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# EQUITY PRICE PREDICTIONS OF SELECTED AFRICAN EMERGING MARKETS

by

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# Abstract

Predicting equity share prices could be useful to various stakeholders. The common methods used to forecast equity share price besides the naïve model are the Autoregressive Conditional Heteroskedasticity (ARCH) and General Autoregressive Conditional Heteroskedasticity (GARCH) models, however, no conclusion has been reached as to which model produces the most accurate predictions. In this research, ARCH and GARCH forecasting models (and their extended variants), as well as the Monte Carlo Simulation, were used to forecast price-weighted equity indices that were constructed from the South African, Nigerian, and Kenyan share markets. These three countries were selected based on their significance in the African continent due to the relative size of their economies and the liquidity of their share markets.

The daily closing share prices for companies listed on the FTSE/JSE Top 40 Index, NSE Top 30 Index, and the NrSE Top 20 Index were collected between the 4th of January 2010 and the 30th of June 2015. The companies that were selected from each of these indices to construct the price-weighted indices for each country, were based on criteria to eliminate bias.

Different autoregressive models were fitted for the mean equation. The EViews statistical programme was used to analyse the data. The ARCH effects were tested using the ARCH LM test. The ARCH/GARCH family models selected were GARCH (2,1), EGARCH (2,2), and EGARCH (2,1) for Nigeria, Kenya, and South Africa respectively.

A Monte Carlo Simulation with 1 200 iterations was also performed to forecast the equity share prices. Post estimation and performance evaluation metrics were performed using the RMSE, MSE, MAD, and MAPE. The results based on the evaluation metrics indicated that the ARCH/GARCH models in-sample forecasts were more accurate than out-of-sample forecasts. The accuracy of the ARCH/GARCH models' predictions was sounder than that of the Monte Carlo Simulation based on the evaluation metrics. Comparing the forecasting models to the actual graphs, in most cases the ARCH/GARCH models were closer to the actuals than the Monte Carlo

Simulation. The accuracy of the model predictions were also influenced by the sample size, the nature of the data, the leverage effect, and the macro economic conditions.

In conclusion, the African equity markets cannot be predicted accurately using the ARCH/GARCH models and the Monte Carlo Simulation. The predictions from the forecasting models are not sufficiently accurate for investors, traders, and company management to use to make informed decisions. However, these predictions are better than the naïve model. The researcher also concluded that the markets are efficient, as the publicly available information cannot be used to gain abnormal returns. This study's findings are similar to those of previous studies carried out in South Africa and globally.

# Key words

ARCH/GARCH models, emerging markets, forecasting, in-sample forecasts, out-of-sample forecasts, Monte Carlo Simulation, predictions.

# DECLARATION OF ORIGINAL WORK

I, Dunmore Kavenga, declare that this minor dissertation is my own unaided work. Any assistance that I have received has been duly acknowledged in the dissertation. It is submitted in partial fulfilment of the requirements for the degree of Master of Commerce at the University of Johannesburg. It has not been submitted before for any degree or examination at this or any other University.

____________________ ____________________

Signature Date

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# Chapter 1

# Introduction and Background to the Study

## 1.1 Introduction

Investing in emerging markets has attracted the attention of researchers and investors. Emerging markets' share price performance is often uncertain due to volatility. Forecasting the future share price performance is important to investors who wish to invest in emerging markets (Ahmed & Zlate, 2014).

### Emerging markets

Emerging markets refer to countries that have an increase in investments and social activities with increased growth and industrial development. These markets are characterised by an increase in domestic consumption and increasingly strong domestic economies. Their reliance on developed countries is reduced, since their trade is growing regionally with neighbouring countries (African Development Bank, 2011). Emerging markets are further characterised by improved domestic finance brought about by increased reserves and reduced government debt. Emerging markets are also characterised by growing infrastructure, such as new roads and other public infrastructure development that facilitates the increased demand of consumer goods and services, like computers and new technology. These developing countries pursue faster growth, and are expanding in terms of global trade and investment (Ahmed & Zlate, 2014).

### Emerging markets in Africa

All African countries are emerging economies. Over the past 20 years, the majority of these countries have experienced rapid economic growth characterised by an increase in their gross domestic product (GDP) and high returns on their investments (African Development Bank, 2011).

The three largest emerging markets in Africa, based on GDP, economic growth, and the liquidity of the markets, are Nigeria, South Africa, and Kenya (NSK) (Tignor, 2015). These three countries also have the highest stock exchange trading volume in Africa (African Securities Exchanges Association (ASEA), 2015). Therefore, these three countries are used in this study as a proxy for the African continent.

The NSK economies contributed more than 50% to the African continent's GDP (World Bank, 2016). Over the last 10 years, NSK have experienced significant economic growth and have received a significant portion of Africa's foreign direct investments (FDIs).

The continent's GDP is expected to grow from its current value of $5 trillion to $15 trillion by the year 2050. It is expected that commodities, services, and manufacturing will generate most of the growth (African Development Bank, 2011). In 2013 Africa was the fastest growing continent in terms of GDP, and its GDP growth is expected to increase by about 200% by 2050 (African Development Bank, 2011).



## 1.2 Background

In terms of the predictability of the equity share prices using statistical models, ambiguity arises out of the conflicting results in the studies that have used different forecasting models, and from the quality of data. No consensus has been reached regarding the best forecasting model, and the accuracy of the forecasts are influenced by micro and macro factors, such as size, the frequency of the data, and the country's economic conditions.

### 1.2.1 Emerging African markets

There has been rapid growth in African equity markets over the past 20 years, along with an increase in stock exchanges and the number of listed companies. The number of listed companies increased from approximately 1 200 in 2005 to approximately

1 900 in 2015, and 40% of the listed companies are from NSK (ASEA, 2015). The increased number of listed companies attracted FDI, and as a result, the FDI increased by approximately 70% to $57 billion between 2013 and 2014 (World Bank, 2016).

The continent's GDP has increased by more than 50% in the last 10 years to reach $3.3 trillion in 2015 (World Bank, 2016). The African continent, as represented by NSK, has diversified economies, and in 2015 the continent had an estimated population of 1.19 billion people, which is expected to increase to 2.48 billion by 2050 (World Bank, 2016).

Since the early 2000s, the high returns on investments in emerging markets have attracted several foreign investors from abroad (Ahmed & Zlate, 2014). Africa is one of the popular emerging markets. According to Miyajima, Mohanty, and Chan (2015), the average return on investment in United States dollars (USD) over the past 10 years in emerging markets was above 12% per annum, compared to the average of 5% per annum in developed markets. Therefore, despite the high risk in emerging markets, investors find them attractive (Ahmed & Zlate, 2014). Predicting the performance of emerging markets assists both foreign and local investors to identify the markets with growth potential. Africa has become an investment hub; it attracts investors from all over the world (Bley & Saad, 2015).



Equity markets have experienced a high level of volatility in the past decade. During the global financial crisis (GFC), large institutions like the Lehman Brothers defaulted and were liquidated, leading to significant financial losses by investors in equity markets. The volatility and financial uncertainties have necessitated the importance for equity market predictions (Kinnunen, 2013).

Since the GFC between 2007 and 2009, modelling and predicting financial equity markets has received a significant attention from various stakeholders, including academics, regulators, investors, and company management (Kinnunen, 2013).

### 1.2.2 Forecasting models

According to the Random Walk Model, future share price movements are independent of historic share price movements, and previous share prices cannot be used to predict future share prices (Jensen & Bennington, 1970).

The Naïve Model is an approximating method in which the previous period's outcomes are used as the current period's predictions, without altering them or attempting to establish causal factors (Lewis-Beck & Rice, 1984). The model is used for comparison against the predictions from the better models (sophisticated models like ARCH/GARCH or Monte Carlo Simulation).

Equity market forecasting is one of the most intensely discussed issues of empirical finance. Three decades ago, financial economists claimed that equity market forecasting was possible (Franses & Van Dijk, 1996; Charles, 2010). Over the past three decades, various researchers in both developed and emerging markets have provided evidence of equity market predictability. The predictability of expected equity market prices has triggered investors' interest (Charles, 2010; Mwamba, 2011; Sensoy, Aras & Hacihasanoglu, 2015).

Forecasting equity prices is an important topic in both academic research and the financial sector. Researchers have developed models like the Autoregressive Moving Average (ARMA) Model, Autoregressive Conditional Heteroskedasticity (ARCH) model, and the Monte Carlo Simulation to predict future equity prices (Bollerslev, 1987; Engle, 1982b; Nelson, 1991). Before these forecasting models were developed, macroeconomic factors and Random Walk models were used to predict future prices. However, due to their weaknesses–such as the inability to take economic changes into account–the models were challenged, which led to the development of sophisticated models, such as ARMA and ARCH, to predict future equity market prices (Meese & Rogoff, 1983).

Currently, no accurate forecasting model exists in either the emerging markets or the developed markets (Kim & Shamsuddin, 2015). This study will determine whether the statistical modelling techniques (ARCH/GARCH models and the Monte Carlo Simulation) rather than the Random Walk model provide better results in predicting future equity prices in African markets, represented by NSK. The purpose of this study was to investigate whether or not the ARCH/GARCH models and Monte Carlo Simulations can be used to predict future equity prices in emerging markets.

The GFC and economic instability (including emerging markets) has increased the necessity for predicting future movements of share prices. The Naïve Model is a forecasting technique that uses previous actuals as a current forecast, without altering it. The debate regarding which forecasting model can better predict equity markets than the Naïve Model is still on-going (Franses & Van Dijk, 1996). There is limited literature on forecasting equity share prices in emerging markets, as many researchers have been more focussed on predicting share prices in developed markets.

This section provided the background to emerging markets and pointed out that improvements in emerging markets in recent years have attracted foreign investors. In the next section the efficient market hypothesis (EMH) will be reviewed, and forecasting models that challenge the EMH will also be discussed.

### 1.2.3 Efficient Market Hypothesis



The EMH is an investment theory that posits that it is impossible to outperform the market because share prices always incorporate and reflect all relevant information (Sewell, 2011). There are three forms of the EMH namely: the weak; semi-strong; and strong forms – depending on the level of information available.

Allen, Brealey, and Myers (2011) and Mishkin and Eakins (2012) conclude that the market efficiency and Random Walk Models are similar, but Timmermann and Granger (2004) and Sewell (2011) dispute this. According to the weak form of the EMH, current share prices reflect all the information contained in the history of the share prices. This information includes data on inflation, money supply, interest rates, information of a company's profit, and dividends paid. The implication is that historical share prices cannot be used to gain above average returns. The weak form of the EMH implies that forecasting that uses historical data cannot yield better predictions.

The semi-strong EMH implies that all public information is discounted into a stock's current share price, which implies that neither fundamental nor technical analysis can be used to achieve superior gains. The strong form of the EMH determines that the equity prices reflect public and private information. Private information is the information that is only accessible to company insiders (Malkiel & Fama, 1970).

Future equity prices are unknown to investors, traders, management teams, and policy makers. It is uncertain how equity markets and the general industry will perform in the future. Considering the GFC and economic changes, it would be beneficial if the future prices of equity, using forecasting models, could be predicted.

Researchers like Engle (1982a), Meese and Rogoff, (1983) and Bollerslev, Chou & Kroner (1992) challenged the EMH, claiming that econometric modelling techniques like ARMA and ARCH can predict share prices. In this study, ARCH/GARCH models and the Monte Carlo Simulation were used to predict equity market prices and the results were evaluated to confirm or contradict the EMH.

Policy makers in emerging markets can use the forecast results to guide them to make policies that benefit the economy and attract foreign investments. Accurate forecasting results could also guide policy makers and leaders in terms of future economic growth based on forecasted equity market prices (Kim & Shamsuddin, 2015).

In this study, the ARCH and GARCH models and the Monte Carlo simulations were used, and the data sample affected by the GFC was excluded as it might have affected the accuracy of the results. There is limited literature on emerging African markets that have used the Monte Carlo Simulation to forecast share prices. This research will add to the literature in this regard.

## 1.3 Findings from the literature review

The literature provided evidence that the accuracy of forecasting models can be influenced by factors such as the economic environment (Meese & Rogoff, 1983). According to Charles (2010), Mwamba, (2011), Smith and Dyakova (2014), and Bley and Saad (2015), asymmetric (advanced models like GARCH and E-GARCH) models are normally more accurate than the symmetric (simpler models like Random Walk and Naïve) models.

When the same forecasting models were used in different economies, the outcomes were different due to the nature of the economy and the quality of the data. Sophisticated forecasting methods proved to be more accurate than simpler methods, regardless of other factors (Samouilhan & Shannon, 2008; Ding & Meade, 2010; Cifter, 2012; Smith & Dyakova 2014; Bley & Saad, 2015).

The accuracy of the ARCH/GARCH forecasting models in comparison to the Monte Carlo Simulation is inconclusive, and the models have performed differently in developed and emerging markets. In the studies of developed economies, different conclusions about the forecasting accuracy of ARCH/GARCH forecasting models were reached. In developed markets, the ARCH/GARCH models were more accurate than the Monte Carlo Simulation (Kinnunen, 2013). Researchers have not used the Monte Carlo Simulation widely to make forecasts in emerging markets (Lux & Morales-Arias, 2013), and therefore, there is a literature gap regarding the accuracy of the Monte Carlo Simulations.



## 1.4 Problem statement

The existing literature indicates that most studies regarding the predictability of equity markets were performed in developed markets (Ding & Meade, 2010). There are limited studies regarding the predictability of equity prices in emerging markets, creating a literature gap, particularly for Africa as an emerging market. Since early 2000 there has been a significant increase in the flow of FDI into Africa, which necessitates evaluating the predictability of African equity markets (Ahmed & Zlate, 2014). Forecasting can help to identify potential investment destinations. Additional literature is required to add to the limited existing literature regarding the predictability of the markets, including African markets.

There is no known forecasting model to accurately forecast future equity prices (Smith & Dyakova, 2014; Ndwiga & Muriu, 2016). Studies that used the ARCH/GARCH models to forecast equity prices and volatility of the listed companies in emerging markets were performed by Gokcan (2000), Samouilhan and Shannon (2008), Botha and Pretorius (2009), Ding and Meade (2010), Cifter (2012), Smith and Dyakova (2014), Bley and Saad (2015), Jahufer (2015), and Ndwiga and Muriu (2016). However, these researchers did not reach consensus.

The data quality in forecasting is an important factor when predicting share prices because it enables reliable and credible forecasts (Samouilhan & Shannon, 2008; Botha & Pretorius, 2009; Ding & Meade, 2010; Cifter, 2012; Smith & Dyakova, 2014).

The ARCH/GARCH family models and the Monte Carlo Simulation were selected to investigate the share price predictability, and to add to the literature. Not many studies have used and compared ARCH/GARCH models and the Monte Carlo Simulation. The available literature is inconclusive regarding the accuracy of the models (Chong, Ahmad & Abdullah, 1999; Gokcan, 2000; Samouilhan & Shannon, 2008; Ding & Meade, 2010; Cifter, 2012; Dyakova & Smith, 2013; Ndwiga & Muriu, 2016).



Fama (1965) established that future returns follow the Naïve Model. However, in recent studies, it emerged that future market prices can be predicted using various forecasting models, but they do not follow the Naïve Model (Meese & Rogoff, 1983; Charles, 2010).

Post the GFC, there is a literature gap regarding the prediction models’ ability to simulate future equity prices in Africa. Current studies indicate that there is an on-going debate regarding the predictability of equity prices in emerging markets, and there is a need for further research in this regard.

The existing literature gap and the significant developments in emerging African markets show a necessity for new research to benefit various stakeholders. This research will be beneficial to various stakeholders such as academics and investors. In the next section, the research questions for this study are provided.

### 1.4.1 Research questions

In this study the following research questions were addressed:

1. Can ARCH/GARCH models and the Monte Carlo Simulation accurately predict equity prices of NSK?
2. Are the ARCH/GARCH models more accurate than the Monte Carlo Simulation?
3. Are the ARCH/GARCH models and Monte Carlo Simulation more accurate than the Naïve Model?

## 1.5 Purpose of the study

The purpose of the study was to investigate whether or not the African equity markets can be predicted accurately using the ARCH/GARCH models and the Monte Carlo Simulation. The study will be of use to various stakeholders including the following:

1. investors: this research is significant to both local and foreign investors as it will allow them to make informed decisions about the markets they wish to invest in;
2. academics and researchers: this study sought to provide knowledge and a basis for further studies on forecasting equity markets in emerging countries;
3. policy makers: the aim of this research was to contribute to policy making by developing a model that can be used to forecast share prices and which will assist policy makers to formulate macroeconomic policies; and
4. company management: provided that the forecasts are accurate, companies can make strategic decisions based on the forecasted movements of equity prices.

## 1.6 Research methodology

The study is quantitative and empirical in nature. Secondary data was analysed using the ARCH/GARCH models and Monte Carlo Simulations.

Secondary data was obtained from the IRESS databases, previously known as the INET BFA and the Thompson and Reuters databases (Anon, 2016). The secondary data sources are reliable because data was extracted from stock exchanges in real time; researchers and corporates use these sources widely.

In this study, the predictability of the selected African equity markets was examined. Exploratory quantitative research was conducted using secondary data and financial econometric models.

The study can be described as exploratory. Exploratory research methodology is described as research that is carried out to shed more light on an on-going debate, and to clear the path for future studies (Zikmund, 2003). Exploratory research was used since there is no proven model to predict share prices in emerging equity markets. Considering that there is no proven best method to forecast equity markets, the study aimed to improve the predictability of equity prices in emerging markets.



The method that was used to assess the predictability of emerging markets in Africa is fully explained in Chapter 3. The quantitative explorative was selected as the appropriate research method to use as this model has been widely used in similar studies.

## 1.7 Collecting and analysing the information

To assess the predictability of equity markets in selected Africa’s emerging markets, secondary data was collected from two reliable secondary data sources, namely the IRESS databases, previously known as the INET BFA and Thompson Reuters (Anon, 2016). Secondary data was extracted for each company that met certain selection criteria, which are explained in Chapter 3. The top index of each country was selected to represent each country.

The forecasting models that were used to analyse the secondary data were the ARCH/GARCH models and the Monte Carlo Simulation. The accuracy of the forecasts was measured using the root mean squared error (RMSE), the mean absolute percentage error (MAPE), the median absolute deviation (MAD), the covariance proportion, the Theil Inequality coefficient, and variance proportion. These are discussed in further detail in Chapter 3.

## 1.8 Limitations of the study

In assessing the predictability of equity markets, the study has the following limitations:

1. only three African countries, based on trading volume and liquidity, were used to represent the continent;
2. each country was represented by a price-weighted index from companies listed on their stock exchanges in an index containing the biggest companies based on market capitalisation, and the majority of the companies (unlisted and listed with medium to small market capitalisations) did not form part of the study;
3. only companies that had been listed for a certain period (five years prior to 2010) and which met certain selection criteria (as outlined in Chapter 3) were selected; and
4. market behaviour was not taken into consideration.



## 1.9 Chapter outline

This chapter provided the background to and the scope of the research. The layout of this study is presented in Table 1.1.

**Table 1.1: Layout of chapters and content**

| CHAPTER | CONTENT |
|---|---|
| **Chapter 1:** | **Introduction and background of the study** |
| **Chapter 2:** | **Literature review** |
| **Chapter 3:** | **Research methodology** |
| **Chapter 4:** | **Results and findings** |
| **Chapter 5:** | **Conclusion** |

*Source: Researcher's own deductions*

# Chapter 2

# Literature review

## 2.1 Introduction

In the previous chapter this research paper's goals and objectives were discussed. In this chapter, the current literature relating to forecasting equity markets is reviewed. A literature review is defined as the analysis of the existing literature in a chosen area of study, and it should indicate the researcher's familiarity with the research subject (Saunders, Lewis & Thornhill, 2012).

In the first section of this chapter, emerging markets are defined, and forecasting in emerging markets is discussed. In the second section of this chapter, the accuracy of the forecasting models is discussed, particularly in terms of how the different forecasting models accurately predict movements in equity markets, in both developed and emerging markets.

In the third section, the accuracy of the forecasting models in recent studies is reviewed, specifically the accuracy of forecasting models in emerging markets. The accuracy of the Monte Carlo Simulation both in developed markets and in emerging markets is also reviewed in this section. The remainder of the section reviews and compares the accuracy of the different forecasting models.

### 2.2.1 Emerging markets

Investments in emerging markets have high returns, in spite of the risk and volatility associated with these countries (David, Henriksen & Simonovska, 2014). Investments in developed markets are associated with low risk and low returns, and some investors in these countries find the returns on investments in emerging markets attractive (Buckley, Clegg, Cross, Liu, Voss, Rhodes & Zheng, 2008). According to the African Development Bank (2011), emerging markets are:

> *countries that have increase in investments and social activities and level of mechanisation in the process of speedy growth and industrial development. Most of these nations have, through an increase in domestic consumption, developed strong domestic economies. Their reliance on developed countries has reduced since their trade is growing regionally with countries nearby. Emerging markets are also improving their domestic finance by increasing reserves and reducing the amount of government debt. Booming infrastructure like new roads and other public infrastructure, with development comes increased demand of consumer goods and services, like computers and new technology. These countries pursue faster growth and are expanding trade and investment around the globe.*

The major cause of the lack of development in emerging markets is a lack of capital. Most of developing countries do not qualify for loans from funding institutions and thus they have to rely on natural resources and foreign investment (African Development Bank, 2011).

## 2.2 Measure of forecasting

In order to forecast the equity share prices in emerging markets, diverse forecasting models can be used. Individual investors and corporates seek to increase their financial assets over time and use various methods to achieve this goal. Investing in emerging equity markets is one way of increasing their financial assets, however, the risk is high and the markets are unpredictable. Therefore, there is a need to forecast the markets. Various models can be used to forecast, and the following are some of the more commonly used measuring variables used to measure the accuracy, i.e. RMSE, MAPE, and MAD.



## 2.3 The importance of forecasting markets

Providing accurate forecasts of equity share prices is paramount in financial markets (van Jaarsveld, 2018). Forecasting of equity share prices assists investors and analysts in several ways, including the basic planning processes concerning portfolio allocation and risk management (Kambouroudis and McMillan, (2015) & Anderson, Bollerslev's and Das, (1998). Accurate forecasting can help investors, fund managers and investment specialists to minimise risk when constructing investment portfolios.

Romero and Kasibhatla (2013) concluded that when investors have access to market data they have the capacity to precisely evaluate the risk and potential returns of investing in certain financial markets over time. Kambouroudis and McMillan (2015) and Hull (2015) stated that the accurate estimation of equity share prices can be valuable when evaluating share values. Forecasting can be used as a guide when selecting the markets and stocks to invest in.

## 2.4 Models for forecasting equity share prices

Different models have been developed to forecast equity markets. The most precise models that researchers use to forecast equity share prices when using time series data, is a group of non-linear econometric models. Campbell, Lo, and MacKinlay (1997) characterise a non-linear process as one in which the current estimation of a time series data is connected non-linearly to past and current values. These sophisticated models include ARCH and GARCH models and the Monte Carlo Simulation.

In finance, share price movement is forecasted using several models, where non-linear econometric models are well-known as accurate models that researchers have used to predict share prices. As stated in Campbell, Lo and MacKinlay (1997) as cited in van Jaarsveld (2018), a non-linear process is a process in which the current value of a series is matched non-linearly to previous and current values. Such non-linear models commonly include ARCH and GARCH models and the Monte Carlo Simulation.

### 2.4.1 Types of ARCH models

The ARCH model was originally presented by Engle (1982b). The difference between ARCH models and conventional econometric models is that ARCH models do not operate under the assumption of a constant variance and allows the conditional variance to change with time. The presumption of consistent variance is also known as homoscedasticity. As highlighted in Hall and Asteriou (2011), homoscedasticity connotes to an equal spread in the variance of the time series. Heteroscedasticity is said to suggest an unequal spread in the variance of a time series.

This is corroborated in Bollerslev (1986), who posit that these ARCH models take into account the difference between such a conditional and unconditional variance and allows a conditional variance to change over time as a function of past errors. Extensions to the ARCH models were made shortly thereafter, with Bollerslev (1986) introducing the extensions as the Generalised ARCH (GARCH) models.

According to Franses and van Dijk (1996), the most notable difference between the GARCH models and the conventional ARCH models is that GARCH models allow for a much more flexible lag structure. Further, GARCH models can effectively remove excess kurtosis in share returns.

Despite the fact that GARCH models have advantages over the standard ARCH model, they also have certain disadvantages, as indicated by Nelson (1991) who concentrated on predicting financial asset returns. He found that because a GARCH model is a symmetric volatility model, the estimating exactness of GARCH models is influenced by the relationship between change in volatility and equity returns. Harrison and Moore (2012) established that there is a negative relationship between equity returns and volatility changes, because a leverage effect was present, which cannot be explained by certain GARCH models (van Jaarsveld, 2018).



Within the family of ARCH and GARCH models, problems could arise between symmetric and asymmetric models. Problems associated with symmetric GARCH models are that non-negativity constraints may be violated by the estimated model and the fact that these models cannot account for leverage effects. However, they can account for volatility clustering and leptokurtosis. Further, symmetric models have a symmetric response of volatility to positive and negative shocks, which is corroborated in Nelson (1991), who established that GARCH models cannot account for the leverage effect.

## 2.5 Empirical literature on forecasting models

Franses and Van Dijk (1996) investigated the predictability of share prices by using three non-linear models, namely the GARCH, the Quadratic GARCH (QGARCH) and the Gleston, Jagannathan, and Runkle (GJR) Model to forecast share market returns. They investigated the share markets of five European countries, namely Germany, Holland, Spain, Italy, and Sweden. The data for the study comprised the weekly closing values of indices listed on each country's stock exchange for a period of nine years between 1986 and 1994. The research focused on whether more complicated models such as the QGARCH and GJR models could forecast asset returns better than the GARCH model. The outcome was that these more sophisticated models predicted asset returns better in all five European countries. Franses and Van Dijk (1996) concluded that better predictions are possible when more variables are used, which is possible with the QGARCH and GJR models.

Chong et al. (1999) used the GARCH model and its extensions (QGARCH and EGARCH) to forecast the indices of Malaysia's Kuala Lumpur Stock Exchange (KLSE). For a period of two years, using daily share price data, the EGARCH model's (Nelson, 1991) predictions were more accurate than the GARCH Model and the Random Walk Model.

Alberg, Shalit and Yosef (2008) conducted a study forecasting share prices using the GARCH, EGARCH, Asymmetric Power ARCH (APARCH), and GJR models. They forecasted the share prices of the indices of Israel's only public stock exchange, the Tel Aviv Stock Exchange's (TESA). In this study, the daily share prices for the TA-35, TA-90, TA-125, and TA Blue Tech indices, which are the top indices based on market capitalisation for the 13-year period between 1992 and 2005, were used. The results Alberg *et al*.'s (2008) study confirmed the predictability of stock markets in the medium term. It was also possible to forecast the day of the week effect with the EGARCH model.

According to Samouilhan and Shannon (2008), extended models such as the EGARCH and Threshold ARCH (TARCH) have gained wider acceptance than the

ARCH and Random Walk models to predict equity price movements. In Samouilhan and Shannon's (2008) study, daily data for the period between February 2004 and September 2006 was used, and they argue that extended models improve predictive accuracy, due to these models' ability to increase the number of variables. Although ARCH model predictions were more accurate for in-sample forecasting, they were inefficient in predicting out-of-sample forecasting. In most of the studies, the extended forecasting models have proven to be more accurate.

Botha and Pretorius (2009) used univariate (ARMA and ARCH) and multivariate (vector autoregressive (VAR), VAR moving average (VARMA) and vector error correction model (VECM)) models to forecast the exchange rate between the South African Rand and the USD. The study used quarterly data between the period of 1990 and 2006. These advanced models yielded better forecast results than the univariate models and the Naïve Model. Botha and Pretorius (2009) concluded that the future movements of exchange rates can be forecasted, and that adding more variables to the forecasting model can improve the forecasts' accuracy.

Cifter (2012) predicted the volatility of the FTSE/Johannesburg Stock Exchange (JSE) All Share Index for a period of 10 years between February 2002 and March 2011 using the GARCH, normal mixture GARCH (NM-GARCH) and Fractionally Integrated GARCH (FIGARCH) models. The study indicated that the South African financial markets can be predicted using these models. Cifter (2012) found that the NM-GARCH and FIGARCH models, in comparison to the GARCH and the Random Walk models, produce more accurate predictions.

Onwukwe, Samson, and Lipcsey (2014) conducted a study in Nigeria for the period 2007 to 2011 using bank share equity prices listed on the Nigeria Stock Exchange. They used both the symmetrical and asymmetrical GARCH models to forecast equity price movements. Their results were similar to Cifter's (2012) results, since in both studies it was established that the asymmetrical; GARCH models, such as the EGARCH and FIGARCH, were more accurate than the symmetrical models, such as the GARCH and ARCH.

The GFC occurred during the period of Cifter's (2012) study, which affected most of the world's economies, including emerging markets. The GFC could negatively affect the accuracy of the predictions, since the GFC is an uncommon event that negatively affected share prices (Cifter, 2012). According to Onwukwe et al. (2014), a study covering the period after the global crisis was necessary to investigate changes in the market's behaviour after the crisis.

Oztekin, Kizilaslan, Freund, and Iseri (2016) used adaptive neuro-fuzzy inference systems, artificial neural networks, and support vector machines' forecasting models to forecast the returns of an emerging market economy (Turkey) for an eight-year period between 2007 and 2014 (which included the period of the GFC). The study used the daily share prices of companies listed on the Borsa Istanbul BIST 100 Index. Oztekin et al. (2016) concluded that minimising the number of factors used in the model led to better predictions. This conclusion contradicted the findings of Samouilhan and Shannon (2008), Botha and Pretorius (2009), Cifter (2012), and Onwukwe et al.'s (2014) findings, which concluded that adding more variables to the model improved prediction accuracy.



Ndwiga and Muriu's (2016) Kenyan study used the daily data of the Top 20 Index on the Nairobi Stock Exchange between January 2001 and December 2014 in an attempt to forecast equity prices of the Top 20 Index. During the period of study, Kenya implemented policy and trading rule changes, which affected the Nairobi market's predictability. The forecast results of both the symmetrical (ARCH and GARCH) and asymmetrical (EGARCH and TARCH) models were inaccurate, due to the longer period of study of 14 years in comparison to Cifter's (2012) 10-year study, as well as the policy changes (Ndwiga & Muriu, 2016).

## 2.6 Empirical literature on the various models' forecasting accuracy

Most researchers conclude that sophisticated forecasting models such as EGARCH, FIGARCH, NMGARCH, and regime-switching GARCH (RSGARCH) produce more accurate forecasting results than the simpler models, such as the ARCH and the Random Walk Model. Poon and Granger (2003) conclude that sophisticated forecasting models produce more accurate forecasts than the Naïve and Random Walk forecasting methods. These results corroborate with Engle (1993), who used statistical models, such as the ARCH, to forecast equity prices. He concluded that the forecasting results using ARCH models were more accurate than the Naïve and Random Walk models (methods).

Bleaney (1998) used the VAR and VECM models to forecast the exchange rate between the Swiss Franc against the USD. Using exchange rate data from 1900 to 1995, the VAR and VECM forecasting models did not produce more accurate results than the Naïve models for both in-sample and out-of-sample forecasts. Botha and Pretorius (2009) disputed these results and concluded that sophisticated models forecast better than simpler models. The differences in results were attributed to economic changes that occurred during the period of study. The results of Bleaney's (1998) study may be different to other studies, due to the 95-year data period.

Ding and Meade (2010) predicted foreign exchange rates, equity indices, equities, and commodities using the GARCH and Exponentially Weighted Moving Average (EWMA) models. The study used the daily price data for the period between January 2001 and December 2006. Ding and Meade (2010) concluded that the EWMA model's (which is a less complicated model) predictions were more accurate than the GARCH model's predictions.

Poon and Granger (2005) followed up their 2003 study using the same data used in their 2003 study. In this research the effect of the time horizon of the predictions on its accuracy was investigated. They concluded that accuracy decreases as the time horizon increases. The forecast for one to 20 days ahead, using the sophisticated models, was more accurate than the forecast for one month ahead. The authors concluded that regardless of the forecasting model used, the duration of the forecast determines the accuracy of the predictions.

Santos, Da Costa Jr., and Dos Santos Coelho (2007) demonstrated that nonlinear statistical simulations, such as multilayer perceptron neural networks (MLP-NN), radial basis function neural networks (RBF-NN), and the Takagi–Sugeno (TS) fuzzy systems are better models to estimate out-of-sample exchange rates between the Brazilian Real and the USD, compared to general statistical simulations models like the ARMA and GARCH models. The results from this research prove that nonlinear simulation models are better predictors than linear simulation models. Santos et al. (2007) concluded that sophisticated models better predict exchange rates than both in-sample and out-of-sample forecasting.

The studies by Santos et al. 2007 and Alberg *et al*. (2008) were challenged by Charles (2010) who forecasted the day-of-the-week effect on the stock exchanges of Athens, Paris, Helsinki, Dublin, Milan, and Zurich, using the daily share prices. The day-of-the-week effect was present in the results for all six European cities. He used GARCH models to predict the daily share prices, and the results indicated that the seasonal effect does not improve the forecasting accuracy on share prices.

Ismail, Karim, and Hamzah (2015) carried out a study in Malaysia (an emerging market) using sophisticated GARCH models to forecast the Islamic unit trust share price performance, namely the Commercial International Merchant Bankers (CIMB)-IDEGF and ARCH/GARCH models. These models produced satisfactory forecast results with more than 50% accuracy. The authors concluded that more sophisticated models perform better in predicting unit trust share prices in Malaysia. The results are similar to the Bley's (2011) findings, where it was concluded that the Gulf Co-operation Council's equity markets are predictable using the GARCH models. From this study, the author concluded that using stochastic forecasting models such as GARCH, can predict equity markets.

A study carried out in India that used symmetrical and asymmetrical GARCH models provided results that were slightly contrary to Ismail et al.'s (2015) results. The data was extracted from India's main stock market and the National Stock Exchange for the period between 3rd of August 1992 to the 21st of September 2012. The prediction accuracy of sophisticated models such as the GARCH, TGARCH, and EGARCH models was low. However, this was largely affected by the 2008 GFC that occurred during the study's period (Tripathy & Gil-Alana, 2015).

According to Harvey (1995), predicting share prices in emerging markets in comparison to developed markets can be difficult, due to the instability of emerging markets. He also established that emerging markets can be predicted, however, the accuracy varies in emerging markets, usually due to changes in macroeconomic variables. The inconsistency in the forecasting results in emerging markets motivated Harvey, Travers, and Costa's (2000) study, in which they used linear forecasting models and neural networks. The study used equity price data from 20 emerging markets, six Latin American markets, eight Asian markets, three European markets, one Middle East market, and two African markets over a seven-year period, i.e. from 1992 to 1997. The authors concluded that the Neural Network and GARCH forecasting models' predictions were more accurate than the Naïve Model's predictions.

Gokcan (2000) used the linear (GARCH) and non-linear (EGARCH) models to forecast share prices. GARCH and EGARCH models were used to forecast share prices in seven emerging countries, namely Argentina, Brazil, Colombia, Malaysia, Mexico, Philippines, and Taiwan for the period between February 1988 and December 1996. Gokcan (2000) concluded that the linear model predictions were more accurate than the EGARCH model's predictions. These results contradict Kumar et al.'s (2003) findings, which concluded that the non-linear models predicted share prices more accurately than linear models. They found that both the GARCH and EGARCH models were more accurate in predicting emerging markets' share prices than the ARCH and the Random Walk models.

Gokcan (2000) and Er and Fidan (2013) conducted a study to forecast share prices in Turkey, an emerging market. They concluded that the GARCH Model can predict share prices better than the Random Walk Model. This implies that sophisticated models cover the data quality gap that usually affects the predictability of emerging markets. However, when using simpler forecasting methods, predictions have a less

than 50% accuracy, as supported by Mishra, Mishra, and Smyth's (2015) findings that established the same conclusions using data from the Indian stock market.
Su, Wang, and Yang's (2009) study focused on out-of-sample forecasting of equity markets. In the study, data from 13 countries in developed markets was used. Well-known developed markets such as Japan, Germany, the United States, and the United Kingdom were included in the study. Both simple and sophisticated models were used in this study to forecast share prices, and they established that sophisticated models were more accurate than the simple models for out-of-sample forecasting. They concluded that forecasting models can be used to predict equity markets.
Kim and Shamsuddin (2015) conducted research in the United States, and their study used GARCH forecasting models and the Monte Carlo Simulation. The study covered the period 1964 to 2013. The authors concluded that equity markets can be predicted. However, they also established that markets cannot be predicted during the periods of market crises, as witnessed by inaccurate forecasts during the periods of 1987, 1997, and during the 2008 GFC. The prediction accuracy of the markets changes during periods of economic crises, as it was determined that the accuracy of predictions declined after the 1997 crisis (Kim & Shamsuddin, 2015). They concluded that regardless of the model used, either a simple or sophisticated model, the share prices during periods of economic crisis cannot be predicted, even in developed economies.

The presence of the weak form of the EMH in emerging African markets was analysed and compared to developed markets (Kumar, Moorthy & Perraudin, 2003). According to Kumar et al. (2003) the emerging markets have no weak form of the EMH, due to high volatility and above average returns in emerging markets.

In this section, the prediction accuracy of the different forecasting models in both developed and emerging markets was discussed. The findings from various studies discussed in this section differ due to the periods covered, and the models and the data used in the various studies. Different authors reached different conclusions regarding the accuracy of the simple (linear models) and sophisticated (non-linear) models in predicting the share prices.

## 2.7 Empirical literature on recent studies in emerging markets

Dyakova and Smith (2013) conducted a study on the predictability of Bulgarian stocks, Bulgarian stock market indices, and 13 South East European stock market share prices. The study included 40 Bulgarian shares, two Bulgarian indices, and 13 European countries, using daily data for the four-year period from 15 March 2004 to 15 March 2008. Dyakova and Smith (2013) concluded that share prices can be predicted, and they concluded that the predictions' accuracy varies according to the market's liquidity, size, and capitalisation. They also determined that illiquid and less traded markets are more predictable than liquid and more traded markets. The non-linear models (EGARCH and TGARCH) produced more accurate results than the linear forecasting models.

Smith and Dyakova (2014) followed up their 2013 study and replicated the same study in African countries. The study was done in six African markets, namely Egypt, South Africa, Tunisia, Kenya, Zambia, and Nigeria, for a period of 14 years, using GARCH forecasting models. They established that some of the African markets are less predictable than others. They further concluded that the most traded and liquid markets, such as the South African, Tunisian, and Egyptian markets, are the least predictable. The converse is true for the less traded markets, such as Kenya, Zambia, and Nigeria.

A study similar to Smith and Dyakova's (2014) study was performed on the Islamic equity markets by Sensoy *et al*. (2015). Their study focused on the Dow Jones Index over a period of 16 years, using GARCH models and non-linear models. The results confirmed the predictability of the markets at different time periods, however the accuracy was insignificant. The market efficiency was slightly different amongst the 12 indices. Sensoy *et al*. (2015) concluded that the markets can be predicted, regardless of whether a simple or sophisticated model is used.

Narayan (2015) used United States market data to predict Asian share prices. The study focused on six Asian countries for a period of 11 years, using GARCH models. He concluded that among the six countries, in-sample forecasts for Malaysia, Singapore, and Thailand were accurate, but inaccurate for China, India, and Korea. The out-of-sample forecasting results proved to be inaccurate for all six Asian countries.

Rahimi and Shahabadi (2014), using the Iran equity market, supported the assertion that equity markets can be predicted. Their study used multi-factor models to predict the Tehran Stock Exchange's (TSE) market share prices for a period of 10 years. The results had a high degree of accuracy (using the sophisticated models), which support the Sensoy *et al*. (2015) and Smith and Dyakova's (2014) findings.

Jahufer (2015) applied Rahimi and Shahabadi's (2014) study methodology to Sri Lanka, one of the fastest growing emerging markets. The asymmetrical models' predictions were more accurate than the symmetrical models when using the daily closing share prices of companies listed on the Colombo Stock Exchange (CSE) over a six-year period. It was found that forecast quality is also linked to the nature of data and the type of economy; therefore, the ARCH/GARCH models are suitable to forecast equity markets in emerging economies.



Bley and Saad (2015) carried out a study in Saudi Arabia, an emerging economy. They concluded that the sophisticated forecasting models (EGARCH, FIGARCH, and TGARCH) are better able to predict share prices than the Random Walk Model. In order to determine the forecast's accuracy, the MAPE, RMSE, Theil Inequality Coefficient, bias proportion, and covariance proportion of the share prices in emerging markets were analysed, and the results indicated that share prices can be predicted using sophisticated forecasting models.

This section presented studies that were performed in the past five years. Using the various forecasting models, the studies indicate that there is no preferred model to forecast share prices in both the sophisticated and simple models. Authors achieved inconclusive results after carrying out studies in different markets using identical forecasting models. The literature proves that there is still a gap in terms of forecasting using the models.

## 2.8 Empirical literature on the Monte Carlo Simulation

The Monte Carlo Simulation is an essential tool used in forecasting share prices, pricing derivatives and securities, and also in risk management (Glasserman, 2013). Robert (2016) also stated that the Monte Carlo Simulation is frequently used in finance and risk management disciplines.

Fukushima (2011) analysed the accuracy of forecasting models, including the Monte Carlo Simulation and GARCH models, to predict the prices of securities, and his results were similar to the results of Tripathy and Gil-Alana (2015), Ismail et al. (2015), Bley (2011), and Mwamba (2011) who concluded that sophisticated models were better predictors than simple models. Fukushima (2011) concluded that the Monte Carlo Simulation and GARCH models are better able than the simpler models, such as the Naïve Model, to predict share prices.

Gupta and Modise's (2012) South African study used different financial variables, including price-earnings and price-dividend ratios, to forecast equity prices. The Monte Carlo Simulation was used to predict price-dividend and price-earnings ratios that directly influenced the equity prices of companies listed on the JSE. In the study, monthly South African data for the period January 1990 to October 2009 was used. The authors concluded that the forecasting accuracy of the Monte Carlo Simulation was high over a short time period. The forecast accuracy decreased after forecasting for a longer period.

A similar study to Gupta and Modise's (2012) study was carried out in China by Liao (2013), who concluded that in China, one of the fastest growing emerging economies, forecasting share prices using the Monte Carlo Simulation was accurate, despite the economic and political factors.

Lux and Morales-Arias (2013) conducted a German study similar to Gupta and Modise's (2012) study, comparing the prediction accuracy of ARCH/GARCH models to that of the Monte Carlo Simulation. They found that the Monte Carlo Simulation's in-sample forecast was better than both the ARCH and GARCH models. The findings from the study contradict Fukushima's (2011) findings.

Degiannakis, Dent, and Floros' (2014) study used the Monte Carlo Simulation and FIGARCH-skT models, and reached a different conclusion to Lux and Morales-Arias (2013). The FIGARCH-skT model produced a forecast that was more accurate than the Monte Carlo Simulation, however, the difference was insignificant. The data used originated in a developed economy, and the results contradicted the results from a similar developed market, i.e. Germany, as concluded by Lux and Morales-Arias (2013).

Compared to other linear forecasting models, such as the simple moving average and exponential moving average models, the Monte Carlo Simulation accuracy was better than the other two models. Using daily data for share prices of companies listed on Jordan's Amman Stock Exchange, for the period January 2010 to December 2014, the Monte Carlo Simulation was considered to be the more accurate model in predicting future share prices, than both the simple moving average and the exponential moving average models. Based on the ARCH/GARCH and Monte Carlo Simulation forecasting models used, the EMH does not hold in Jordan, as the forecasting models can predict the future movements of security prices (Alrabadi & Alijarayesh, 2015).

Sonono and Mashele (2015) conducted a study in South Africa, an emerging economy, using the daily price data of the FTSE/JSE Top 40 index. They used the Monte Carlo Simulation and advanced ARCH/GARCH models to forecast share prices. They found that the Monte Carlo Simulation's forecasting results were less accurate than the advanced ARCH/GARCH models' forecasting results.

## 2.9 Summary

The literature reviewed indicates that there is still a gap in terms of the performance of the different forecasting models in emerging markets. The emerging markets receives attention from international investors and researchers and new literature is required to bridge the gap. Sonono and Mashele's (2015) conclusions are in line with the Alrabadi and Alijavayesh's (2015) findings that the efficient market hypothesis does not exist in emerging economies, since the forecasting models predict the future movements of security prices better than the Random Walk and Naïve models.

From the literature consulted by the researcher, it is evident that several studies have been performed in both emerging markets and developed markets regarding the accuracy of predictions of equity markets. However, the findings are inconclusive as to whether or not equity markets can be forecasted, which forecasting models produce better results, and whether or not the factors that influence the accuracy of market predictability are similar in different markets?

The general consensus was that asymmetric forecasting models in both developed and emerging markets provide more accurate results than the symmetrical models for both in-sample and out-of-sample forecasts. The literature reviewed indicates that there have been a number of global studies on equity markets' predictability. The research results from different countries and markets were inconsistent, and indicated that different factors influence the predictability of the equity prices in different markets. The literature shows that most of the studies' predictions that included the GFC period were relatively poor, which led to the conclusion that economic conditions can influence the forecasting accuracy.

The Monte Carlo Simulation was used in conjunction with the ARCH/GARCH models and other forecasting models. In four of the studies, it was found that the Monte Carlo Simulation provided more accurate forecasting results than the ARCH/GARCH models and its derivatives. In contrast, in five of the studies, the opposite results were found. Thus it is inconclusive as to which models produce more accurate results.

# Chapter 3

# Research methodology

## 3.1 Introduction

In this chapter the steps and procedures used in this research are discussed. The chapter provides a detailed explanation of the criteria used in selecting the relevant data, the methodology the researcher adopted, and the models used to process the data collected.

## 3.2 Research question

Can statistical forecasting models predict future equity market share prices in the selected emerging African markets (NSK) using historical share price data?

### 3.2.1 Research objectives

The main study objectives were:

- to investigate whether or not equity market prices of the NSK markets can be predicted using statistical models and the Monte Carlo Simulation;
- to determine which models produce more accurate predictions; and
- if statistical forecast ability is determined, can investors exploit it to consistently receive abnormal returns?

The following questions were also investigated:

- Can ARCH/GARCH and their extended models such as EGARCH, T-GARCH, and M-GARCH and the Monte Carlo Simulation accurately predict equity prices of the NSK markets?
- Are the ARCH/GARCH and extended models more accurate than the Monte Carlo Simulation?

- Can ARCH/GARCH and extended models and the Monte Carlo Simulation predict share prices more accurately than the Naïve Model?

## 3.3 Research strategy

A research strategy is the overall plan that guides the researcher to answer the research questions (Bless, Higson-Smith & Sithole, 2013:132), and the quality of the research strategy influences the quality of the results. Strategies that were implemented to assess whether or not the ARCH/GARCH models and the Monte Carlo Simulation can forecast the NSK markets' equity prices using historical share price data, are discussed in the following section.

### 3.3.1 Research paradigm

The research approach for the study was quantitative, and therefore the appropriate research paradigm was positivism. Thomas (2010:34) defines positivism as "research that assumes that the reality is objectively given and is measurable using properties which are independent of the researcher and his or her instruments". In light of Thomas' (2010) submission, realistic assumptions were used to interpret the results from the forecasting methods used in this research.

### 3.3.2 Research method

According to Rajasekar, Philominathan, and Chinnathambi (2006), research methods are tools, steps, and algorithms that are used to conduct research. This also includes the necessary procedures that are implemented during the process of research to obtain the expected results.

Quantitative research and qualitative research are two well-known research methods (Saunders, Lewis & Thornhill, 2003). The secondary data used in this study were quantitative in nature, and therefore, the appropriate research method is quantitative research. According to Rajasekar et al. (2006), quantitative research is based on the measurement of quantity, and the results are numeric. Quantitative research has an advantage over qualitative research in that results are easily measured, and further analysis can be performed easily, depending on reasonability.

Quantitative research analysis results are objective since there is no room for the researcher's opinion (Castellan, 2010). The aim of this study was to predict the equity markets in NSK. Therefore, the researcher used historical data from reliable sources in order to arrive at objective findings, which remove personal, subjective opinions.

### 3.3.3 Research design

The study used daily equity share prices from the FTSE/JSE Top 40, the NSE Top 30, and the NrSE 20 indices from the selected three African countries (NSK).

Similar previous studies focussed on forecasting of the South African Rand/USD exchange rate, share prices, value at risk (VaR) and equity returns (Botha & Pretorius, 2009; Cifter, 2012; Samouilhan & Shannon, 2008). Samouilhan and Shannon (2008) used ARCH/GARCH models to forecast the FTSE/JSE Top 40 equity index, and Cifter (2012) used ARCH forecasting models to predict share prices for the companies listed on the FTSE/JSE All Share Index. Alberg et al., (2008) used GARCH and its extended forecasting models to forecast Israel's TESA's index returns.

## 3.4 Research instrument

One of the most important components of research design is the research instrument because it is used to collect data or information. A research instrument is a tool that is used to collect information (data) that is used to answer research questions; it is required in both quantitative and qualitative research (Saunders et al., 2003).

To evaluate the accuracy of the predictions, the researcher used inferential statistics. The inferential statistics used to measure the predictability of equity markets in NSK emerging markets included the statistical significance of means, variance, RMSE, MAD, and MAPE.

## 3.5 Sampling strategy

Sampling is the process of carefully selecting a certain portion of the whole population to represent the whole population, in order to produce results that are truly representative of the whole population. Alternatively, it can also be defined as a method of selecting units or samples to be used in research to generate results that represent the whole population (Thompson, 2012; Zikmund, Babin, Carr & Graffin, 2012).

The judgemental sampling method is a non-probability sampling technique that the researcher uses to select a sample based on his or her knowledge, experience, and professional judgement (Zikmund et al., 2012). The judgemental sampling technique allows the researcher to select samples with certain characteristics that are comparable. Additionally, this technique avoids the danger of inadequacy of data, as the samples are selected based on their merits. However, the major shortfall of the judgemental sampling technique is that it can be biased, as it might represent the selected samples only, rather than the entire population (Ellison, Farrant & Barwick, 2009).

To investigate whether or not the selected emerging African equity market prices can be predicted accurately, a judgemental sampling method was considered appropriate and used, as there were a limited number of primary data sources that could contribute to the study. This sampling method facilitated the selection of the most traded African equity markets, based on the availability of data, and its ability to represent the whole African continent.



### 3.5.1 Target population

Population refers to the whole data set that is of interest to the researcher. In this study, it refers to African equity markets. The target population refers to a group of items/objects that are selected for the research (Saunders et al., 2003). The target population comprised all the African equity markets that qualified to be selected for the study. Africa was selected because it has become the hub for investment, offers high investment returns, and there is much potential for development.

To determine whether or not the emerging African equity markets can be predicted accurately using the selected statistical forecasting models, the population comprised all 54 countries of the African continent. However, it was not possible to collect data for the entire continent's equity markets, and therefore a sample to represent the whole population was drawn from the African equity markets.

### 3.5.2 Sample size and selection

Three African countries were selected based on their trade volume and the liquidity of their equity markets. The three countries were NSK (ASEA, 2015). The data covered the five and half-year period from beginning of 2010 to mid-2015, and eliminated the data recorded during the 2008 GFC.

The rationale behind the selection of this period lies in the length of the period, as well as the exclusion of the 2008 GFC, which could affect the accuracy of forecasted results. Data after June 2015 was excluded due to 'Nenegate', which refers to when Jacob Zuma, who was president of South Africa at the time, dismissed Nhlanhla Nene as finance minister, and replaced him with a relatively unknown member of parliament, Des van Rooyen. This caused an unpredictable movement in the South African financial markets.

The NSK represent the largest economies in Africa, based on the GDP, since their combined GDP contributes almost 50% of the entire continent's GDP (World Bank, 2016:33).



## 3.6 Data collection method

The historical equity share price data used in this research was extracted from IRESS databases, previously known as the INET BFA and Thompson Reuters databases (Anon, 2018). These data sources are well recognised for secondary data in South Africa and abroad, and they are widely used by researchers and corporates (Botha & Pretorius, 2009). The use of the secondary data from these two recognised sources ensures the reliability and validity of the results.

The daily share prices of the companies listed on the FTSE/JSE Top 40 Index, the NSE Top 30 Index, and the NrSE 20 Index that met the selection criteria, were used.

The share prices of companies listed on the JSE were obtained from Thompson Reuters, and from IRESS databases for companies listed on the NSE and the NrSE.

Table 3.1 indicates the indices, the countries they represent, and the number of companies in each index.

**Table 3.1: Indices**

| Country | Index |
|---|---|
| South Africa | FTSE/JSE Top 40 Index |
| Nigeria | Top 30 Index (NSE 30) |
| Kenya | NrSE 20 Share Index |

*Source: Researcher's own deduction*

### 3.6.1 FTSE/JSE Top 40 Index

The FTSE/JSE Top 40 Index is a market capitalisation weighted index consisting of the 40 largest companies ranked by market capitalisation, included in the FTSE/JSE All Shares Index. The FTSE/JSE Top 40 Index was established on 21 June 2002 (Bloomberg, 2016). The number of companies listed on FTSE/JSE Top 40 Index is maintained at a minimum of 40, plus a few, to make provision for companies that might delist or lose significant value to the extent that it ceases to qualify for inclusion on the index (Bloomberg, 2016).



### 3.6.2 Nigeria Top 30 Index

The NSE 30 tracks the 30 largest companies listed on the NSE, based on market capitalisation and liquidity. Only shares issued, which require no further payment to the company by shareholders, are included in the index (NSE, 2016). The NSE has exactly 30 companies listed from any industry, as long as it is within the gazetted market capitalisation and liquidity.

### 3.6.3 Nairobi Top 20 Index

The NrSE 20 Index was established in July 2007, after the Trading and Compliance Committee saw a need to establish it. The NrSE 20 Index comprises 20 listed companies based on their financial results during the period under review. Unlike the FTSE/JSE Top 40 and NSE Top 30 indices, the committee annually selects the NrSE 20 Index companies, based on trading volume activities. It must have a free float of at least 20%, high profitability, and an exceptional and consistent dividend pay-out record (NrSE, 2014:1-4).

### 3.6.4 Data summary

The researcher constructed a separate price-weighted index for each country by eliminating the companies that were listed five years prior to or delisted during the period of study. This was done to eliminate possible anomalies and share prices that might exceed the intrinsic value during the initial public offering period.

Based on the criteria, 37 of the 40 companies that formed part of the FTSE/JSE Top 40 Index were used to construct the South African index. For the NSE, 26 of the 30 companies that formed part of the Top 30 Index were used to construct the Nigerian index, and 19 of the 20 companies that formed part of NrSE 20 Index were used to construct the index that represented Kenya.

## 3.7 Data analysis



Data analysis is the process of cleaning, converting, and modelling raw data into useful information (Saunders et al., 2003). Secondary data was modelled using the ARCH and GARCH forecasting models and its variants and the Monte Carlo Simulation, to produce the results that are presented in the next chapter.

The results from the different forecasting models were analysed based on their ability to accurately forecast equity prices. Forecasts from the ARCH/GARCH models and their variants and the Monte Carlo Simulation were compared to actual equity prices that were recorded on a particular day. The outcomes of each of the forecasting models were also compared to other studies performed in other emerging and developed markets globally.

To determine the predictability of the emerging African equity markets' share prices, time series data was used. The time series data is the most appropriate type of data that can be used to predict the equity markets' share price data.

The results from the forecasting models were further compared to the Naïve Model. The models that were used in the study are discussed in the next paragraph.

### 3.7.1 Models

The ARCH/GARCH models and their extended models and the Monte Carlo Simulation were used to forecast the NSK equity markets.

#### 3.7.1.1 Autoregressive-moving-average models

Yule (1926) initially introduced the AR model. Slutzky (1937) further supplemented the AR model by adding the moving average (MA) to the model. Wold (1939) merged the two models (i.e. AR and MA) to produce a new model called the ARMA model, which is used to model stationary time series data. It has the stationarity assumption as long as the appropriate order of *p* for AR terms and *q* for MA terms are constant over time.

The data should be stationary, because non-stationary data cannot be used to forecast, as the results may be spurious and may indicate false relationships between variables. Time series data that is not stationary can be made stationary by applying statistical techniques so that it can be analysed using ARMA models. Stationary data as opposed to non-stationary data produces better forecasts, because the means, variance, and covariance of stationary data do not change over time.

The ARMA equation is presented by the following equation:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \cdots + \phi_p x_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

where:

$x_t$ is the actual value;

$\varnothing_i$ and $\varnothing_j$ are coefficients;

$\alpha$ are the parameters of the autoregressive part of the model;

$\theta i$ are the parameters of the moving average part; and

*p* and *q* are integer constants usually called autoregressive and moving averages.
*Source: Hall and Asteriou (2011)*

The ARMA model was selected using the Akaike Information Criterion (AIC) and Schwarz Criterion (SIB). The AIC and SIB are the models most widely used to select the best ARMA equation (Ding & Meade, 2010). The ARMA was automatically calculated using EViews 9.1 software.

The best selected ARMA models were used as the mean equations for the ARCH/GARCH models. The linear ARMA equation is converted into a variance equation; it is used as a mean equation for an ARCH/GARCH equation.

#### 3.7.1.2 ARCH/GARCH Models

Engle (1982b) first introduced ARCH when he was forecasting the mean and variances of inflation in the UK. He was motivated by the limitations of the models that were available at the time. Two important assumptions of the ARCH model are that changes in variance, as well as observations of data points, are independent of previous values, which implies that the data must be stationary. Because the share price data was not stationary, they were differenced once to become stationary. The ARMA equation was also used in the ARCH/GARCH model.

The ARMA equation was tested using the stationary roots and correlogram, and when it fits the model, it was used as the mean equation for the ARCH/GARCH model.

The basic ARCH (p, q) model has two equations, namely a conditional mean equation and a conditional variance equation. Both mean and variance equations are estimated simultaneously, since the variance is a function of the mean. The mean equation is used to predict the variable's conditional mean. The mean equation needs to be correctly specified before estimating the ARCH/GARCH model (Engle, 1982a; Meese & Rogoff, 1983).

The variance equation predicts the variance process as a type of autoregressive process. Both mean and variance equations form a system that is estimated together, using maximum likelihood. Maximum likelihood is a way of forecasting the parameters of a statistical model. The variance equation is important, because if not correctly specified, the variance predictions will not be valid or reliable (Bollerslev, Chou & Kroner (1992).

Engle (1982b) described the ARCH model as a discrete time stochastic process ($Y_t$) defined by the following equation:

$Y_t = e_t h_t^{1/2}$

where:

$Y_t$ = discrete time stochastic process;

$h_t$ = time varying positive and measurable function of information set at time t; and

$e_t$ = white noise or error term.

The ARCH equation has a mean of zero and a variance of one. The variables are normally, independently, and identically distributed.

Bollerslev (1987) introduced a general model based on Engle's ARCH model four years later, commonly referred to as general ARCH (GARCH). The purpose of this model was to improve the ARCH model and to provide an alternative and more flexible structure. The GARCH model has a time-varying volatility process, which is a function of previous volatility.

For the GARCH and its extended models, the variance is denoted by $h_t$ for GARCH (p, q), where *p* and *q* are lag length. The lag length *q* is determined by the best fitting AR(*q*) model from the ARMA equation. The lag length *p* was automatically computed in EViews 9.1. The GARCH (*p; q*) equation is presented by:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

where:

$h_t$ = stationary return series;

$\sigma_t$ = conditional variance;
$\alpha_0$, $\alpha_i$, $\beta_j$ = unknown parameters;
$y^2_{t-i}$ = the set of all information through time $t$ –i;
$q$ = the order of GARCH term $h_{t-j}$; and
$p$ = the order of ARCH term $y^2_{t-i}$.

*Source: Brooks (2008)*

Nelson (1991) initially introduced the Exponential GARCH (EGARCH) model, which is defined by the following equation:

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2$$

where:

$g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))$;

$\omega$, $\beta$, $\alpha$, $\theta$ and $\lambda$ are coefficients. ;

$Z_t$ may be a standard normal variable or come from a generalized error distribution; and

$\sigma_t^2$ is the conditional variance,

*Source: Brooks (2008)*

The left side of the equation is the conditional variance. The implication is that the leverage effect is exponential, and that the predictions of the conditional variance are guaranteed to be positive.

Each variable, in both the mean and variance equation, plays a critical role in producing unbiased forecasts. The inclusion of an additional variable or exclusion of a variable will result in inaccurate predictions. The variables in each equation are standardised, and were not altered in the standard ARCH/GARCH or extended models.

### 3.7.1.3 Forecasting using ARCH/GARCH and extended models

A requirement when using ARCH, GARCH, and their extended models to forecast is that the input data must be distributed normally; therefore, the first step is to perform a stationarity test. The data for all three countries was tested for stationarity using the Augmented Dickey Fuller (ADF) Test and the Phillips Perron (PP) Test. The ADF and PP tests are recognised methods of testing stationarity (Samouilhan & Shannon, 2008). The results for both the ADF and PP tests, after data was differenced once, were the same for the three countries, and confirmed stationarity. The two stationarity tests (ADF and PP) produced the same results; an alternative test using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) method was not conducted because the ADF and PP tests confirmed stationarity.

After confirmation that the data was stationary, it was used to build the ARMA equation. The lag length of the ARMA equation was automatically calculated in EViews 9.1. The selected ARMA equation was diagnosed using the roots, correlogram, and impulse response to determine whether or not the equation could be used to forecast.

The selected ARMA equation was used as a mean equation for the ARCH model. The first step was testing for the presence of ARCH effects in order to proceed to forecast the equity market using the ARCH/GARCH models. Forecasting using the ARCH/GARCH models can only be performed when the ARCH effects are present.
The appropriate ARCH/GARCH and extended models were selected based on the positivity of variables, variance equation, R-squared, and the equation diagnostic criteria stated for the ARMA equation.



After the appropriate model was selected, in-sample forecasting was done in EViews for the three-month period between April and June 2015. For an out-of-sample forecast, the appropriate model for each country was selected. The forecast was made for the same period.

The accuracy of the forecast was measured using the RMSE, MAPE, Theil Inequality Coefficient, and MAD. The RMSE is a measure of the difference between the actual values observed against the predicted values; a high value (in relation to the data set) indicates that the model is not accurate. MAPE measures the prediction accuracy of a forecasting method in statistics, compares the forecast value and the actual value, and expresses the difference as a percentage deviation from the actual value.

### 3.7.2.1 The Monte Carlo Simulation

The Monte Carlo Simulation produces distributions of possible outcome values (Boyer-Kassem, 2014). The Monte Carlo Simulation is an automated mathematical technique that makes predictions using quantitative analyses, and can be used for decision-making by various stakeholders, including investors, company management, and policy makers. The scientist Monte Carlo, first introduced the technique while working on an atomic bomb (Boyer-Kassem, 2014).

The Brownian Motion Model is defined as the irregular motion of small particles suspended in a liquid or a gas, caused by the medium's molecules bombarding the particles (Brown, 1827). The Brownian Motion Model was fundamental to the development of the Monte Carlo Simulation. The Monte Carlo Simulation uses the same concept of random outcomes within a regulated range, similar to the Brownian motion model (Sonono & Mashele, 2015). The historical data was copied to a spread sheet, and the Brownian Motion Model was applied to the data in order to forecast future equity prices. The simulation was done using the Geometric Brownian Motion equation:

$$dS_t = S_t \, \mu \, dt + S_t \sigma \, dW_t$$

and

$$dW_t = \varepsilon \sqrt{dt}$$

where:

$S_t$ is the equity price at time $t$;

$dt$ is the time step;

μ is the drift, the anticipated rate of change for share price;

σ is the volatility;

$W_t$ is a Wiener process - one-dimensional Brownian motion; and

ε is a coefficient of a standard normal distribution, i.e. with a mean of zero and standard deviation of one.

*Source: Vose (1996)*

Each of the variables is vital to obtain the expected results; omitting one variable from the equation will result in spurious forecasts.

The two equations can be combined, resulting in the following equation:

$$dS_t = S_t\, \mu\, dt + S_t\, \sigma\, \varepsilon \sqrt{dt}$$

The result of converting this equation into finite difference is:

$$\Delta S_{t+\Delta t} = S_t\, \mu\, \Delta t + S_t\, \sigma\, \varepsilon \sqrt{\Delta t}$$

The ε in the equation is standardised, and therefore follows a normal distribution with a mean of zero, and standard deviation of one.

*Source: Vose (1996)*

The share price as at 30 June 2015 was used as the current share price to predict the share price of the next trading day. The historical share price returns were calculated using natural logarithms. The calculated returns were used to calculate the data's mean and standard deviation. The annual trading days were constant at 250 for all three countries, and this was used to calculate the delta.

The three-month forecast was performed in a Microsoft Excel spread sheet using the Monte Carlo Simulation formula. The Monte Carlo Simulation requires at least 800 iterations, and in the present study, 1 200 iterations were performed, which were sufficient to avoid discrepancies (Sonono & Mashele, 2015). The accuracy of the forecast results was measured using MAPE, RMSE, and MAD.



Researchers (Botha & Pretorius, 2009; Cifter, 2012; Samouilhan & Shannon, 2008) who completed similar studies, used similar forecasting models (ARCH/GARCH and Monte Carlo Simulation). The accuracy of the forecasting models that they used was evaluated and they were compared to each other; using different forecasting models reduces the chances of bias in results.

### 3.7.3 Comparing ARCH/GARCH and the Monte Carlo Simulation

The forecasting accuracy of the ARCH/GARCH and their extended models compared to the Monte Carlo Simulation were measured using the RMSE, MAPE, and MAD.

## 3.8 Validity and reliability of data

Validity is the extent to which the results obtained actually represent the researcher's idea (Dane, 2000). Reliability refers to the concept of getting the same results after several tests are done repeatedly (Carmines & Zeller, 1979).

Secondary data was extracted from the Thompson Reuters and IRESS databases, previously known as INET BFA, which are reliable data sources that are widely used by corporates and researchers.

### 3.8.1 Validity of measurement

Equity market share prices were the variables used to evaluate the emerging markets' predictability. To ensure that the design was valid, experts in the field (Botha & Jagunola, 2017) were consulted, and validity tests were done. Impulse response, roots, and correlogram diagnostic checks were done on all of the models used in this study.

### 3.8.2 Reliability

When the data collected was stationary, the forecasting equation was built using the autoregressive integrated moving average (ARIMA) equation, which is a generalisation of the ARMA equation. The model with the smallest AIC and SIB was selected. The lowest AIC indicates that the model is closer to the true estimates and the lowest SBIC indicates that the model is likely to be unbiased. After the most appropriate model was selected, ARCH effects were tested. The ARCH/GARCH models were selected based on their significance levels and the equation's variables. Diagnostic tests were conducted on the selected models using the GARCH graph, actual, fitted, and residuals, covariance matrix, correlogram, and Q-statistics.

The ARCH/GARCH model fitting the selection criteria selected was used to predict the equity prices for each of the three selected emerging African markets. For each country, two forecasts were made, in-sample forecasting and out-of-sample forecasting. The results from the ARCH/GARCH models were compared to similar studies done on emerging and developed markets.

To measure the accuracy of the results, MAPE, RMSE, MAD, Theil Inequality coefficient, variance, and bias proportion were used.

To minimise the weakness of the models, this study used two different models to validate the outcomes of each model.

## 3.9 Ethical considerations

Research ethics are defined as the appropriateness of a researcher's actions towards all the stakeholders during the study process (Saunders et al. 2003). No stakeholders were harmed in any way during the entire study process, as the data used was publicly available.

## 3.10 Limitations

The aim of the research was to investigate whether or not equity markets in selected emerging African economies could be predicted using historical trading data over a period of five and half years that ended in June 2015. This period excluded major economic events like the 2007/2008 GFCs. However, the effects that these events could have had on the predictions' accuracy were not researched.

The researcher selected three African countries based on set criteria with the result that significant economies in Africa that were not liquid, such as Ghana and Egypt (ASEA, 2015), were excluded. The countries selected were represented by indices that excluded small listed and all unlisted companies.

## 3.11 Summary

This chapter presented the research process that was followed to analyse the predictability of equity markets in selected emerging African markets. The procedures used to obtain and analyse the data were discussed.

The sample choice was based on trading volumes, represented by the FTSE/JSE Top 40 Index, the NSE Top 30 Index, and the NrSE 20 Index. Secondary data was extracted from the Thompson Reuters and IRESS databases, previously known as

INET BFA, from the period January 2010 to June 2015. The selected companies listed on the indicated indices of each country were utilised to measure the predictability of equity markets in emerging African markets.

This study applied a quantitative research method and a positivist research paradigm. To evaluate the predictability of equity markets in emerging African markets, ARCH/GARCH and their extended models and the Monte Carlo Simulation were used. The results were measured for accuracy using MAPE, RMSE, and MAD.

The results obtained from the statistical analysis are presented in the next chapter, which answers the main research question as to whether or not statistical forecasting techniques can be used to accurately predict share prices of equity markets in selected emerging African markets.

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# Chapter 4

# Results and findings

## 4.1 Introduction

In the preceding chapters the study background, a discussion of existing literature, and a description of the methodology used was presented. In the methodology chapter, the steps and procedures that were followed to produce the results presented in this chapter were explained. Analyses were performed in the context of the conceptual theories, and analogies are made to literature in previous chapters.

The research methodology chapter established that the quantitative method was the most appropriate method to measure the predictability of share price movements in emerging markets. Forecasting was performed using the ARCH/GARCH and extended models and the Monte Carlo Simulation. The accurateness of the forecasts was measured using the RMSE, MAPE, and MAD, which are measures of the robustness of the variability of a univariate sample, Theil Inequality Coefficient, variance proportion, bias proportion, and covariance proportion.



This chapter comprises four sections. The first section describes the sample and data used. The second section provides an analysis of the data, and is divided into two sub-sections, namely the ARCH/GARCH and extended models results and the Monte Carlo Simulation results. The third and fourth sections describe the study's reliability and validity respectively.

## 4.2 Sample description

To measure the predictability of share prices in emerging markets, a sample of three African countries, based on their stock exchanges' trading volumes and liquidity, were selected. The NSK countries represented by the NSE, the JSE, and the NrSE respectively, were selected.

A price-weighted index was constructed for each of the three countries' stock exchanges. For South Africa, companies were selected from the JSE/FTSE Top 40 Index, for Nigeria, companies were selected from NSE Top 30 Index, and for Kenya, companies were selected from NrSE Top 20 Index.

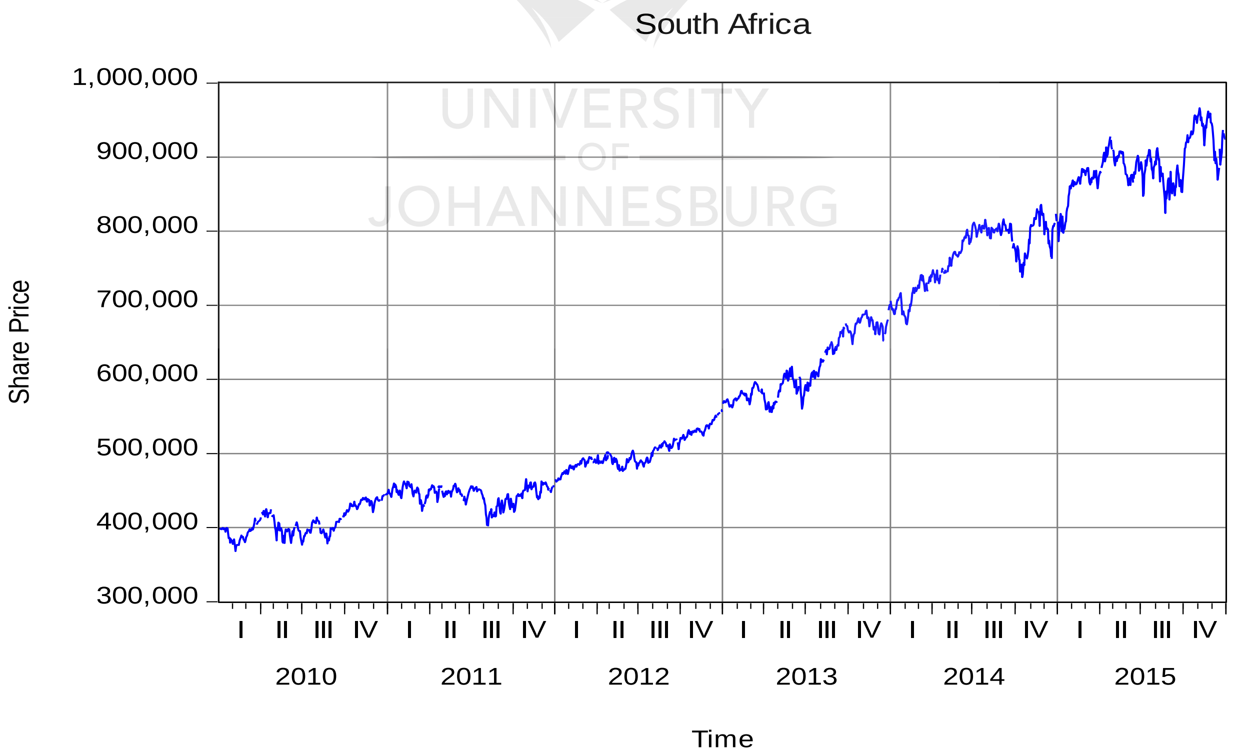
## 4.3 Data analysis

Each index was first analysed using descriptive statistics. Thereafter, the data was tested for stationarity and the presence of ARCH effects and the forecasting models were constructed and diagnosed for their appropriateness to forecast.

### 4.3.1 Data description

Figure 4.1 indicates the constructed price-weighted JSE index movement over the period of study from January 2010 to June 2015.

**Figure 4.1: Johannesburg Stock Exchange price-weighted index**

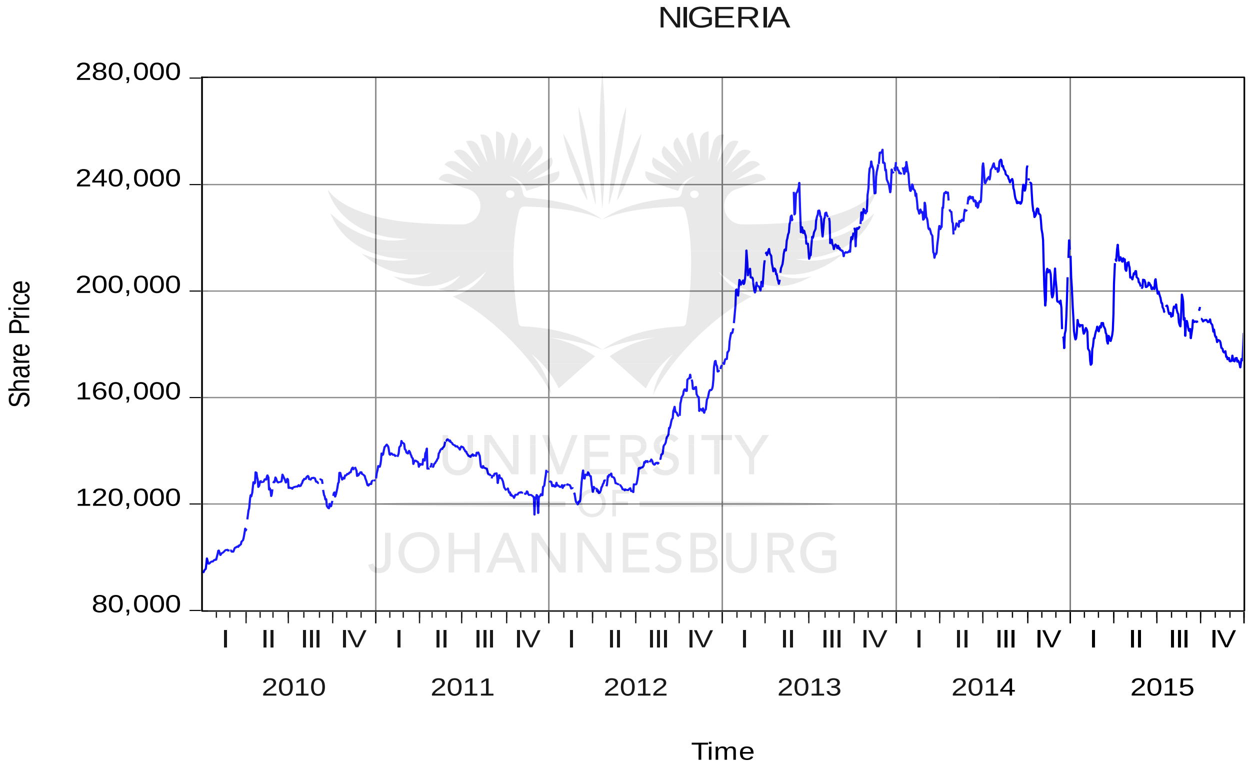



*Source: EViews output*

South Africa's price-weighted equity index increased by more than 100% from 400 000 at the beginning of 2010, to almost 1 000 000 at the end of June 2015. South Africa's significant growth over this period is linked to significant growth of the companies in the FTSE/JSE Top 40 Index, as well as the depreciation of the South African Rand against other major currencies (Cifter, 2012). In this period, the South African Rand depreciated against the USD by almost 100%. The real growth rate was almost constant (South African Reserve Bank, 2016).

Figure 4.2 indicates the Nigerian price-weighted index.

**Figure 4.2: Nigerian Stock Exchange price-weighted index**

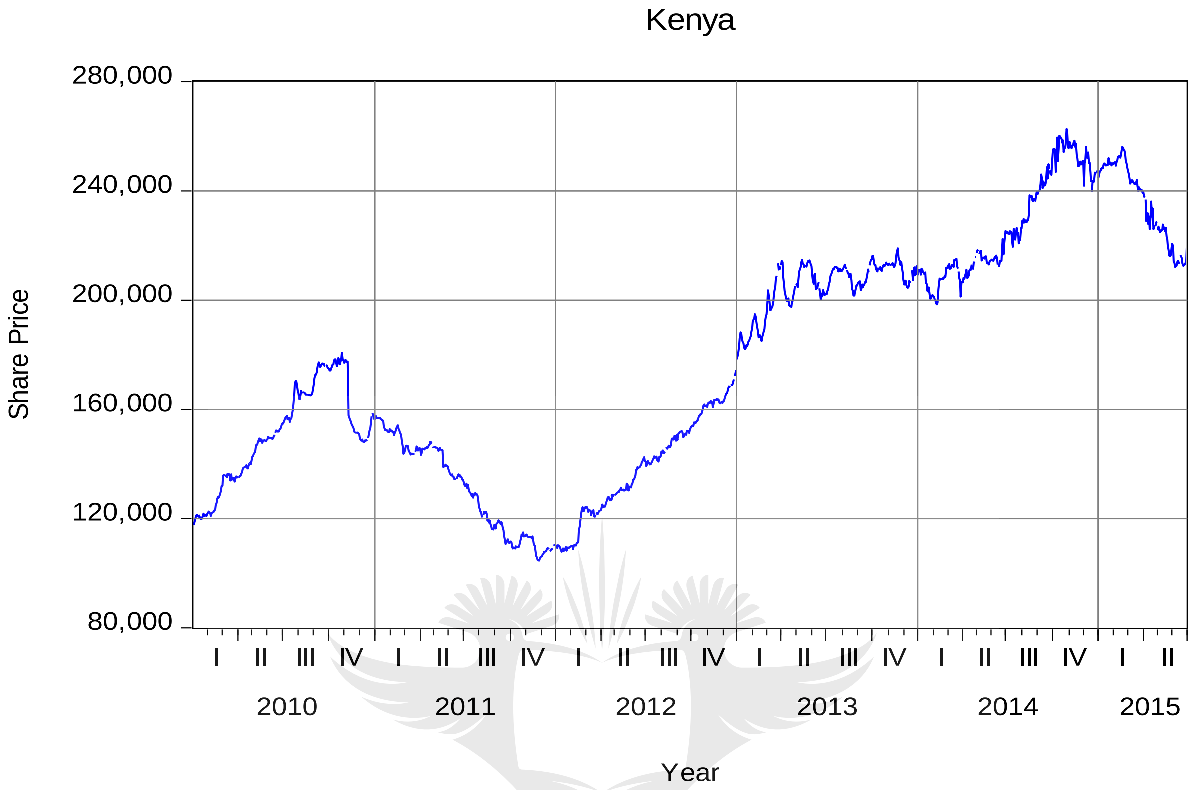



*Source: EViews output*

Figure 4.2 indicates that the NSE price-weighted index increased by 167%, from 90 000 to over 240 000 over the period. There was a 102% increase in the index between the third quarter of 2012 to the third quarter of 2014, and a significant decline in the last three quarters of 2015. The exchange rate between the Nigerian Naira and USD remained constant over the same period.

Figure 4.3 indicates Kenya's price-weighted index.

**Figure 4.3: Kenya's price-weighted index**




*Source: EViews output*

The Kenyan price-weighted index increased by more than 100% from 120 000 in 2010 to above 240 000 in 2015. Kenya's NrSI experienced a significant increase in share prices between the second quarter of 2011 and the second quarter of 2014, and a slight decline in the last quarter of 2015. The Kenyan Shilling exchange rate to the USD remained almost constant (XE, 2016).

The real GDP of all the three countries experienced growth of approximately 5% per annum combined. Although there were some increases in the GDP, as well as declines, on average the real GDP levels of all the three countries increased at a combined average of approximately 5% per annum (African Development Bank, 2011).

The historical trends for the Nigerian, South African, and Kenyan economies indicate that the naïve method cannot predict equity indices. The increases in the indices of the NSK emerging markets over the period of the study could not have been forecasted by the Naïve Method.

The descriptive statistics analyses of data for NSK are summarised in Table 4.1.

**Table 4.1: Descriptive statistics analyses of data for NSK**

| | **NIGERIA** | **SOUTH AFRICA** | **KENYA** |
|---|---|---|---|
| **Mean** | 172291.6 | 604708.8 | 178221.0 |
| **Median** | 172706.0 | 556101.5 | 178250.0 |
| **Maximum** | 253059.0 | 966270.0 | 262665.0 |
| **Minimum** | 94092.00 | 368271.1 | 104545.0 |
| **Std. Dev.** | 44836.30 | 177211.2 | 43162.61 |
| **Skewness** | 0.189306 | 0.474497 | 0.028812 |
| **Kurtosis** | 1.585805 | 1.775611 | 1.786168 |
| **Observations** | 1448 | 1500 | 1469 |

*Source: Researcher's own deduction*



All countries experienced a significant growth in share price indices. The high standard deviation indicates that the equity share prices experienced rapid growth. The data range (difference between the minimum and maximum) as a percentage was almost similar for all countries.

### 4.3.2 The ARCH/GARCH forecasts

A normality test was performed on the data. The results from the normality test indicated the presence of positive skewness for all three countries, high standard deviation when expressed as percentages of the average (approximately 30%), and kurtosis, which were below the standard (three) for normal distribution. The skewness and the kurtosis deviated from those of normally distributed data, indicating that nonnormality was present (as shown in table 4.1). The unit root test was subsequently performed, and the test results are presented in Table 4.2.

**Table 4.2: Unit root results**

| Markets | Level | | First difference | |
|---|---|---|---|---|
| | **ADF** | **PP** | **ADF** | **PP** |
| **Nigeria** | 0.88155 | 0.90653 | 6.38874e-58 | 6.337904e-58 |
| **South Africa** | 0.09157 | 0.14796 | 6.38904e-58 | 6.387904e-58 |
| **Kenya** | 0.95189 | 0.95531 | 6.38904e-58 | 6.388754e-58 |

*Source: Researcher's own deduction*

In Table 4.2 it is indicated that the data for all three countries was not stationary after the ADF and Phillips Perron tests were performed. At zero degrees of freedom, the probability value for all three countries exceeds 0.05, therefore, the null hypothesis that data was not stationary could not be rejected, resulting in the conclusion that the data was not stationary. At one degree of freedom (first difference), the probability value for all the three countries is below 0.05, therefore, the null hypothesis can be rejected, the alternative hypothesis accepted, and data was stationary.

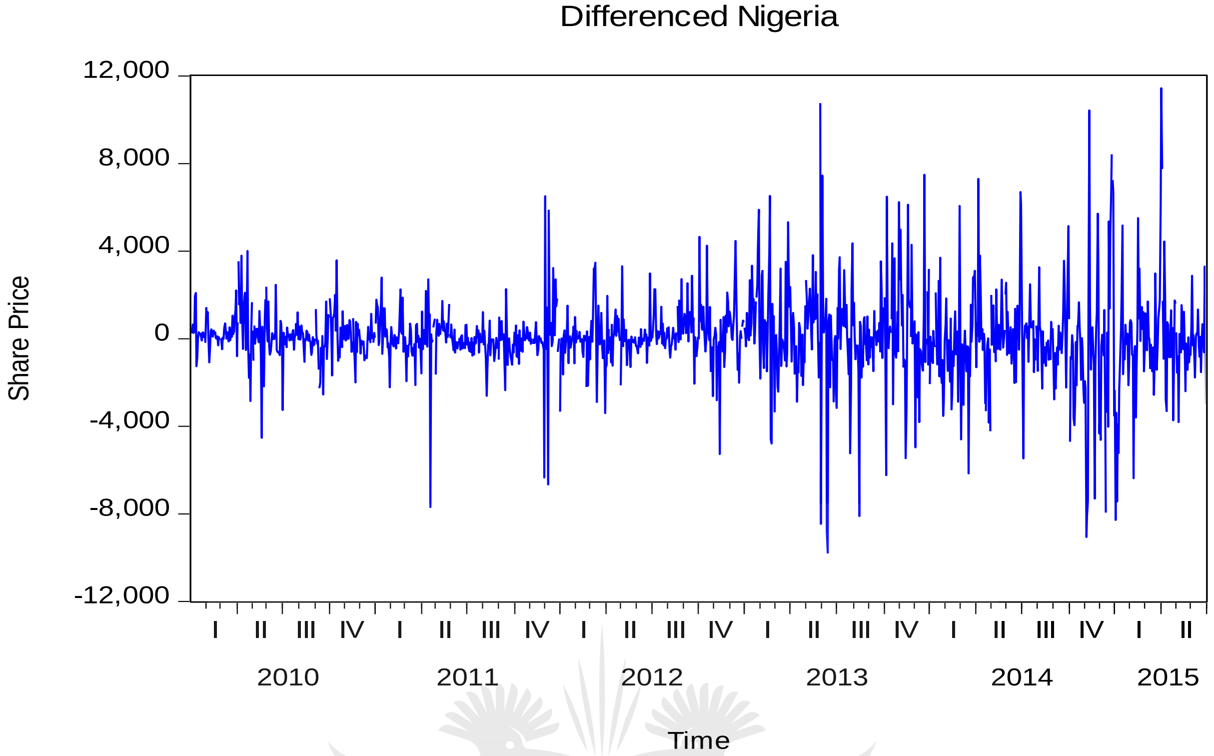
At zero degrees of freedom, the two testing models proved that the data was not stationary for any of the three countries. The null hypothesis was not rejected for all three countries, because the p-values exceeded a 5% significance level.

The data was differenced to one degree of freedom and became stationary. The two unit root testing models, i.e. the ADF and PP tests, had similar results, indicating that the data was stationary after the first difference. At first difference, the p-value was below the 5% significance level for all three countries, and the null hypothesis was rejected.

### 4.3.3 Differenced data

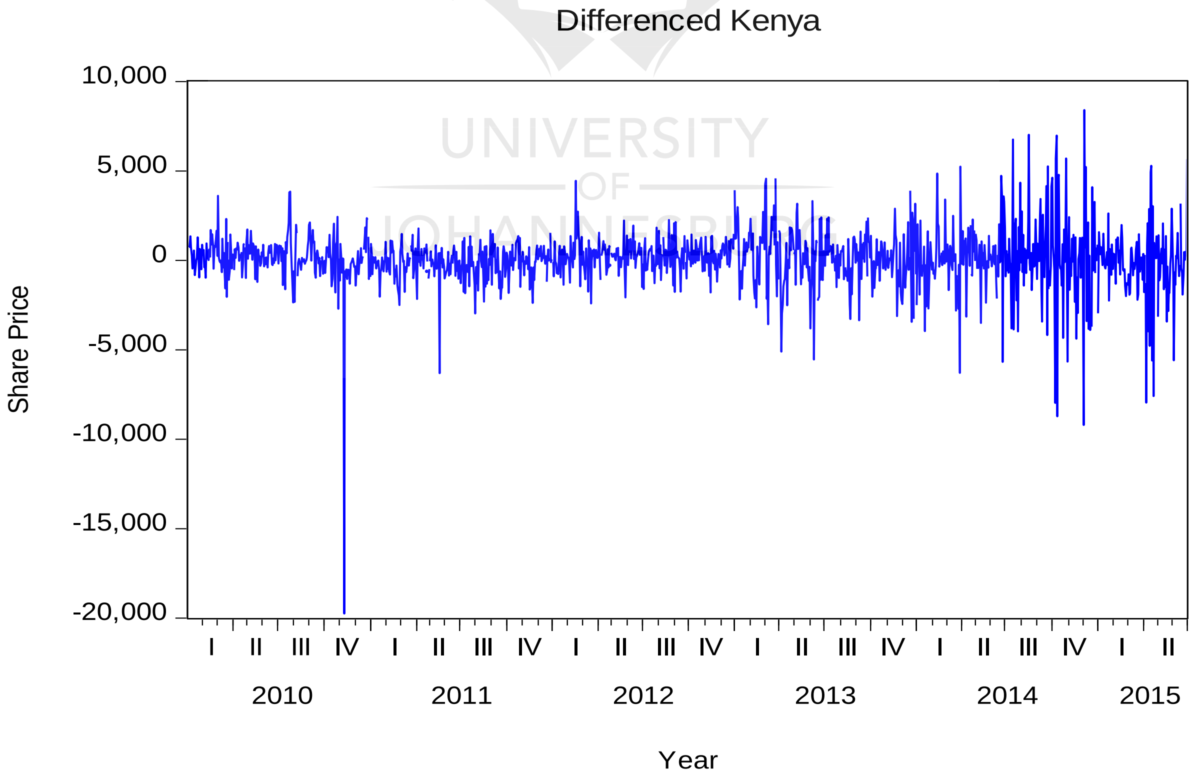
Figures 4.4, 4.5, and 4.6 present the differenced data for the three constructed indices of the NSK stock markets.

**Figure 4.4: Nigeria's price-weighted index differenced**



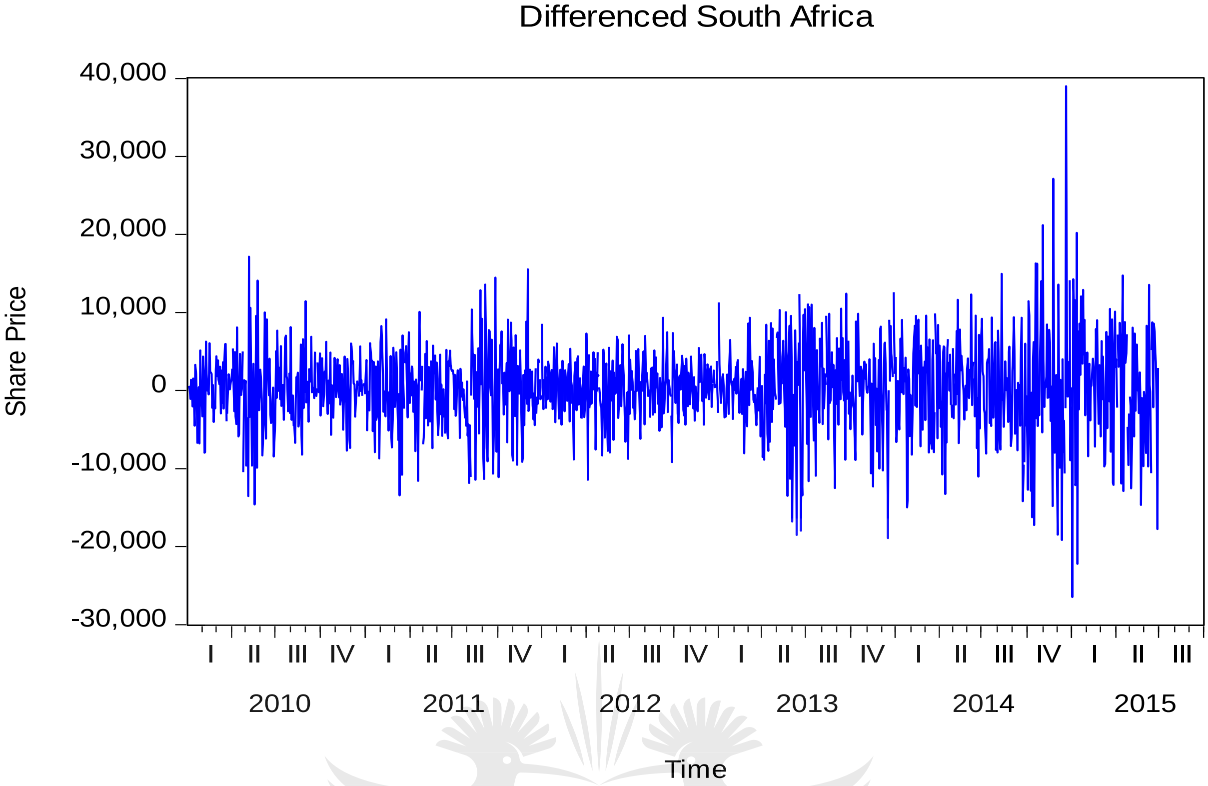

*Source: EViews output*

**Figure 4.5: Kenya's price-weighted index differenced**




*Source: EViews output*

**Figure 4.6: JSE price-weighted index differenced data**




*Source: EViews output*

Based on the differenced equity index share price data and the visual inspection of Figures 4.4, 4.5, and 4.6, the data was stationary with constant means although they were still volatile. The completed stationarity tests, using the ADF and PP tests, lead to the conclusion that the equity share price data for all three countries was stationary after first differencing.

### 4.3.4 Estimating the ARMA model

This section presents the ARMA models for each of the countries under study. The most appropriate ARMA models were selected using the EViews 9.1 software.

#### 4.3.4.1 Nigeria: ARMA Model

The automatic ARMA forecasting function in EViews 9.1 was used to select the most appropriate ARMA model, giving the lowest AIC and the SIB criteria. The lowest AIC was selected because it provided the model closest to the true estimates. The lowest

SIB provided the model that was most likely to be true. The appropriate ARMA model was ARMA (7,6) with the following equation:

Nigeria *c ar(1) ar(2) ar(3) ar(4) ar(5) ar(6) ar(7) ma(1) ma(2) ma(3) ma(4) ma(5) ma(6)*
Table 4.3 indicates the variables for Nigeria's ARMA (7,6).

**Table 4.3: ARMA (7,6) - Nigeria**

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 178811.0 | 40506.67 | 4.414360 | 0.0000 |
| AR(1) | 0.680003 | 0.367156 | 1.852080 | 0.0640 |
| AR(3) | 0.052784 | 0.246878 | 0.213807 | 0.8307 |
| AR(4) | 0.124474 | 0.328916 | 0.378436 | 0.7051 |
| AR(5) | 0.061700 | 0.398822 | 0.154706 | 0.8771 |
| AR(6) | 0.040677 | 0.383223 | 0.106144 | 0.9155 |
| AR(7) | 0.037134 | 0.156309 | 0.237571 | 0.8122 |
| MA(1) | 0.582897 | 0.369157 | 1.578994 | 0.1143 |
| MA(2) | 0.471773 | 0.463250 | 1.018397 | 0.3085 |
| MA(3) | 0.395916 | 0.471618 | 0.839485 | 0.4012 |
| MA(4) | 0.263001 | 0.394471 | 0.666718 | 0.5050 |
| MA(5) | 0.208123 | 0.334155 | 0.622833 | 0.5334 |
| MA(6) | 0.062039 | 0.112144 | 0.553208 | 0.5801 |

*Source: EViews output*

The ARMA (7,6) model had an AIC of -6.3709 and a SIB criterion of -6.3471. Table 4.3 indicates all the individual observations (AR (1-7) and MA (1-6)) with the exception of AR (2) are noteworthy at the 5% significance level, indicating that the null hypothesis can be rejected, and the presumption can be made that the variables were greater than zero. The R-square value of 4.98% and the adjusted R-squared value of 4.86% was less than 5%, therefore the conclusion was that the model could be used for predicting equity prices, and there was no multi-co-linearity.

### 4.3.4.2 Kenya: ARMA Model

For Kenya, the outcomes from the EViews 9.1 indicate that the ARMA (5,5) was the appropriate model with the following equation:Kenya *c ar(1) ar(2) ar(3) ar(4) ar(5) ma(1) ma(2) ma(3) ma(4) ma(5)*

Table 4.4 indicates the variables for Kenya's ARMA (5,5).

**Table 4.4: ARMA (5,5) - Kenya**

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 170800.0 | 279694.4 | 0.610667 | 0.5414 |
| AR(1) | 0.219281 | 7.487271 | 0.029287 | 0.9766 |
| AR(2) | 0.292400 | 7.435779 | 0.039323 | 0.9686 |
| AR(3) | 0.170804 | 1.742723 | 0.098010 | 0.9219 |
| AR(4) | 0.154187 | 2.850538 | 0.054090 | 0.9569 |
| AR(5) | 0.145474 | 1.960097 | 0.074218 | 0.9408 |
| MA(1) | 0.157531 | 7.425189 | 0.021216 | 0.9831 |
| MA(2) | 0.458764 | 4.880278 | 0.094004 | 0.9251 |
| MA(3) | -0.046186 | 5.095164 | -0.009065 | 0.9928 |
| MA(4) | 0.058561 | 4.948423 | 0.011834 | 0.9906 |
| MA(5) | 0.239684 | 3.079781 | 0.077825 | 0.9380 |

*Source: EViews output*

Table 4.4 indicates that all the coefficient values were positive except for *ma(3),* which was negative, and all the coefficient values were insignificant at the 5% level. The R-squared and adjusted R-squared values indicate that the accuracy of the model was statistically acceptable. In conclusion, the low F-statistic also supported that the model was significant at 5% significance level.

#### 4.3.4.3 South Africa: ARMA Model

Using EViews 9.1 software, the model that was selected was the ARMA (4,5) represented by the following equation:

South Africa *c ar(1) ar(2) ar(3) ar(4) ma(1) ma(2) ma(3) ma(4) ma(5)*

Table 4.5 indicates the variables for South Africa's ARMA (4, 5).

**Table 4.5: ARMA (4, 5) – South Africa**

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 20489900 | 4.40E+08 | 0.046591 | 0.9628 |
| AR(1) | 0.209478 | 0.006187 | 33.85979 | 0.0000 |
| AR(2) | 0.278451 | 0.020309 | 13.71073 | 0.0000 |
| AR(3) | 0.247427 | 0.028464 | 8.692645 | 0.0000 |
| AR(4) | 0.264622 | 0.040971 | 6.458737 | 0.0000 |
| MA(1) | 0.793366 | 0.028435 | 27.90096 | 0.0000 |
| MA(2) | 0.409673 | 0.041114 | 9.964325 | 0.0000 |
| MA(3) | 0.224336 | 0.054755 | 4.097076 | 0.0000 |
| MA(4) | -0.040896 | 0.036555 | -1.118752 | 0.2632 |
| MA(5) | 0.014909 | 0.028509 | 0.522952 | 0.6010 |

*Source: EViews output*

Table 4.5 indicates that all the variables were positive except ma(4), which was negative, and all variables were significant at the 5% level, except ma(4) and ma(5). The R-squared and adjusted R-squared values indicate that the models accuracy was statistically acceptable and could be used for the ARCH/GARCH forecasts. The low F-statistic also supports that the model was significant at a 5% significance level.

### 4.3.5 ARMA equation diagnostics

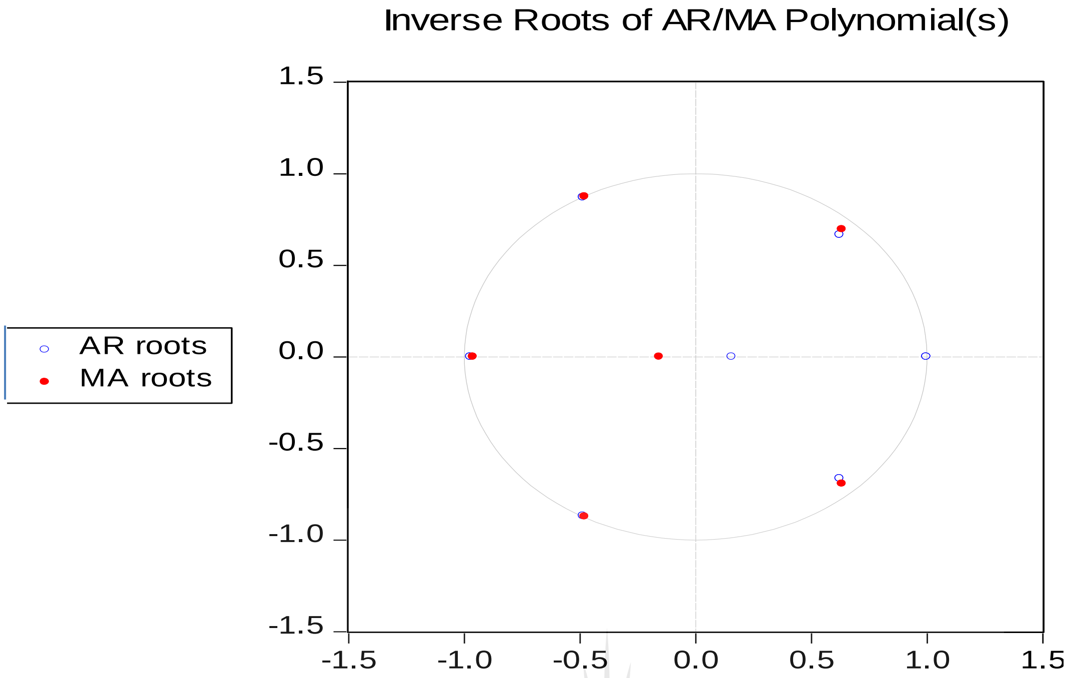
The selected models were diagnosed using the roots, correlogram, and the impulse response.



#### 4.3.5.1 Nigeria: ARMA diagnostics

After estimating the ARMA (7,6) model for the data-generating process, the model was examined using the ARMA equation diagnostics: the roots; correlogram; and impulse response and the results are presented in Figures 4.7 to 4.9.

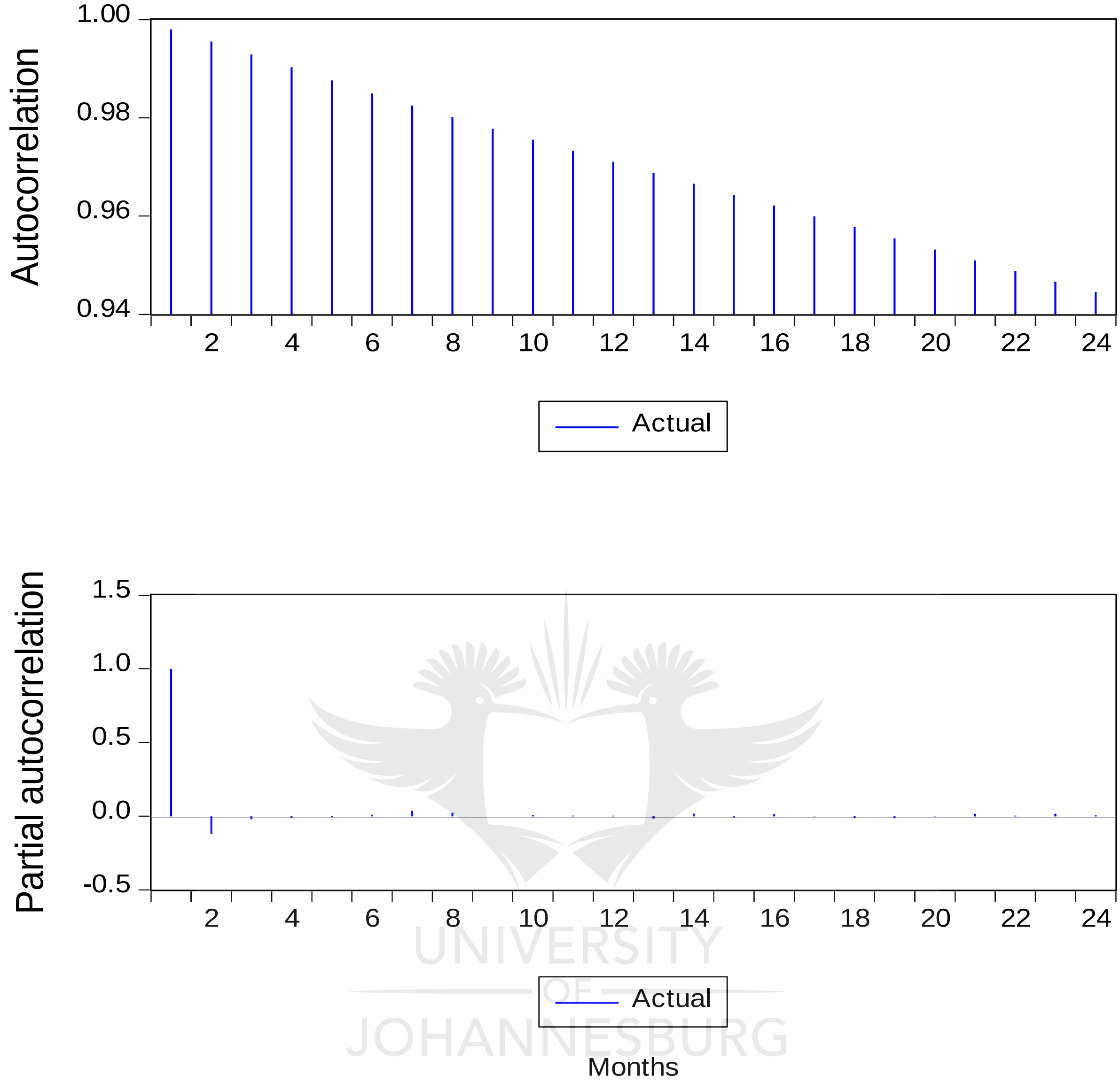
**Figure 4.7: ARMA diagnostics (roots)**




*Source: EViews output*

Figure 4.7 indicates the ARMA diagnostics (roots) for Nigeria. The roots view displays the inverse of the roots of the AR and MA characteristic polynomial. In EViews, the roots can be displayed as a table or as a graph. If the ARMA process is stationary, all AR roots should lie inside the unit circle, and if invertible, all MA roots should lie inside the unit circle.

**Figure 4.8: ARMA diagnostics (correlogram)**

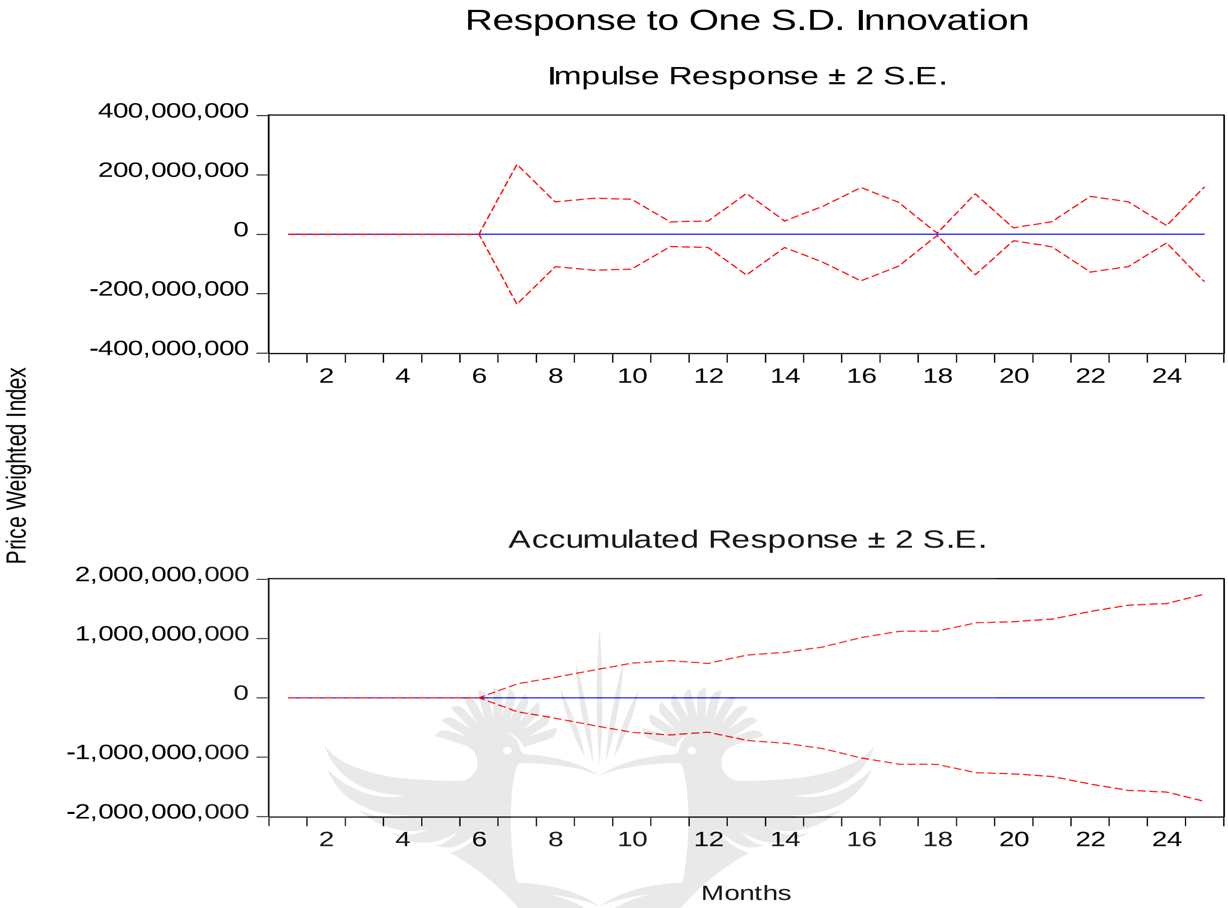





*Source: EViews output*

Figure 4.8 indicates the ARMA diagnostics correlogram for Nigeria. The correlogram view compares the autocorrelation pattern of the structural residuals and the estimated model for a specified number of periods. The results indicate a difference of less than 6% between the actual and estimated (theoretical) autocorrelations, which indicates that the model is properly specified. The graphical view of the actual and the ARMA model correlogram indicates that there may be a degree of misspecification in relation to the estimated ARMA, because the estimates were not exactly equal to actual.

**Figure 4.9: ARMA diagnostics (response)**




*Source: EViews output*

Figure 4.9 indicates the ARMA diagnostics impulse response for Nigeria. The ARMA impulse response measures the standard deviation shocks and time period to revert back to initial results. It follows the response to a one-time shock, and the results indicate that standard deviation shocks occurred and disappeared quickly, and possessed no memory of previous events. Likewise, the accumulated response value converged to ultimate effect in the long run, as indicated in Figure 4.9. The two red lines on the Accumulated Response graph in Figure 4.9 diverged from the zero line from month six, but still within the range of two. This indicated that it had a short memory.

The results of the three ARMA diagnostic tests presented in Figures 4.7, 4.8, and 4.9 indicate that the ARMA model can be used for forecasting. The roots were within the circle, the correlogram's autocorrelations and partial autocorrelations indicate that the model was properly specified and the impulse response indicated that ARMA had short memory (market shocks do not affect the data for a long period).

#### 4.3.5.2 Kenya ARMA diagnostics

The appropriate model was the ARMA (5,5) and it was diagnosed using three methods namely: the roots; correlogram; and impulse response. The resultant graphs were similar to Figures 4.7, 4.8, and 4.9 and are therefore not repeated here. The ARMA diagnostics (roots) indicated that both AR roots and MA roots lay inside the unit circle. The correlogram's autocorrelations and partial autocorrelations indicate that the model was properly specified, and the impulse response indicates that ARMA had a short memory. Similar to results for Nigeria, all three diagnostic tests indicated that the model could be used to forecast.

#### 4.3.5.3 South Africa ARMA diagnostics

The three diagnostic methods namely: the roots; correlogram; and impulse response were used to analyse the ARMA (4,5) model. The resultant graphs were similar to Figures 4.7, 4.8, and 4.9 and are therefore not repeated here. ARMA diagnostics (roots), both AR roots and MA roots, lay inside the unit circle. The correlogram's autocorrelations and partial autocorrelations indicate that the model was properly specified, and impulse response indicates that ARMA had short memory. All three methods indicated that the ARMA model could be used as the mean equation for the ARCH/GARCH model.



### 4.3.6 Testing for ARCH effects

In order to use the ARCH/GARCH models to forecast, ARCH effects must be present in the data. The selected ARMA equations were tested for the ARCH effects using the EViews software.

#### 4.3.6.1 Nigeria: Testing ARCH effects

The first step was to test for the presence of ARCH effects in order to proceed to forecasting the equity market using the ARCH/GARCH models. The results of testing for ARCH effects is presented in Table 4.6.

**Table 4.6: Testing ARCH effects (Nigeria)**

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 7.606135 | Prob. F(1,1345) | 0.0059 |
| Obs*R-squared | 7.574610 | Prob. Chi-Square(1) | 0.0059 |

*Source: EViews output*

Table 4.6 indicates that the ARCH LM test (testing for ARCH effects) yields an F-statistic of 7.606135, which exceeds the 95% confidence level. The Chi-Square (1) test statistic also had a p-value of 0.0059, which is less than the 5% significant level. The null hypothesis that there are no ARCH (1) effects was rejected, and therefore the presumption was that there were ARCH effects. Therefore, the ARCH/GARCH model can be used to forecast.

#### 4.3.6.2 Kenya: Testing ARCH effects

The ARMA model was tested for heteroskedasticity in order to use the ARCH/GARCH models to forecast. The results are presented in Table 4.7.



**Table 4.7: Testing ARCH effects (Kenya)**

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 10.12535 | Prob. F(1,1377) | 0.0015 |
| Obs*R-squared | 10.06604 | Prob. Chi-Square(1) | 0.0015 |

*Source: EViews output*

Table 4.7 indicates the results of the test for ARCH effects for Kenya. The ARCH LM test yielded a test statistic of 10.12535, which exceeded the 95% critical value for the Chi-Square (1) test statistic (the p-value was 0.0015 which was less than the 5% significance level). The null hypothesis that there were no ARCH (1) effects was rejected in favour of the alternative hypothesis that there were ARCH effects present.

The F-statistic test p-value (0.15%) was below the 5% significance level, and confirms that the null hypothesis could be rejected. It was concluded that ARCH effects were present.

#### 4.3.6.3 South Africa: Testing ARCH Effects

In order to use the ARCH/GARCH model to forecast, heteroskedasticity must be present. The ARCH test results for South Africa’s JSE price-weighted index are presented in Table 4.8.

**Table 4.8: Testing ARCH effects (South Africa)**

Heteroskedasticity Test: ARCH

| | | | |
|---|---|---|---|
| F-statistic | 9.154990 | Prob. F(1,1369) | 0.0025 |
| Obs*R-squared | 9.107460 | Prob. Chi-Square(1) | 0.0025 |

*Source: EViews output*

Table 4.8 indicates the results of the test for ARCH effects for South Africa. Based on the results in Table 4.8, there were ARCH effects, and the ARCH/GARCH model can be used to forecast. The ARCH LM test yielded a test statistic value of 9.15499, which exceeded the 95% critical value, and the p-value of 0.25% was below the 5% significance level. The null hypothesis that there were no ARCH (1) effects was rejected in favour of the alternative hypothesis that ARCH effects were present. The F-statistic test results indicated a p-value of 0.25%, which is below the 5% significance level, and confirms that the null hypothesis can be rejected. Both the F-statistic and p-value indicated that ARCH effects were present.

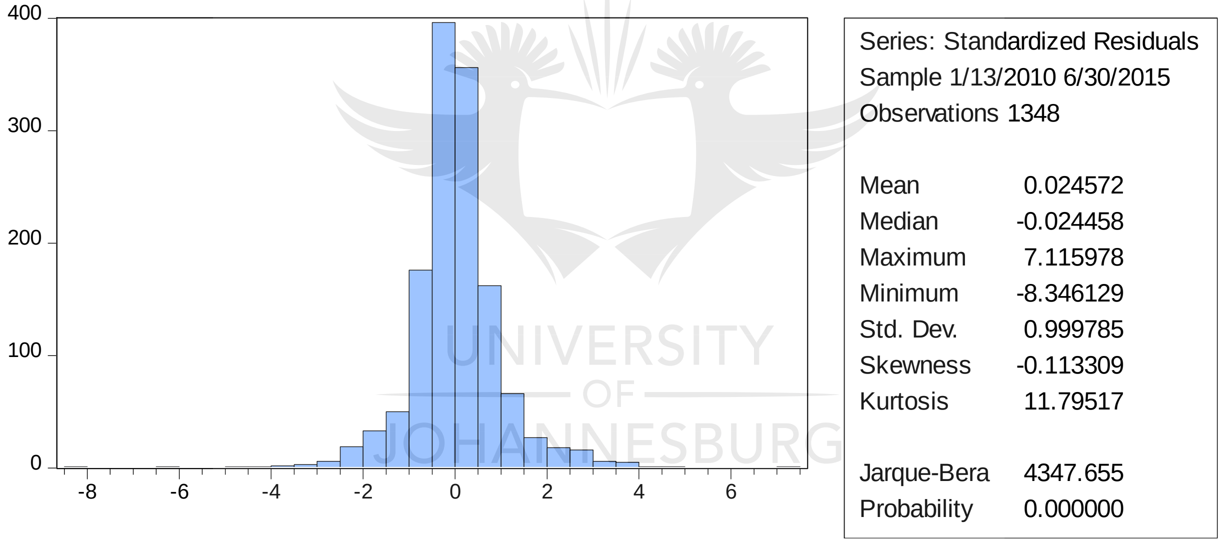
### 4.3.7 Estimation procedure

The ARCH/GARCH estimation model is divided into two sections: the upper section provides the standard output for the mean equation; and the lower section shows the variance equation. The results from ARMA diagnostics indicate that the variables for the mean equation and the variance equation were statistically significantly different from zero at the 95% confidence level.

#### 4.3.7.1 Nigeria: Estimation model

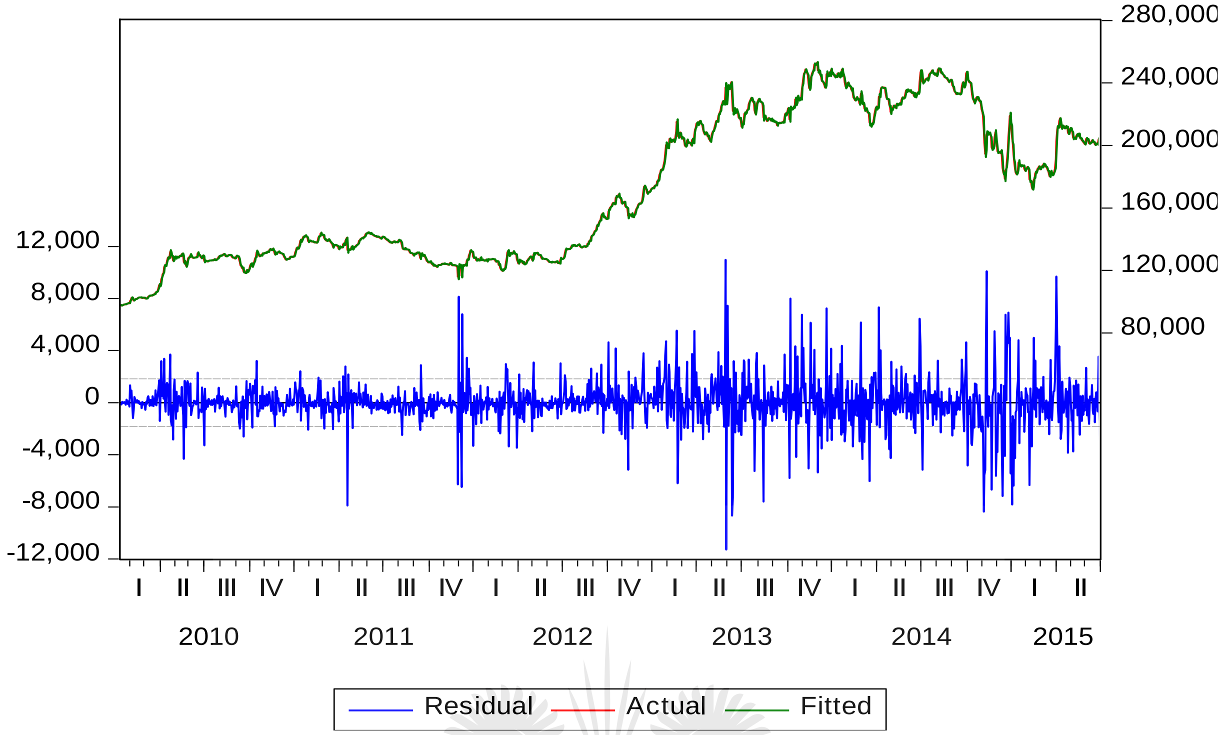
The appropriate model was selected based on the positivity of variables, the variance equation, R-squared, and the AIC and SIB criterion mentioned for the ARMA equation. The researcher used the trial and error method to select the most appropriate model. Several trials were carried out, and the model with the most positive and significant variables, low values in the variance equation, and low R-squared, and adjusted R-squared was selected. The appropriate forecasting model was the GARCH (2,1) based on the selection criteria used. The GARCH (2,1) model selected was diagnosed using the GARCH graph, covariance matrix, and actual, fitted and residuals in EViews. The results are presented in Figure 4.10 and 4.11; both indicated that the model was acceptable and could be used to forecast.

**Figure 4.10: GARCH (2,1) diagnostics**




*Source: EViews output*

**Figure 4.11: GARCH (2,1) Diagnostics**




*Source: EViews output*

#### 4.3.7.2 Kenya: Estimation model

A trial and error method was used to select the most appropriate model. Several trials were done and the model with positive and significant variables, low values in the variance equation, and low R-squared and adjusted R-squared were selected. Based on set selection criteria, the EGARCH (2,2) was selected as the appropriate model and diagnosed to examine whether or not it was adequate for forecasting. The diagnostic testing results indicate that the model was adequate and could be utilised for forecasting. The probability value, F-statistic, R-Squared, and adjusted R-Squared were positive and significant.

#### 4.3.7.3 South Africa: Estimation model

A trial and error method was used to select the most appropriate model. Several trials were done, and the model with positive and significant variables, low values in the variance equation, low R-squared, and adjusted R-squared were selected. Based on the selection criteria, the most appropriate model for forecasting the South African equity market is EGARCH (2,1). Comparative diagnostic models were used to assess the appropriateness of the EGARCH (2,1) model, and the results (similar to Figure 10 and 11) indicate that the model can be utilised for forecasting.

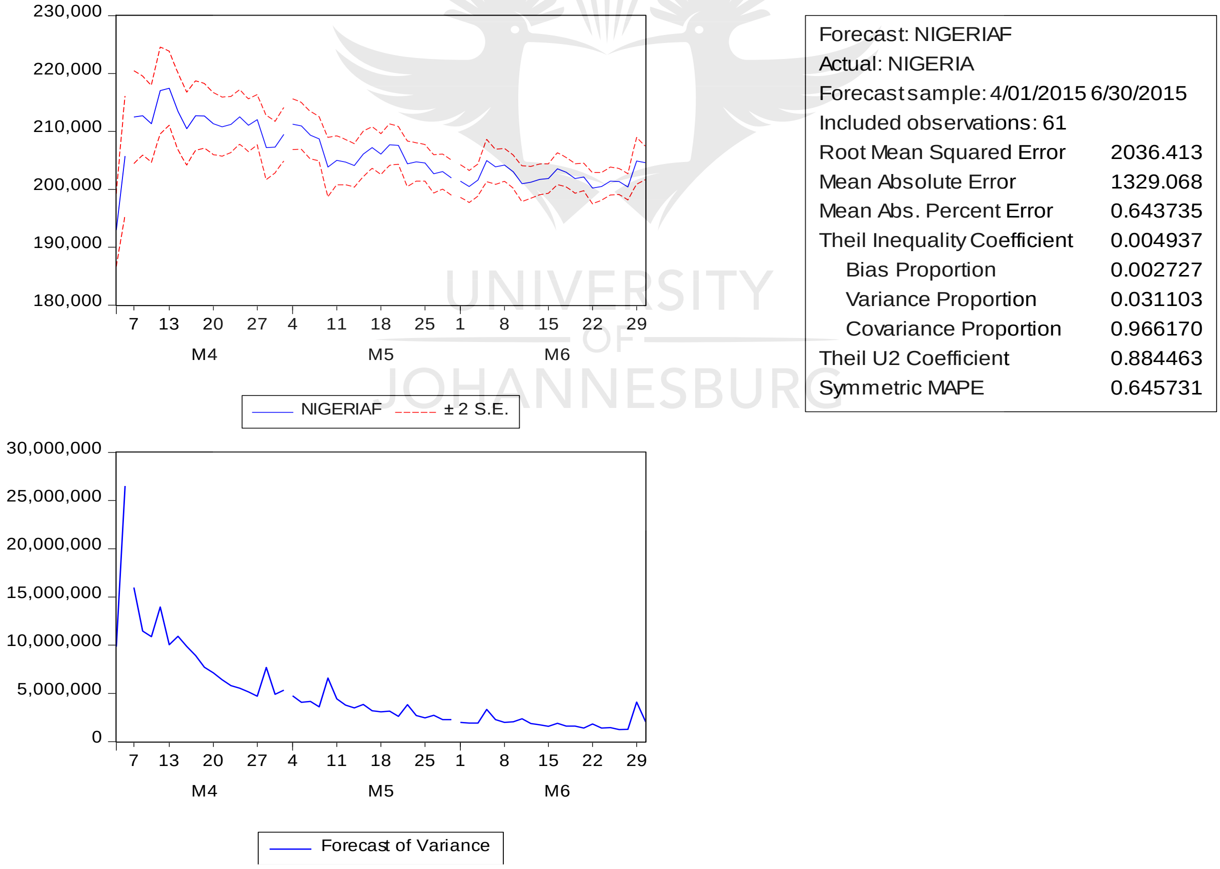
### 4.3.8 In-sample forecasting

Forecasting is defined as utilising historical data to predict the future. In-sample forecasting uses available data to forecast known data, and this was used for the initial forecasting model estimation and selection.

#### 4.3.8.1 Nigeria: In-sample forecasting

The GARCH (2,1) model was used to forecast three-month equity prices for Nigeria's weighted share price index. The results of the three-month forecast are presented in Figure 4.12.

**Figure 4.12: Nigeria's in-sample forecast**




*Source: EViews output*

The results presented in Figure 4.12 indicate the GARCH (2,1) model's accuracy in predicting Nigeria's price-weighted index for a three-month period. The RMSE exhibited a value of 2 036.41, which was relatively low, due to the large index values used, and was below 1% when expressed as percentage of the mean. The RMSE is a measure of the difference between the actual values observed against the predicted values; a high value indicates that the model is not accurate. In statistics, the MAPE measures a forecasting method's prediction accuracy. The results in Figure 4.12 indicate a small MAPE of 0.6437% that was in consonance with the RMSE, implying that the predictions were statistically accurate.

The Thiel Inequality Coefficient measures the difference between the maximum possible entropy of the data and the observed entropy. The Theil Inequality Coefficient of 0.004937 presented in Figure 4.12 is small, indicating that the predictions were accurate. It is in line with the other forecasting measures, such as the RMSE, which indicates that the predictions were close to the actual.

Bias measures systematic error. A bias value of zero indicates no systematic error and an accurate forecast. Figure 4.12 indicates a bias of 0.002727 that suggests that forecast results should be accurate.



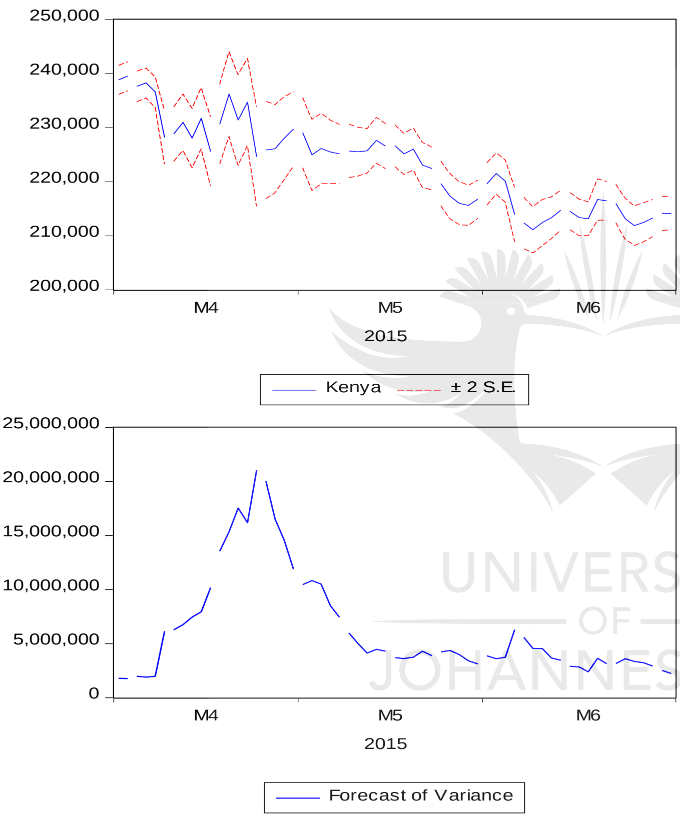
Covariance proportion measures unsystematic errors, and the value of 0.9661 (which is very close to one, due to the large index values used) indicates that the prediction was not accurate. Variance proportion measures the ability of the forecasts to replicate the actual figures. The results indicate a variance proportion of 3.11%, which is less than 5%, an indication that the forecasting results were acceptable.

The forecasts of Nigeria's price-weighted equity index generated by this model were only marginally better than the Naïve Model's forecasting results. The RMSE and Theil Inequality Coefficient indicate that the forecasts were accurate. However, the variance proportion (3.11%) and covariance proportion (0.9961) indicated that there was a significant variance between the forecasts and the actual values. Bleaney (1998) and Cao and Soofi (1999) confirm that the ARCH/GARCH models' forecasting accuracy is more precise than the Naïve Model, however, they cannot be relied on to predict future equity movements. Therefore, the GARCH (2,1) predicted Nigeria's equity prices better than the Naïve models.

### 4.3.8.2 Kenya: In-sample forecasting

The EGARCH (2,2) model was used to forecast three-month equity prices for Kenya's price-weighted index. The results are presented in Figure 4.13.

**Figure 4.13: Kenya's in-sample forecasting**




| | |
|---|---|
| Forecast: KENYA | |
| Actual: KENYA01 | |
| Forecast sample: 4/01/2015 6/30/2015 | |
| Included observations: 61 | |
| Root Mean Squared Error | 2729.997 |
| Mean Absolute Error | 1893.388 |
| Mean Abs. Percent Error | 0.842413 |
| Theil Inequality Coefficient | 0.006118 |
| Bias Proportion | 0.011849 |
| Variance Proportion | 0.011735 |
| Covariance Proportion | 0.976415 |
| Theil U2 Coefficient | 1.035569 |
| Symmetric MAPE | 0.839925 |

*Source: EViews output*



Figure 4.13 indicates the Kenyan forecasting results. It demonstrates how accurately the EGARCH (2,2) predicted Kenya's share price index for a period of three-months. The RMSE of 2 729.99 was low, and it contributed to the high index values, indicating that the forecasting model was accurate. The RMSE expressed as a percentage of the mean was approximately 1.2%, which was low. Figure 4.13 indicates a MAPE of 0.8424%, which supports the RMSE, implying that the predictions were accurate.

The Theil Inequality Coefficient of 0.006118 (which is small and close to zero), presented in Figure 4.13 supports the other forecasting measures presented, such as the RMSE. A low Theil Inequality Coefficient indicates that predictions were accurate and in consonance with the RMSE and MAPE values.

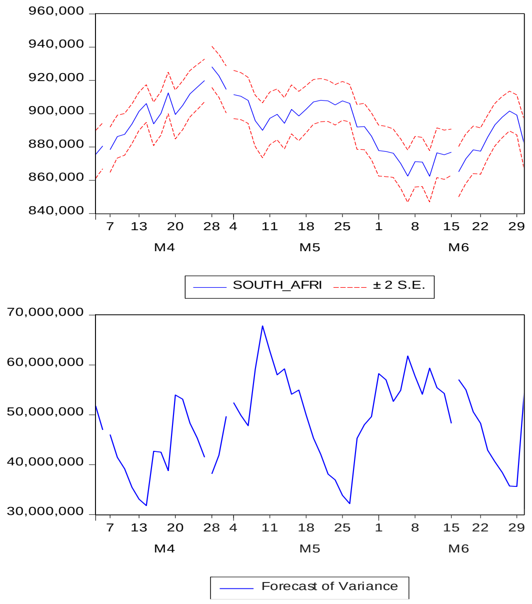
Figure 4.13 indicates a bias of 0.011849, which is small in relation to the benchmark of one, indicating that predictions were accurate, which supports the RMSE figure that indicate that predictions were accurate.

The forecasts of Kenya's price-weighted equity index generated by the ARCH/GARCH models were marginally better than the Naïve forecasting results. The forecasting measures are contradicting. Most of the results indicate that there was a small variance between the forecasted and the actual values. It was concluded that the accuracy of the forecast was not conclusive, and therefore did not have value for decision-making.

**4.3.8.3 South Africa: In-sample forecasting**

The EGARCH (2,1) model was used to forecast three-month in-sample equity prices for South Africa's JSE price-weighted index. The results are presented in Figure 4.14.

**Figure 4.14: South Africa's in-sample forecast**




| | |
|---|---|
| Forecast: SOUTH_AFRI | |
| Actual: SOUTH_AFRICA | |
| Forecast sample: 4/01/2015 6/30/2015 | |
| Included observations: 60 | |
| Root Mean Squared Error | 6910.335 |
| Mean Absolute Error | 5661.048 |
| Mean Abs. Percent Error | 0.634625 |
| Theil Inequality Coefficient | 0.003866 |
| Bias Proportion | 0.000000 |
| Variance Proportion | 0.000029 |
| Covariance Proportion | 0.999971 |
| Theil U2 Coefficient | 0.979337 |
| Symmetric MAPE | 0.634153 |

*Source: EViews output*

The results presented in Figure 4.14 indicate the prediction accuracy of the EGARCH (2,1) model in predicting South Africa's JSE price-weighted index for a three-month period. The RMSE of 6 910.33, which was low relative to the index values used, indicating that there was a small variance between the actual and the forecasted values. The RMSE expressed as a percentage of the mean of 1.14% indicated that the results were accurate. The results in Figure 4.14 indicate a low MAPE of 0.6346%, which is also an indication that the predictions were accurate.



The Theil Inequality Coefficient of 0.003866 was low, indicating that the forecast was accurate, which supports the other forecasting measures (MAPE and RMSE).

Figure 4.14 indicates a bias of 0.00000, which is low, indicating that the prediction was accurate, which supports the RMSE indicator. The covariance proportion of 0.999971 is high, almost one. This indicates a deviation of the forecast from the actual share price. The results in Figure 4.14 indicate a low variance proportion of 0.000029, indicating the opposite, that the forecast was accurate.

The forecasts of South Africa's JSE price-weighted index generated by this model are better than Naïve forecasting results. However, the forecasting measures were contradictory, which is an indication that the predictions were accurate and better than the Naïve models' predictions.

An analysis of the predictions of the three selected African economies indicate that some of the results comparing different measuring variables were contradictory. The ARCH/GARCH models were more efficient prediction models in comparison to the Naïve Model. Despite the ARCH/GARCH models being better than the Naïve Model, the models cannot be relied on as methods to predict the future share prices of the NSK equity markets.

### 4.3.9 Out-of-sample forecasting

Out-of-sample forecasting involves using data that is currently unavailable to predict the future equity prices. The forecasted numbers were compared to the actual numbers, and the formula was applied to calculate the RMSE, MAPE, and MAD.
Table 4.5 indicates the measuring variables for each model used.

**Table 4.5: ARCH/GARCH versus Monte Carlo Simulation**

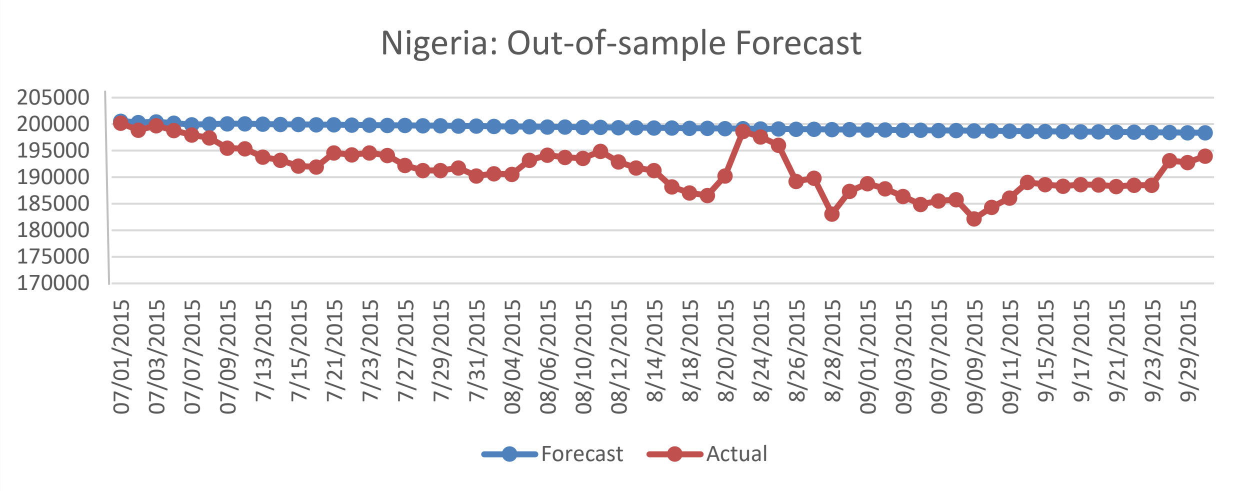
| | Nigeria | | Kenya | | South Africa | |
|---|---|---|---|---|---|---|
| | *ARCH/GARCH* | *Monte Carlo* | *ARCH/GARCH* | *Monte Carlo* | *ARCH/GARCH* | *Monte Carlo* |
| **MAD** | 7 868.67 | 13 762.76 | 4 337.16 | 13 869.95 | 21 322.51 | 28 625.72 |
| **MSE** | 76 832 061.55 | 222 348 512.53 | 28 171 048.17 | 268 561 075.20 | 675 816 764.20 | 1 238 356 136.91 |
| **RSME** | 8 765.39 | 14 911.36 | 5 307.64 | 16 387.83 | 25 996.48 | 35 190.28 |
| **MAPE** | 0.0416 | 0.0726 | 0.0208 | 0.0679 | 0.0247 | 0.03 |

*Source: Researcher's own deduction*

#### 4.3.9.1 Nigeria: Out-of-sample forecasting

The GARCH (2,1) model was used to forecast three-month equity prices for Nigeria's price-weighted index. The results of the three-month out-of-sample forecast are presented in Figure 4.15.

**Figure 4.15: Nigeria' out-of-sample forecast**




*Source: Researcher's own deduction*

Figure 4.15 illustrates the three-month out-of-sample forecast for Nigeria. For the three-month out-of-sample forecasts, the RMSE of 8 765.39 was low because of the large index values used and the period covered, indicating that it was an accurate model. The RMSE expressed a percentage of approximately 5%, which was low, indicating that the results were accurate. The RMSE for the three-month period was 8 765.39, which was higher than the RMSE obtained using the in-sample forecast (2 036.41), indicating that the in-sample forecast was more accurate than the out-of-sample forecast.

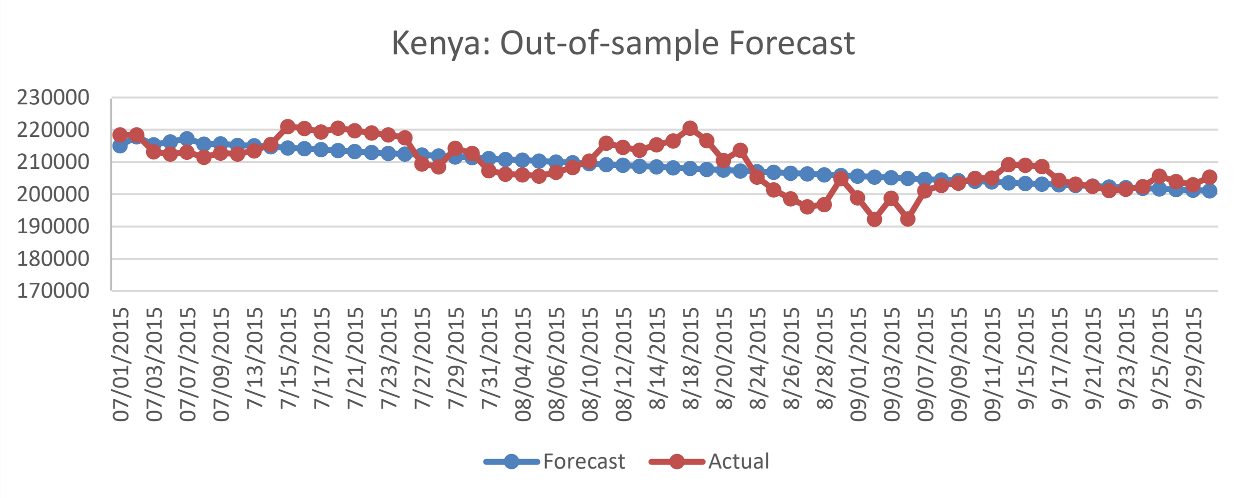


The MAPE for the three-month out-of-sample forecast was 4.156%, which was small, indicating that the results were accurate. The MAD was 7 868.66, which was low relative to the large index values used. These results were confirmation that the in-sample forecast was more accurate than the out-of-sample forecast.

**4.3.9.2 Kenya: Out-of-sample forecast**

The EGARCH (2,2) model was used to forecast three-month equity prices for Kenya's price-weighted index. The results are presented in Figure 4.16.

**Figure 4.16: Kenya out-of-sample forecast**




*Source: Researcher's own deduction*

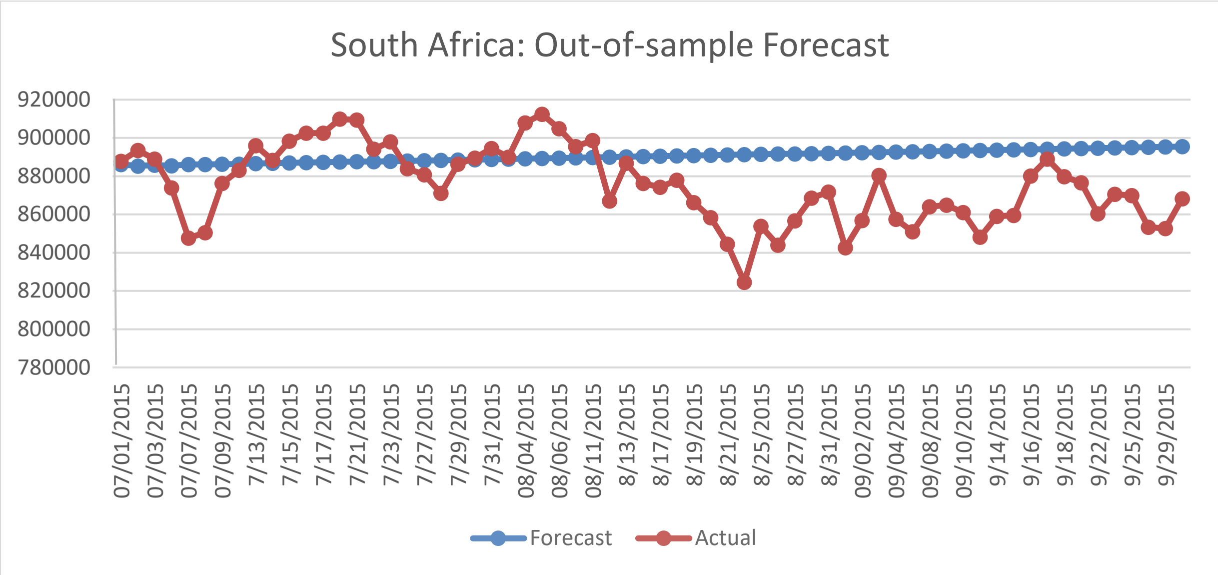
Figure 4.16 indicates the three-month out-of-sample forecast for Kenya. The three-month out-of-sample RMSE was 5 307.64, which was low and as a result of large index values used and the period covered, indicating that it was an inaccurate model. The RMSE expressed as a percentage of mean was approximately 3%, which is low, indicating the forecast's accuracy. The RMSE for the three-month period was 5 307.64, which was two times higher than the 2 729.99 obtained for the in-sample forecasting; therefore the in-sample forecast was more accurate than the out-of-sample forecast.

The MAPE for the three-month out-of-sample forecast was 2.079%, which was low relative to the index values used, indicating that the results could be statistically accurate. The results show a MAD value of 4 337.16, which was low, indicating that the predictions deviated from the actual values insignificantly. These results confirmed that in-sample forecasting is more accurate than out-of-sample forecasting.

#### 4.3.9.3 South Africa: Out-of-sample forecast

The EGARCH (2,1) model was used to forecast three-month in-sample equity prices for South Africa's JSE price-weighted index. The results are presented in Figure 4.17.

**Figure 4.17: South Africa's out-of-sample forecast**




*Source: Researcher's own deduction*

Figure 4.16 illustrates the three-month out-of-sample forecast for South Africa. The three-month out-of-sample forecasts results had an RMSE of 25 996.476, indicating that the forecasting deviated from the actual values. The RMSE expressed as a percentage of mean was 5.29%, which indicates that the model was accurate in statistical terms. The RMSE for the three-month period was 25 996.476, which was more than three times higher than the 6 910.33 for the in-sample forecast; therefore in-sample forecasting is more accurate than out-of-sample forecasting.



The MAPE for the three-month out-of-sample forecast was 2.468%, which was low, indicating that the results were statistically accurate. The MAD was 21 322.50, which was high, indicating that the forecasts deviated from the actual values. The results indicated that in-sample forecasting was more accurate than the out-of-sample forecasting.

Compared to Nigeria and Kenya's price-weighted index predictions, South Africa's JSE price-weighted index out-of-sample forecasts were the least accurate. Despite the high variations between the forecasted and actual values, the forecasting models were more accurate than the Naïve Model. The results confirm that for NSK, in-sample forecasts were more accurate than out-of-sample forecast. The increased inaccuracy of out-of-sample forecasting is significant, because in order to utilise the predictions, out-of-sample forecasting is required.

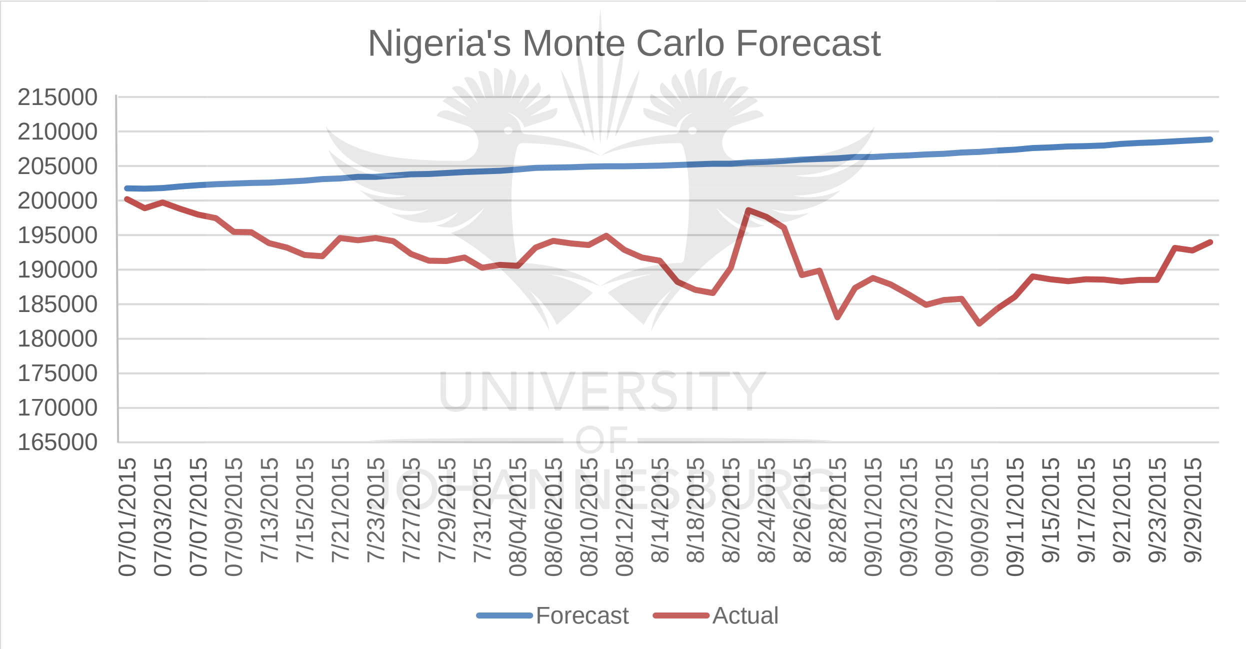
## 4.3.10 Monte Carlo Simulation

The three-month-ahead Monte Carlo Simulation used in this research had 1 200 iterations. The results for each of the NSK countries are presented in this section.

### 4.3.10.1 Nigeria's Monte Carlo Forecast

Figure 4.18 indicates the forecast for a 90-day period. There were some discrepancies between the actual values and the Monte Carlo Simulation forecast.

**Figure 4.18: Nigeria's Monte Carlo forecast**




*Source: Researcher's own deduction*

The three-month-ahead Monte Carlo forecasts' accuracy was assessed by the RMSE, which was 14 911.355. The RMSE was higher than the 2 036.41 (in-sample) and 8 765.39 (out-of-sample) ARCH/GARCH model forecasts. Figure 4.18 indicates that the deviation between the actual values and forecast increased over time.

The MAPE for the three-month-ahead Monte Carlo forecast was 7.255%, which indicates that the results were statistically inaccurate at a 95% confidence interval. The implication is that there was more than a 90% probability of no variance between the actual and the forecasted values. The results show a MAD of 13 762.75, which was low relative to the index values, indicating a deviation between the forecast and the actual values, but it was higher than the MAD value (7 868.66) for ARCH/GARCH for out-of-sample forecasting.

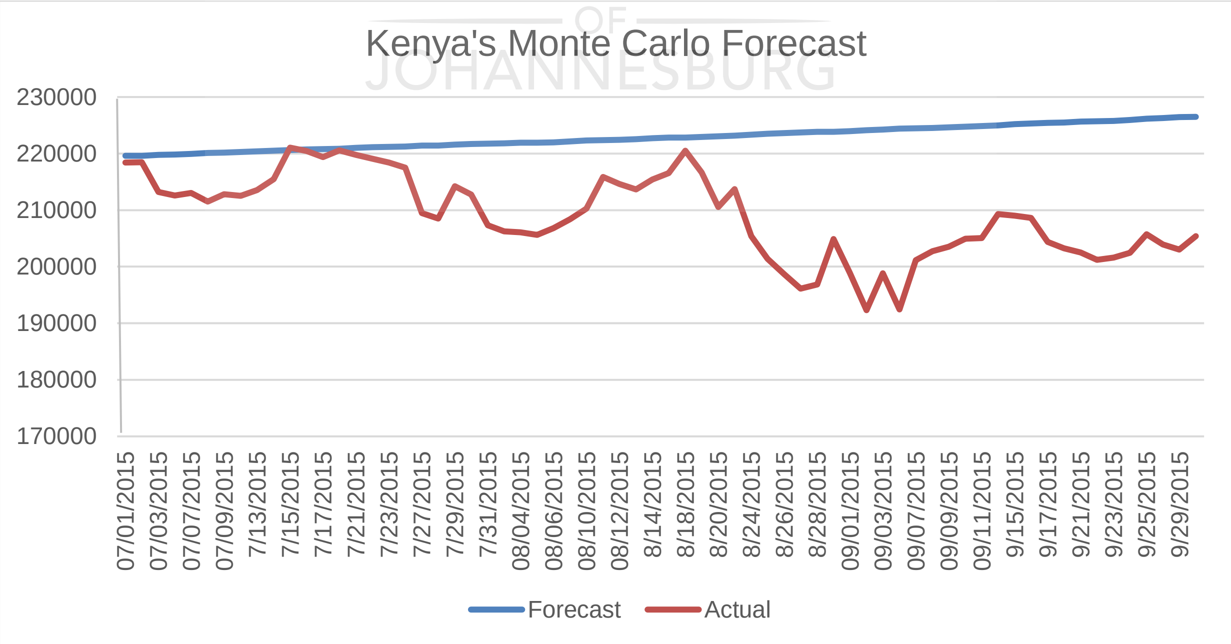
Figure 4.18 indicates that the Monte Carlo Simulation 90-days-ahead predictions were inaccurate because of the deviation of approximately 6% from the actual values and the contradiction of the measuring variables. The forecasting results were better than the Naïve Model, however they cannot be used for economic purposes.

#### 4.3.10.2 Kenya’s Monte Carlo forecast

Figure 4.19 indicates the three-months-ahead Monte Carlo forecast for Kenya. The deviation of the forecast and the actual values for the first half of the period were lower than the values for the last half of the period, indicated by a widening gap as the period of forecast increased.



**Figure 4.19: Kenya’s Monte Carlo forecast**




*Source: Researcher’s own deduction*

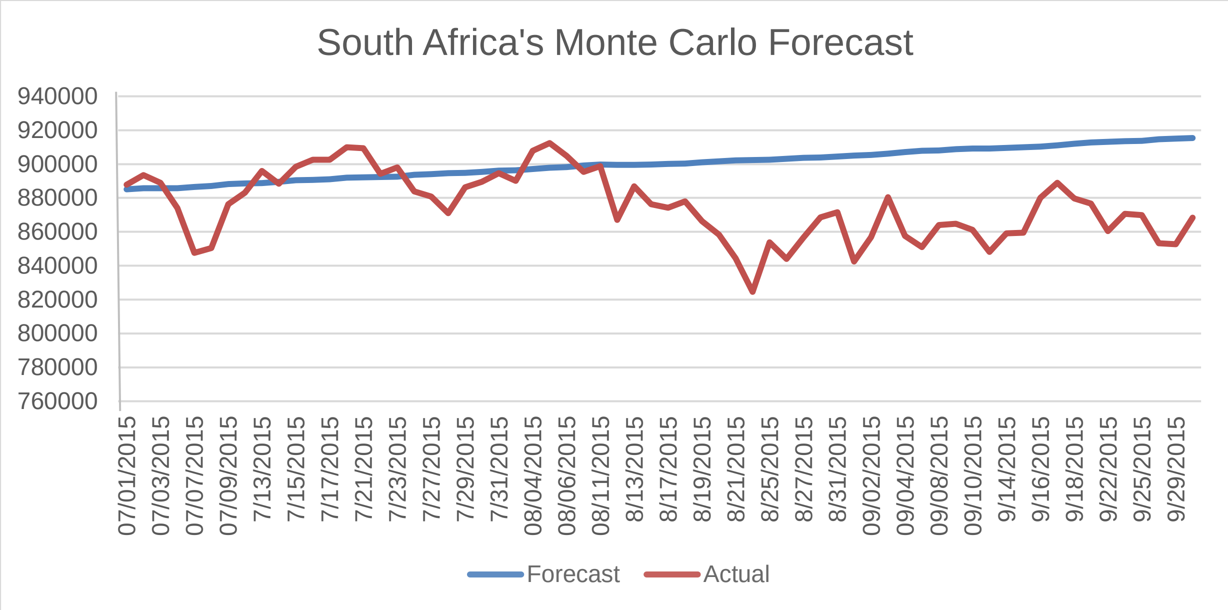
The three-month-ahead Monte Carlo forecasts were assessed using the RMSE, which at 16 387.83 was higher than 2 729.99 and 5 307.64 for ARCH/GARCH's in-sample and out-of-sample respectively. This demonstrates that that the forecast was inaccurate and that stakeholders cannot rely on the Monte Carlo Simulation Model for investment decision-making purposes.

The MAPE for the three-month out-of-sample forecast was 6.7882%, which indicates that the results were accurate. The MAPE indicates that there was a 90% probability of achieving an accurate forecast. The MAD value of 13 869.949, expressed as a percentage of mean was approximately 7%, which was low relative to large index values. This indicated a deviation between the forecast and the actual values and it was higher compared to the MAD value (4 337.16) for ARCH/GARCH for out-of-sample. This MAD value indicates that the results were statistically inaccurate at a 95% significance level.

#### 4.3.10.3 South Africa's Monte Carlo forecast

Figure 4.20 indicates the three-month-ahead Monte Carlo Simulation forecast. The movement of the actual equity prices recorded and the forecast using the Monte Carlo Simulation were consistent for the duration of the forecast.

**Figure 4.20**: **South Africa's Monte Carlo forecast**




*Source: Researcher's own deduction*

The three-month-ahead Monte Carlo forecast for South Africa assessed using the RMSE, was 35 190.284, which is high, compared to 6 910.33 and 25 996.476 for ARCH/GARCH's in-sample and out-of-sample respectively. Despite the large index values used, the RMSE indicates that the predictions deviated substantially from the actual values. This demonstrates that the forecast was inaccurate and stakeholders cannot rely on the Monte Carlo Simulation model for investment decision-making purposes.



The MAPE for the three-month Monte Carlo forecast was 3.3182%, indicating accurate results. The MAD value was 28 625.717, expressed as a percentage of mean was approximately 6%, and was low due to large index values. This indicated a small deviation between the forecast and the actual values but it was higher than the MAD value (21 322.50) for ARCH/GARCH for out-of-sample. The results indicate that the predictions were statistically accurate. The measuring variables contradicted each other; MAPE indicating that the predictions were accurate and RMSE and MAD indicating otherwise.

#### 4.3.11 Summary of ARCH/GARCH versus the Monte Carlo Simulation

Higher measuring variables in Table 4.6 indicate that predictions were less accurate than the actual share prices. The accuracy measuring variables, MAD, MSE, RMSE, and MAPE were lower for the ARCH/GARCH models than for the Monte Carlo Simulation. Therefore, the ARCH/GARCH models' predictions were more accurate than the Monte Carlo Simulations for all three countries. This is an indication that the ARCH/GARCH models were more accurate than the Monte Carlo Simulation.

## 4.4 Reliability

Reliability is concerned with the results and their credibility. The sample of the three countries used was representative of the continent, as the combined GDP of the three countries constitutes more than 50% of the African continent's total GDP. Botha and Pretorius (2009) and Cifter's (2012) studies established that forecasting results can be accurate. The forecasts predicted were better than Naïve Model, however, the forecasts were not sufficiently accurate to be relied upon for investment decision-making.

## 4.5 Validity

To ensure the research findings' validity, the same variables used in previous studies were applied in this study. The sample represents selected African economies, with each country represented by a selected equity index. The methods of measurement utilised to evaluate the accuracy and validity of the predictions of equity markets were RMSE, MAPE, variance proportion, and MAD.



## 4.6 Summary

The forecasting accuracy of the ARCH/GARCH models and the Monte Carlo Simulation were measured and analysed, and the findings were presented in this chapter.

The models' forecasting accuracy was tested for a period of three-months-ahead, using five and a half year historical share price data. The period selected was not affected by economic instability, and no extraordinary economic events occurred during this period. Different market conditions prevailed in the different African countries selected during the period of study.

ARCH/GARCH forecasting models and their variants, as well as the Monte Carlo Simulation were used to determine whether or not equity share prices could be predicted using historical data, and whether or not the markets were efficient. The ARCH/GARCH models' in-sample forecasting was more accurate than the out-of-sample forecasting. The ARCH/GARCH models' forecasting was also more accurate than the to the Monte Carlo Simulation predictions.

Using the results presented, the researcher concluded that uncertainty in the less traded markets (Kenya) was high, and therefore the probability of getting accurate forecasts were lower than the highly traded markets (South Africa). The results indicate that the accuracy of predictions improved as the market tradability increased. Nigeria's market was more tradable than Kenya's market, and the prediction accuracy for Kenya's price-weighted index was better than Nigeria's, but still not as good as the predictability of the South African market. High trading activities meant greater accuracy in predicting future equity prices using the ARCH/GARCH and the Monte Carlo Simulation forecasting models.

In the next chapter the motivation for undertaking the study is presented, as well as a discussion of the results and conclusions that were reached. Recommendations and suggestions for further research are also provided.



# Chapter 5

# Findings, conclusions, and recommendations

## 5.1 Introduction

In the previous chapter, the researcher presented the results of share market forecasting in the NSK countries using ARCH/GARCH models and the Monte Carlo Simulation. In this chapter, the motivation for undertaking the study is provided, as is a discussion of the results and the conclusions that were reached. Recommendations and suggestions for further research are also provided.

## 5.2 Reason for undertaking the research

This research was undertaken to establish whether or not the ARCH/GARCH models and the Monte Carlo Simulation could accurately predict emerging African equity markets.

The researcher measured and compared the accuracy of the ARCH/GARCH models and the Monte Carlo Simulation. The measuring variables MAPE, MAD, MSE, and RMSE were used to compare the models' accuracy.

In this research paper, the possibility for investors to obtain above average returns by using the forecasting models to predict future equity movements was explored. The results indicate that the ARCH/GARCH models and the Monte Carlo Simulation can better predict future equity movements than the Random Walk Model. However, above average returns cannot be obtained by using the forecasted values, and the forecasts cannot be used to make investment decisions.

## 5.3 Summary of the findings

The findings of this research are presented and compared to the research objectives in this chapter.

### 5.3.1 Accuracy of the forecasting models

Table 5.1 indicates the measuring variables for each model used.

**Table 5.1: ARCH/GARCH versus Monte Carlo Simulation**

| | Nigeria | | Kenya | | South Africa | |
|---|---|---|---|---|---|---|
| | *ARCH/GARCH* | *Monte Carlo* | *ARCH/GARCH* | *Monte Carlo* | *ARCH/GARCH* | *Monte Carlo* |
| **MAD** | 7 868.67 | 13 762.76 | 4 337.16 | 13 869.95 | 21 322.51 | 28 625.72 |
| **MSE** | 76 832 061.55 | 222 348 512.53 | 28 171 048.17 | 268 561 075.20 | 675 816 764.20 | 1 238 356 136.91 |
| **RSME** | 8 765.39 | 14 911.36 | 5 307.64 | 16 387.83 | 25 996.48 | 35 190.28 |
| **MAPE** | 0.0416 | 0.0726 | 0.0208 | 0.0679 | 0.0247 | 0.03 |

*Source: Researcher's own deduction*

Higher measuring variables in Table 5.1 indicate that predictions were less accurate than the actual share prices. The accuracy measuring variables, namely MAD, MSE, RMSE, and MAPE were lower for ARCH/GARCH models than for the Monte Carlo Simulation. Therefore, the ARCH/GARCH models' predictions were more accurate than the Monte Carlo Simulations for all three countries. This is an indication that the ARCH/GARCH models are more accurate than the Monte Carlo Simulation.

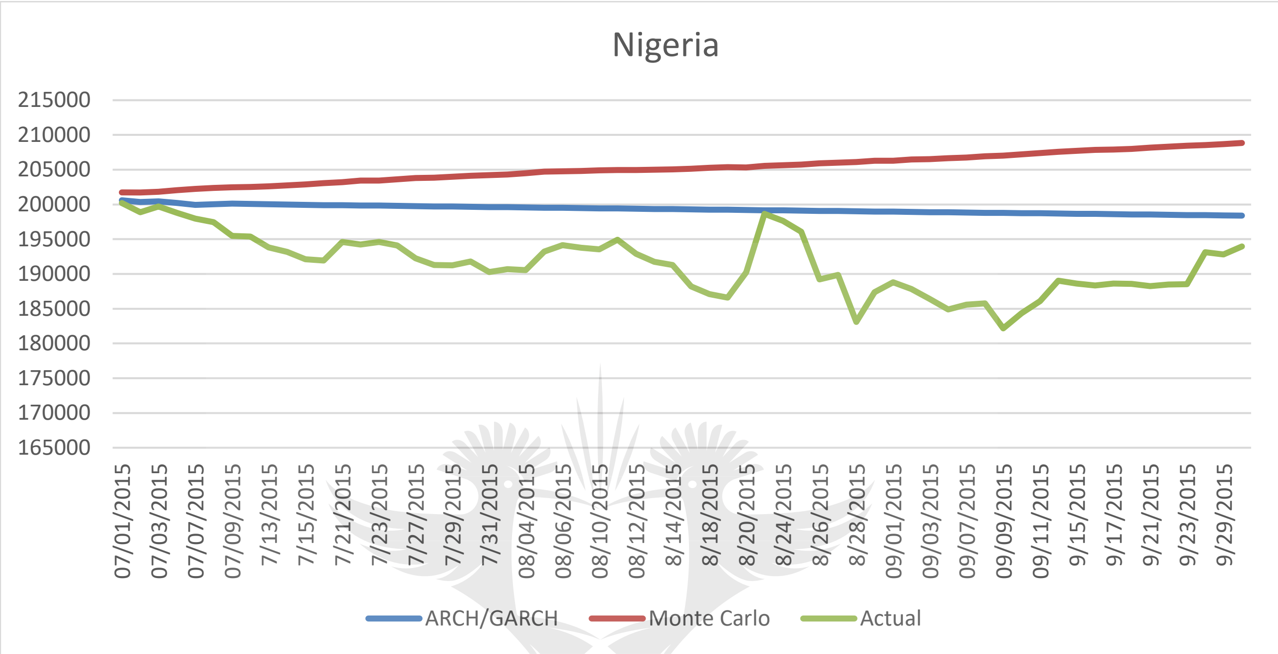
### 5.3.2 The Monte Carlo Simulation versus ARCH/AGRCH models

The forecasting models that were used to predict NSK's equity share prices were compared based on accuracy. The accuracy of the models was measured using the linear graphs presented in Figures 5.1, 5.2, and 5.3 for each country.

#### 5.3.2.1 Actual versus Monte Carlo Simulation versus ARCH/GARCH models: Nigeria

Figure 5.1 indicates the forecast for the two forecasting models used to forecast Nigeria's equity market.

**Figure 5.1: Actual versus Monte Carlo Simulation versus ARCH/GARCH**




*Source: Researcher's own deduction*

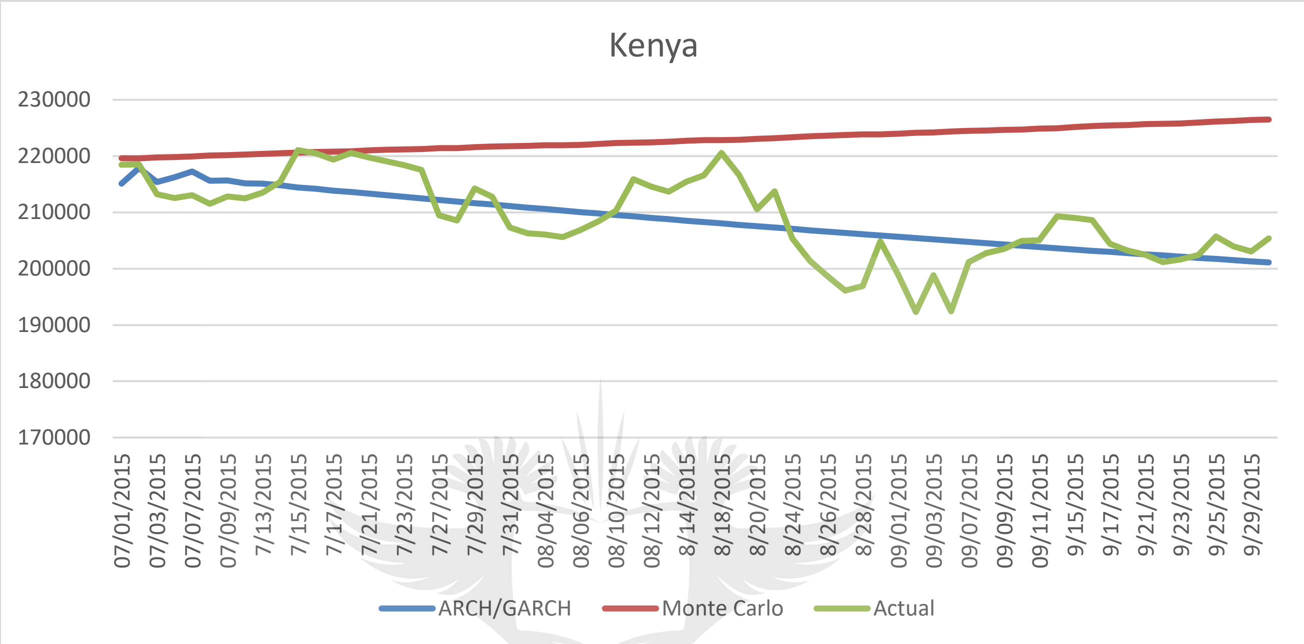


Initially, the accuracy of the predictions did not differ much, but the difference increased as time progressed. The predicted values of the Monte Carlo Simulation were higher than the predicted values of the ARCH/GARCH models. For the three-month period, the actual values were below both ARCH/ARCH and Monte Carlo Simulation predictions. However, the ARCH/GARCH predictions were similar to actual values than was the Monte Carlo Simulation, illustrating that ARCH/GARCH models provided more accurate predictions than the Monte Carlo Simulation.

### 5.3.2.2 Actual versus Monte Carlo versus ARCH/GARCH Models: Kenya

Figure 5.2 indicates the graphical predictions presentation of the three months predictions of Kenya’s Top 20 Index using the two forecasting models.

**Figure 5.2: Actual versus Monte Carlo Simulation versus ARCH/GARCH**




*Source: Researcher’s own Deduction*

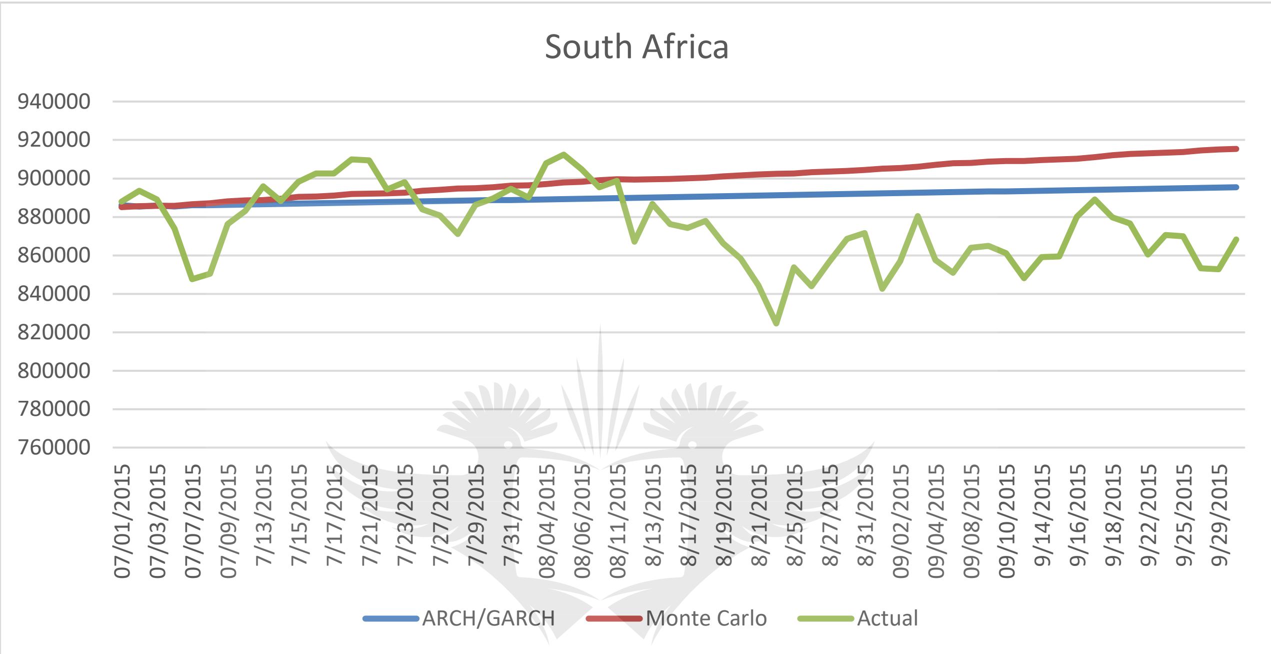


Similar to the results for Nigeria presented in Figure 5.1, both forecasts for Kenya were close to the actual values during the initial period. However, the difference increased with time. The Monte Carlo Simulations throughout the forecasting period were higher than the ARCH/GARCH predictions. For the first half of the forecasting period, both ARCH/GARCH and Monte Carlo Simulation predictions were close to the actual values, and thereafter the difference increased as the actual values declined. The ARCH/GARCH models’ predictions were more similar to the actual values than the Monte Carlo predictions were. Similar to Nigeria, the ARCH/GARCH models’ predictions were better than Monte Carlo Simulation predictions.

#### 5.3.2.3 Actual versus Monte Carlo Simulation versus ARCH/GARCH models: South Africa

Figure 5.3 indicates the predictions for South Africa's FTSE/JSE Top 40 Index using the ARCH/GARCH models and the Monte Carlo Simulation.

**Figure 5.3: Actual versus Monte Carlo Simulation versus ARCH/GARCH**




*Source: Researcher's own Deduction*



The results for South Africa in Figure 5.3 are similar to those presented in Figures 5.1 and 5.2 for Kenya and Nigeria respectively, where the difference between the actual values and the two predictions increased with time. However, unlike the two predictions presented, the difference between both the Monte Carlo Simulation and the ARCH/GARCH models' predictions and the actual values were smaller for the first half of the forecasting period. The Monte Carlo Simulation predictions were higher than the ARCH/GARCH models from 09 July 2015 until the end of the forecasting period. Both ARCH/GARCH and Monte Carlo Simulation predictions deviated from the actual values from 11 AUGUST 2015 until the end of the period. However, despite the deviation, the differences between the ARCH/GARCH model forecasts and the actual values were less than they were for the Monte Carlo Simulation.

### 5.3.3 Predictability of emerging markets

Although the forecasting results deviate from the actual share prices, they can be useful for stakeholders because they provide the direction in which the markets are expected to move. However, the forecast results are not sufficiently accurate to be exploited by investors to earn above average returns.

### 5.3.4 Are the emerging markets efficient?

Based on the results presented, an investor cannot use historical equity prices to accurately predict future equity prices. This is in line with Fama's (1965) Efficient Markets Theory. The emerging markets in Africa are efficient because forecasting using the historical data cannot produce above average returns, and future share prices cannot be predicted using publicly available information.

## 5.4 Findings

Based on the results of this research, it is concluded that the African equity markets cannot be predicted accurately using the ARCH/GARCH models and the Monte Carlo Simulation. Therefore stakeholders, including investors, traders, and company management, cannot use the predictions from the forecasting models to make informed decisions. However, the forecasting results for both ARCH/GARCH models and the Monte Carlo Simulation are better than the Naïve Model's predictions.

## 5.5 Contribution of the study

The research was undertaken to establish whether or not emerging African markets can be forecasted using the ARCH/GARCH models and the Monte Carlo Simulation. The results from this study contradict Dyakova and Smith's (2013) study of developed markets, where it was reported that forecasting models can predict equity prices.

This research study adds to the literature regarding the use of the forecasting models to predict share prices in emerging markets. The literature from developed markets indicates that less traded markets have higher forecasting accuracy than most traded markets. and the reverse is true in emerging markets.

Only a limited number of studies have been performed using ARCH/GARCH models and the Monte Carlo Simulation to forecast equity share prices, particularly in emerging markets.

The results from this research are useful for stakeholders because they provide information regarding the direction in which share prices are expected to move. However, the forecasts are not sufficiently accurate for investors and traders to use in, for instance, rebalancing investment portfolios. Neither can company management and policy-makers make informed decisions based on the models' predictions.

The results provide a comparison of the forecasting accuracy of the ARCH/GARCH models and the Monte Carlo Simulation. They also provide evidence that ARCH/GARCH models are more accurate than the Monte Carlo Simulation in predicting equity prices in the African market.

## 5.6 Limitations

This research only used the indices of the three African countries (NSK) selected based on their trading volume and liquidity. The other less liquid countries and companies listed on the African stock exchanges and unlisted companies were excluded.



The sample selected excluded investment destinations in Africa that are not listed and that are less traded.

Emerging markets, specifically in Africa, are influenced by political situations and instability, such as drastic policy changes or changes in government with different economic policies. The effect of political change impacts emerging equity markets and this impact cannot be forecasted using the models.

## 5.7 Recommendations for further research

In future studies more African countries could be included. In addition, a similar study could be done in other emerging markets outside of Africa. A study that includes shocks caused by uncommon events, such as political changes or economic crises, could also be undertaken. Additionally, other forecasting models, such as artificial neural networks, could be used to predict the future equity share prices.

## 5.8 Final remarks

The major objectives of this study was to investigate whether or not the equity share prices in emerging markets could be predicted using ARCH/GARCH models and the Monte Carlo Simulation, as well as determining the accuracy of the forecasting models. This study also investigated whether or not investors could use forecasted results to make investment decisions.

The research also sought to provide additional research on emerging African markets. Having reviewed all the published literature relating to the forecasting of equity share prices, it was found that the majority of these studies focussed on developed countries, mostly European countries. From the limited amount of African studies reviewed, it was also noted that similar findings were obtained regarding the forecasting of equity markets in emerging markets.

The researcher managed to achieve the study's objectives. It was concluded that the predictions of equity market prices in emerging African markets, using the ARCH/GARCH models and the Monte Carlo Simulation, were statistically accurate at 95% and 90% significance levels. . However, this is not sufficiently accurate for investors and other stakeholders to use to predict equity prices, to the extent that higher returns rather than the industry average can be achieved.

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