volatility that help investors determine the risk-reward parameters of their investments. It is important that the ARCH/ GARCH volatility models achieve their purpose of being able to model and forecast volatility. The level of the volatility forecasted influences investors' investment decisions. The level of volatility captured has the potential of attracting risk-aggressive (high-risk appetite) or risk-averse (low-risk appetite) investors depending on the investors risk appetite.

Empirical studies reviewed in this paper focused on the trend of volatility, therefore, it is evident that volatility exists in stock markets and expected market returns are dependent on the performance of the particular stock market in which investors wish to invest.

Chapter 3 successfully achieved the following theoretical objectives, reviewed the sectoral analysis of the South African JSE sectors. The emphasis of Chapter 3 was on the top five sectors, emphasising the historical trends of the South African stock market. The influence of macroeconomic variables on investment was discussed. Lastly, the top five sectors were unpacked in a sense of how individual investment in each sector is affected by the main macroeconomic variables: real GDP, inflation and interest rates. These three main macroeconomic variables drive the performance of each sector, in turn impacting the economic growth of the South African economy.

Macroeconomic factors do not only affect the South African economy but also investors that invest in the South African economy. A positive relationship exists between macroeconomic factors impacting investment decisions and the macroeconomic environment. This relationship implies that companies with increased investment reductions become less attractive to investors and value the factors influencing these investment decisions. Investment decisions are very important to the performance of an economy. Through previous similar studies, there has not been clear evidence as to which sector provides the highest return. However, this study can provide guidance to investors based on the results achieved from using the ARCH/ GARCH models, as to which model is the best volatility-capturing model. As a result, the most volatile sector provides the highest return, which is precisely the investment intention of most investors.

Chapter 4 made use of the ARCH/ GARCH models and their model extensions to determine the most volatile JSE sector from the top five selected sectors according to their market capitalisation. A panel of 3501 daily observations from 2002 to 2015 were used to analyse the most volatile sector. This chapter followed a quantitative approach to analyse the top five JSE sectors and the volatility forecasting models, which were used in Chapter 5 to determine the most volatile sector.

Chapter 4 also focused on the original ARCH model and its model extensions to the GARCH, TGARCH/ GJR and EGARCH models. The ARCH and GARCH models are aimed to handle issues like the variance of error terms, heteroscedasticity and volatility clustering. These models are used on a large scale for handling time-series heteroscedastic models. The main aim of these models is to provide a volatility measure, for example, standard deviation. The volatility measure can then be used in making financial decisions affecting the analysis of risk and selection of portfolios for investors. ARCH/ GARCH models have been found very useful, especially when it comes to analysing or forecasting volatility. This study only forecasted the level of volatility of each of the top five JSE sectors.

The ARCH model is not flexible enough to capture the persistence in volatility. There is not much tangible proof that the GARCH model is outperformed. When the ARCH family of competing models are compared to each other, it is seldom found that some of the models outperform the GARCH model. To some extent, this was unexpected in this study because the GARCH model could not generate a leverage effect; hence, the extension of the TGARCH/ GJR and EGARCH models.

Chapter 5 achieved all four empirical objectives of the study. The various volatility-capturing models have created debates in the past, with various theories opposing which model is the best volatility-capturing model. In Chapter 5, several tests were conducted in each sector to determine the most volatile sector. In summary of the conducted tests, the descriptive statistics introduced the data in a more meaningful way. Correlation analysis measured the strength of the top five JSE sectors. The preliminary investigation displayed a brief analysis of the performance of each sector between 2002 and 2015. Unit root testing determined whether the results of this study were stationary or not. Results of this study indicated stationarity level, which means that the results are not spurious where else non-stationarity indicates spurious results. It is important to determine ARCH effects in all mean equations before estimating and selecting the best volatility capturing model. The volatility determination section determined the most volatile sector as per the econometrics equation criterion (Brooks, 2014). Diagnostic tests were used to confirm if the estimated models were robust. The risk premium estimation for each sector was to estimate the best model in the mean. Lastly, the spill-over test was the last empirical objective which was achieved using the DCC model was to test the movement amongst the sectors.

Results presented in Chapter 5 revealed two models as the best volatility-capturing models. The results established in this chapter indicate that the EGARCH and TGARCH models are the best volatility capturing models, this was the first empirical objective met. In conclusion, the JSE consumer goods sector is the most volatile sector due to its standard deviation value and the deviation of this sector's returns to its mean value; the standard deviation is the most accurate measure of volatility. This was the second empirical objective which was achieved. The third empirical objective was to compare the level of volatility across the top five sectors of the JSE, this was met by using the standard deviation as an accurate measure of volatility across all sectors.

6.3 CONCLUSION

This study aimed to determine the most volatile sector in the top five JSE sectors. The study showed that various volatility-capturing models can be used to measure the level of volatility. The study further made a comparison between the sectors by conducting various tests, as indicated in Chapter 5. The salient findings in this study indicated that in descriptive statistics for all sectors, p-values were significant at 0.05, therefore, concluding that residuals are not normally distributed. The JSE consumer goods sector, has greater standard deviation than the JSE industrial, financial, basic materials and consumer services sectors, which means that the consumer goods sector is more volatile than the other four sectors; the standard deviation is an effective measure of volatility. The correlation analysis showed that there is a linear relationship between some of the JSE sectors because the sectors compared to each other have a correlation of one. There is no linear relationship between some of the JSE sectors when the correlation is zero. Unit root testing is a stationarity test; the above tests were conducted because the stationarity of a series can strongly impact the behaviour and properties of a series, which can result in series being spurious because of non-stationarity. Therefore, the results of this study indicated that JSE sectors' series is stationary at level, meaning that the series used in this study is not spurious.

The ARCH effect test results showed that for all JSE sectors, p-values were less than the significance level of 0.05, meaning a null hypothesis can be rejected. Therefore, all JSE sectors have ARCH effects. For model selection, the model with the lowest AIC and SC values in each sector is classified as the best model. The lag selection is determined according to the AIC and SIC selection criterion. The Hannan-Quinn (HQ) criteria confirmed that the best model is between the TGARCH and EGARCH models, as both models resulted in the lowest AIC and SIC value. The risk premium test was to determine the statistical significance of a coefficient for each sector. All the sector coefficients were significant except for the financial sector. The dynamic conditional correlation between the JSE sectors showed stability and co-movement because all p-values were significant at a 0.05 significance level.

6.4 LIMITATIONS AND RECOMMENDATIONS

This study did not examine the JSE sectors that did not contribute the highest toward market capitalisation. Additionally, the study did not use all the GARCH model extensions to determine the level of volatility in each JSE sector due to time constraints. Therefore, further research can analyse all the JSE sectors and explore other GARCH model extensions. This study can be conducted in countries where activities or financial decisions made in the respective country can impact the South African economy. This study only focused on the top five JSE sectors according to market capitalisation and not all ten sectors that the JSE is made up of. To conduct the level of volatility in a sector, various other model extensions of GARCH can be employed, which might be more effective measures of volatility.

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ANNEXURE A: ETHICS CLEARANCE DOCUMENT

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VAAL TRIANGLE CAMPUS

FACULTY OF ECONOMIC SCIENCES AND INFORMATION TECHNOLOGY

ETHICS CLEARANCE DOCUMENT

Dissertation (M)	X
Thesis (PhD)	
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SUPERVISOR						
Study Leader / Promoter / Author(s)	MS SJ Ferreira					
STUDENT / AUTHOR						
Name	K Makoko					
Student / Staff Number	23569395					
Registered Title of Dissertation or Thesis or Project Title of Article	Modelling return volatility on Johannesburg Stock Exchange sectors					
School	Accounting		Economics	X	Information Technology	
ETHICAL CLEARANCE						
Ethics clearance number	ECONIT-2017-020					
Date (of Ethics Sub Committee Meeting)	5 May 2017					

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CHAIRPERSON: ETHICS COMMITTEE

10 May 2017 ....
DATE

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RESEARCH DIRECTOR

10 May 2017 ....
DATE