EVALUATION OF FORECASTING PERFORMANCE OF DIFFERENT SAMPLING INTERVALS OF SHARE PRICES OF NAIROBI SECURITIES EXCHANGE USING GARCH MODELS

BY

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DECLARATION

DECLARATION BY THE STUDENT

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DEDICATION

This research thesis is dedicated to my parents Mr. and Mrs. Joseph Rop for standing with me and for me through the thick and thin, and more specifically in ensuring that my pursuit of higher education becomes a reality. I'm truly grateful for having them in my life; their good examples have taught me to work hard for the things I aspire to achieve.

ABSTRACT

Prediction of the stock market has been of enormous interest for the past decades, as having an accurate idea of its future performance can help traders invest more appropriately and timely to maximize profits; Better forecasts translate to better risk management and better option pricing for the stock market products. This thesis examined and evaluated the forecasting ability of Nairobi Securities Exchange (NSE) share prices at different time points using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Time series models. Daily, weekly and monthly share prices of specific companies listed in the Nairobi Securities Exchange were utilized in the research study. The study covered the period from 3rd January 2006 to 31st January 2012. In order to obtain the most favorable forecasts, appropriate models were first determined for each time point for the companies chosen from amongst the lower order GARCH models that is GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2). Lower order GARCH models were utilized because of their simplicity and their ability to capture the stylized features exhibited by financial time series. In each case, the best fitting GARCH models were chosen based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Models with the least AIC and BIC values were preferred. Parameter estimation and model fitting were done using the chosen models. Adequacy of the chosen models was done using Ljung Box and Lagrange Multiplier Autoregressive Conditional Heteroskedasticity (ARCH LM) tests. The selected models were then utilized in forecasting. One month ahead prices and forecasting performance of daily, weekly and monthly returns were compared using statistical forecasting accuracy measures such as Mean Absolute Errors (MAE), Root Mean squared Errors (RMSE) and MAPE for each company so as to determine intervals with best forecasting ability. The intervals with the least mean errors were considered to have the best predictive ability as compared to the other time points. Three companies namely; National Bank of Kenya (NBK), East African Portland cement and the Kenya Airways (KQ) were selected purposively because of their consistency in the NSE for the period of study and were also representative of three sectors namely; Finance and Investment, Industrial and Allied and Commercial and services as categorized in the NSE. The data was obtained from NSE and analyzed using the R software version 3.1.0 and results presented in tables and graphs. The results revealed that GARCH (1, 1) models performed well in modeling most return series for companies investigated especially for daily and monthly returns. GARCH (2, 1) seemed better for KQ weekly data while GARCH (2, 2) performed poorly for all the data sets. While comparing the forecasting performance of each time point based on the selected models, daily data gave better prediction, followed by weekly and lastly monthly returns. This suggests that the models generally perform well when modeled with higher frequency data.

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LIST OF ABBREVIATIONS

ACF	Autocorrelation function
ADF	Augmented Dickey Function
AIC	Akaike Information Criteria
ARCH	Autoregressive Conditional Heteroskedasticity
AR	Autoregressive
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ASEA	African Stock Exchanges Association
BIC	Bayesian Information Criteria
EA PORT	East African Portland cement
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
I	Integrated
IGARCH	Integrated Generalized Autoregressive Conditional Heteroskedasticity
Ltd	Limited
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
NBK	National Bank of Kenya

NSE	Nairobi Securities Exchange
KQ	Kenya Airways
RMSE	Root Mean Squared Error
SME	Small-to-medium sized Enterprises

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CHAPTER ONE

INTRODUCTION

1.1 Background information

Stock market, also termed as equity market is a place where securities, shares and bonds of publicly held companies are issued and traded either through exchanges or over-the-counter markets. The main purpose of a stock market is to provide a platform where investors can buy and sell shares without necessarily having to move from one place to the other looking for prospective buyers.

The stock market plays a pivotal role in the growth of the sectors listed in the Securities exchange and the commerce of the country through the mobilization of resources. It makes it possible for idle money and savings to be invested in productive activities for the economy to grow, money needs to shift from less to more productive activities. Moreover, according to Singh (2011), history has shown that the price of shares and other assets is an important part of the dynamics of economic activities, and can influence or be an indicator of the social mood. An economy where the stock market is on the rise is considered to be an up-and-coming economy. In fact, the stock market is often considered the primary indicator of a country's economic strength and development.

Rising share prices, for instance, tend to be associated with increased business investment and vice versa. Share prices also affect the wealth of households and their consumption. Therefore, central banks tend to keep an eye on the control and behavior of the stock market and, in general, on the smooth operation of financial system functions (Singh, 2011).

The stock market is also the primary source for companies to raise funds for business expansions or setting up new business ventures. If a company wants to raise some capital for the business it can issue shares of the company that is basically part ownership of the company in the public market.

To trade in the stock market, the buyers and sellers agree on a price of a product, in this case, the transaction of "shares" which represent an equity or ownership interest in a particular company.

Participants in the stock market range from small individual retail investors, institutional investors such as mutual funds, banks, insurance companies to larger hedge fund investors, who can be based anywhere in the world. Their orders usually end up with a professional at a stock exchange, who executes the order of buying or selling as required.

Stock markets are dynamic environments where many factors come in to play in arriving at prices but in most cases it is dictated by supply and demand, where supply equals the willing sellers and demand equals the willing buyers. The current price is where their mutual interests intersect. That intersection is a moving target so at one moment there is more supply than demand and at some other moment the balance may shift to more demand than supply. Other factors that influence share prices include; company news and performance, industry performance, investor sentiments, economic factors (Interest rates, inflation & deflation rates), political shocks and so forth.

The NSE is an institution that deals in exchange of securities issued by publicly quoted companies and the Government. It is part of the broader market referred to as financial market.

The NSE began in the early 1920s while Kenya was considered a colony under British control. It was an informal marketplace for local stocks and shares; there was no formal market, rules or regulations to govern stock brokerage activities. Trading took place on gentleman's agreement in which standard commissions were charged with clients being obligated to honour their contractual agreements of making good delivery and settling relevant costs. By 1954, a true stock exchange was created when the NSE was officially recognized by the London Stock Exchange as an overseas stock exchange. After independence, the stock exchange continued to grow and became a major financial institution. The NSE is part of the African Stock Exchanges Association (ASEA) founded in the early 1990s to create a way for all the stock exchanges in Africa to communicate and stay organized. There are about 20 exchanges in the ASEA. NSE is one of the largest stock exchanges in Africa, with the fourth largest trading volume across the continent. There are more than 20 licensed stock brokers at the exchange. Currently the NSE is trading more than a 100 million shares each month, and plays a large role in the economic growth of Kenya. It is now one of the most active capital markets and a model for the emerging markets in Africa in view of its high returns on investment and as a well-developed market structure (Ogum et al., 2005)

There are more than 50 businesses and companies listed in the Nairobi Stock Exchange, including Sasini Tea and Coffee Ltd., Kenya Airways, Jubilee Insurance, Kenya

Commercial Bank Ltd., and KenGen Ltd. These companies trading in the NSE have been subdivided into Agriculture; Manufacturing and Allied segments; Finance and Investment and Commercial services. Most of the businesses in the exchange are in the financial or industrial sectors, though agriculture and other commercial services are also represented. Also listed are treasury bonds issued by the Government of Kenya. Occasionally, there are also privately issued corporate bonds as well.

The prices of financial securities which are traded in the financial markets as well as interest rates and foreign exchange rates are subject to constant variability. Thus their returns over the various periods are notably volatile i.e. there is up and down movement of prices, rates return and so forth. The up and down movement of prices is not a bad thing per se but if the price movements are particularly sharp or high variability happens within short periods of time, it increases risks and uncertainties and can cause delays in business investments as it scares away investors who mainly adopt a "wait and see" attitude and makes decision making difficult. As a matter of fact, excess volatility may cause crisis and crashes in the financial markets. It is also well known that higher benefits or returns on investments usually come with a great deal of risks, so changes and trends in the stock market will automatically be of great interest to investors and other market participants.

Volatility cuts across finance and is an important variable in pricing financial derivatives, selecting portfolios, measuring and managing risks more accurately (Wagalla et al., 2011).

Forecasting volatility is a crucial and demanding financial matter which has attained extensive attention in the past few decades. It is widely accepted that though returns of financial securities prices are more or less unpredictable on daily as well as monthly basis, return volatility is forecastable along with vital inference for financial economies and risk management (Torben et al., 2009). Good forecasts therefore become extremely important in making financial decisions.

First, the knowledge of volatility could guide traders on the risk of holding an asset or the value of an option, thus enabling enormous returns on their investments. Good forecasts also provide reasonable forecasting confidence interval (Engle et al., 2005). Moreover, reliable models shed further light on the data generating process of the returns (Hongyu & Zhichao, 2006). These estimates also give insight of the robustness of the economy and the directions of monetary and fiscal policy making.

Trading in stock market has achieved massive attractiveness all over the world in the past few decades. The increasing diversity of financial index related instruments, along with the economic growth enjoyed in the past few years has broadened the dimension of global investment opportunity to both individual and institutional investors (Alam et al., 2013). Thus being able to appropriately forecast volatility is of great importance to all the interested parties, as well as for the growth of the country's economy.

With the recent advancements in technology and communication, and subsequent automation of trading activities, real-time stock market information on the listed securities facilitates price discovery for the interested persons at whatever times of interest.

The key motivation of this research was to examine share prices of selected companies at three different intervals that is daily, weekly and monthly share prices in order to determine the time points from which more accurate volatility estimates and forecasts can be made in order to optimally guide the trading activities at the Nairobi Securities Exchange.

A time series approach was utilized to achieve this, because according to Fama (1965), “the past behavior of a security’s price is rich in information concerning its future behavior. History repeats itself in that ‘pattern’ of past price behavior will tend to recur in the future. Thus, if through careful analysis of price charts one develops an understanding of the ‘patterns’ this can be used to predict the future behavior of prices and in this way increase expected gains.”

Moreover, future prices being uncertain, they must be described by probability distributions, thus statistical methods become a natural way to investigate prices. Time series methods have also been found to be able to predict many financial time series (Swarzch, 2013). He further argues that time series models are the ultimate tool for letting the “data speak for themselves” because all inferences are based on the observed series.

1.2 Scope

The research study focused on GARCH model estimation and specification and subsequently forecasting using daily, weekly and monthly share prices for three chosen companies that trade in the Nairobi Securities Exchange. These companies are National Bank of Kenya, East African Portland Cement and the Kenya Airways. The chosen companies have been trading consistently in the Nairobi Securities Exchange for the study period and are representative of three sectors namely; Finance & Investment, Industrial & Allied and Commercial services as categorized in the Nairobi Securities Exchange.

1.3 Statement of the problem

Modeling of the stock market has witnessed a significant attention and subsequent increase over the last three decades. Focus has been to identify efficient models that can be applied to particular stock exchange data for forecasting and prediction of volatility which is an important variable in financial decision making. However, the time points to obtain best volatility forecasts have not been exhaustively studied despite the massive generation of stock exchange data at a very frequent rate. The aim of the study was therefore to determine the best time points from amongst daily, weekly and monthly share prices for the selected companies listed in the NSE that can be reliably employed to characterize the share prices volatility and produce best predictions to enable investors maximize profits and guide trading and policy making activities at the NSE.

1.4 Objectives of the study.

1.4.1 General objectives

The main objective of the study was to determine the sampling intervals which give best forecasts for the representative sectors of the NSE using lower orders GARCH models.

1.4.2 Specific objectives

i. To fit GARCH models for daily share prices for the 3 selected companies

ii. To fit GARCH models for weekly share prices for the 3 selected companies

iii. To fit GARCH models for monthly share prices for the 3 selected companies

iv. To compare forecasts with the actual values in order to determine the best sampling intervals for each company from daily, weekly and monthly returns.

1.5 Justification.

Generally, the investors at the NSE are faced with the problem of deciding which shares to buy, hold or sell in order to maximize profits and minimize losses, thus the main objective was that of finding reliable time points that can guide them in their investment decision making. The study will therefore go a long way in providing evidence based decision making guide that will majorly assist investors in making the right moves at the right time. This will not only ensure enormous returns on their investments but also economic boosts for the country because loses will be minimized. Moreover, the study will assist policy makers and other interested parties in the planning and control of business operations. The research will also add to the existing literature on the NSE as well as financial time series applications to interested scholars.

CHAPTER TWO

LITERATURE REVIEW

2.1 Time series

Time series analysis is a form of statistical data analysis on a series of sequential data points that are usually measured at equal time intervals over a period of time. The most common characteristics or patterns of a time series are increasing or decreasing trend, cyslic, seasonality, and irregular fluctuations. Time series forecasting takes the analysis from the time series data and tries to predict how the data may be in the near future, based on what it has been in the past. This is especially important in the field of stock market investment as traders and investors, want to make the right moves at the right times to maximize financial profit. Thus creating an accurate forecast based on time series analysis methods can provide an accurate prediction of what is to come in the near future.

Time series Analysis concerns the analysis of data collected over time for instance, weekly, monthly, quarterly and so forth. Usually the intent is to discern whether there is some pattern in the values collected to date, with the intention of short term forecasting-to use as the basis of business decisions. The aim of time series is to summarize the properties of a time series and characterize its salient features. The main reason for modeling a time series is to enable forecasts of future values to be made. Forecasts are usually made by extrapolation.

Essentially, time series analysis is rooted in the idea that the past tells us something about the future; the question is how to go about interpreting the information encoded in the past events and furthermore, how we are to extrapolate future events based on this information, constitute the main subject matter of time series analysis.

A great deal of data in business, economics, engineering and natural sciences occur in the form of time series where observations are dependent. Box and Jenkins (1976) defined that the technique available for the analysis of such a series of dependent observation is called time series analysis. Kottegoda (1980) defined time series as a set of observations that measure the variation in time of some aspect of phenomena, such as share prices of certain companies over a certain period of time.

Statistical analysis of time series data started a long time ago (Yule, 1927) and forecasting has an even longer history. Objectives of the two may differ in some situation but forecasting is often the goal of time series. Applications played a key role in the development of time series methodology in business and economics. Time series analysis is used among other purposes to describe, control, predict and forecast processes

Tsay (2000) in the publication of Time Series Analysis stated that ‘Forecasting and Control by Box and Jenkins in 1970 was an important milestone for time series analysis. It provided a systematic approach that enables practitioners to apply time series methods in forecasting. It popularized the Autoregressive Integrated Moving Average (ARIMA) model by using an iterative modeling procedure consisting of identification, estimation, and model checking.

Once an ARIMA model is built and judged to be adequate, forecasts of future values are simply the conditional expectations of the model if one uses the minimum mean squared error as the criterion. The success of ARIMA models generated substantial research in time series analysis. However, the history of time series analysis was not smooth. First of all, time series analysis was originally divided into frequency domain and time domain approaches. Proponents of the two approaches did not necessarily see eye to eye, and there were heated debates and criticisms between the two schools. The time domain approach uses autocorrelation function of the data and parametric models, such as the ARIMA models, to describe the dynamic dependence of the series (Box et al., 1994). The frequency domain approach focuses on spectral analysis or power distribution over frequency to study theory and applications of time series

Models for time series data can have many forms and represent different stochastic processes. When modeling variations in the level of a process, there are three broad classes of practical importance these are; AR, I model, MA models. These three classes depend linearly on previous data points. A combination of the three ideas produces ARMA and ARIMA models. The generalization of the three models produces the Auto Regressive Fractionally Integrated Moving Average (ARFIMA) model

An AR model is a representation of a type of random process; as such, it describes certain time-varying processes. The autoregressive model specifies that the output variable depends linearly on its own previous values. The notation AR (p) indicates an autoregressive model of order p. The AR (p) model is defined as

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad 2.1$$

Where $\varphi_1,\ldots,\varphi_p$ are the parameters of the model, c is a constant, and ε_t is white noise.

The Moving Average (MA) model is a common approach for modelling univariate time series models. MA(q) refers to the moving average model of order q, it is defined as:

$$X_t = \mu + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_q \varepsilon_{t-q} \qquad \text{2.2}$$

Where μ is the mean of the series, the $\theta_1,\ldots,\theta_q$ are the parameters of the model and the ε_t, $\varepsilon_{t-1},\ldots$ are white noise error terms. The value of q is called the order of the MA model. This can be equivalently written in terms of the backshift operator B as

$$X_t = \mu + (1 + \theta_1 B + \ldots + \theta_q B^q)\, \varepsilon_t \qquad \text{2.3}$$

Therefore a MA model is conceptually a linear regression of the current value of the series against current and previous (unobserved) white noise error terms.They are used in time series to describe stationary events. Fitting a moving average model is more complicated than fitting an Autoregressive model because the error terms are not observable.

The Autoregressive Moving Average models(ARMA) consists of two parts, the Autoregressive part and the Moving Average part.The model is then referred to as ARMA(p,q) where p is the order of the autoregressive part and q is the order of the moving average part i.e. it contains the AR(p) and MA(q) models. ARMA models are sometimes called Box Jenkins models after Box and Jenkins (1970) who expounded an iterative method for choosing and estimating them. ARMA model allowed greater flexibility in fitting of actual time series.

The main drawback of linear stationary models is their failure to account for change in volatility i.e. the width of the forecast intervals remain constant even as new data become available, unless the parameters are changed.

Among other types of non-linear time series models, there are models to represent the changes of variance over time (heteroskedasticity). These models represent autoregressive conditional heteroskedasticity (ARCH) and among others the GARCH model. Here changes in variability are related to, or predicted by, recent past values of the observed series. This is in contrast to other possible representations of locally varying variability, where the variability might be modeled as being driven by a separate time-varying process, as in a doubly stochastic model.

In describing ARCH behavior we focus on the error process. In particular, we assume that the errors are an innovative process i.e. we assume that the conditional mean of the errors is zero. The error process is written as $\varepsilon_t = \sigma_t z_t$ where σ_t is the conditional standard deviation and the z_t terms are a sequence of independent zero mean, unit variance normally distributed variables.

Suppose one wishes to model a time series using an ARCH process. Let ε_t denote the error terms (return residuals, with respect to a mean process) i.e. the series terms. These

ε_t are split into a stochastic piece z_t and a time-dependent standard deviation σ_t characterizing the typical size of the terms so that $\varepsilon_t = \sigma_t z_t$

The random variable z_t is a strong white noise process. The series σ_t^2 is modeled by

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon^2_{t-i} \qquad \text{.......... 2.4}$$

Where $\alpha_0 > 0$ and $\alpha_1 \geq 0$, $i > 0$

An ARCH (q) model can be estimated using ordinary least squares. A methodology to test for the lag length of ARCH errors using the Lagrange multiplier test was proposed by Engle (1982). This procedure is as follows:

Estimate the best fitting autoregressive model AR (q)

$$y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i y_{t-i} + \varepsilon_t \qquad \text{.......... 2.5}$$

Obtain the squares of the error $\hat{\varepsilon}^2$ and regress them on a constant and q lagged values:

$$\hat{\varepsilon}_t^2 = \hat{\alpha}_o + \sum_{i=1}^{q} \hat{\alpha}_1 \hat{\varepsilon}_{t-i}^2 \qquad \text{.......... 2.6}$$

Where q is the length of ARCH lags.

The null hypothesis is that, in the absence of ARCH components, we have $\alpha i = 0$ for all i=1, 2, 3…,q. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated α_i coefficients must be significant.

The concept of the ARCH model was introduced by Engle in 1982, in his seminal paper; the paper measured the time-varying volatility. His model was based on the idea that a natural way to update a variance forecast is to average it with the most recent "surprise." While conventional time series and econometric models operate under the assumption of constant variance, the ARCH process allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. According to Engle (2004) an ARCH process is a mechanism that includes past variances in the explanation of future variances.

Although the ARCH model might be only a few decades old, the original ARCH model and its various generalizations have been applied successfully in numerous economic and financial data series of many countries and have literally revolutionized empirical work in financial economics, particularly in modeling of stock returns, interest rates, inflation rates, exchange rates and so on. It is employed commonly in modeling financial time series that exhibit time-varying volatility clustering i.e. periods of swings followed by periods of relative calm.

In the empirical application of the ARCH model a relatively long lag in the conditional variance equation called for, and to avoid problems with negative variance parameters a fixed lag structure is typically imposed.

If an autoregressive moving average model (ARMA model) is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedasticity (GARCH) model. (Bollerslev, 1986)

The GARCH model was introduced by Bollerslev to overcome the ARCH limitation. It generalized ARCH to make it more realistic i.e. to allow for both a longer memory and a much more flexible lag structure. The extension of the ARCH process to GARCH process bears much resemblance to the extension of the standard time series AR process to the general ARMA process and, this allows a more parsimonious description in many situations.

In that case, the GARCH (p, q) model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ε^2) is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + ... + \alpha_q \varepsilon^2_{t-q} + \beta_1 \sigma_{t-1}^2 + ... + \beta_p \sigma_{t-p}^2 \quad \text{......2.7}$$

Summarizing we get

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2_{t-i} + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \quad \text{......2.8}$$

In the ARCH (q) process, the conditional variance is specified as a linear function of past sample variances only, whereas the GARCH (p, q) process allows lagged conditional variances to enter as well.

Extensive empirical evidence suggests that GARCH (p, q) is more parsimonious than ARCH (q) model and provides a framework for deeper time varying estimation. According to Kun (2011), one of the outstanding features of GARCH (p, q) is that it can effectively remove the excess kurtosis in returns. Particularly, the standard GARCH (1, 1) model is widely recognized and the most popular for modeling volatilities in many financial time series.

Generally, when testing for heteroskedasticity in econometric models, the best test is the White test. However, when dealing with time series data, this means to test for ARCH/GARCH errors.

Although GARCH has good performance for explaining volatility clustering and leptokurtosis in financial time series, it cannot explain the leverage effect. It is however, probably the most commonly used financial time series model and has inspired dozens of more sophisticated models.

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model by Nelson (1991) is another form of the GARCH model. He extended the ARCH methodology to better describe the behavior of return volatility. His study is important because of the fact that it extended the ARCH methodology in a new direction, breaking the rigidity of GARCH and ARCH specification. Nelson listed the following as major drawbacks of the GARCH Model; the lack of symmetry in the response to shock, the need to impose parameter restrictions to ensure positivity of the continual variance and that measuring persistent is difficult.

His most important contribution was to propose a model to test the hypothesis that the variance of return was influenced differently by positive and negative excess returns, his study found out that not only was the statement true, but also that excess returns were negatively related to stock market.

It was introduced to capture the asymmetric effect formally, an EGARCH (p, q):

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2 \quad \text{.......... 2.9}$$

Where

$$g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|)) \quad \text{.......... 2.10}$$

σ_t^2 is the conditional variance, ω, β_k, α_k, θ and λ are coefficients, and Z_t may be a standard normal variable or come from a generalized error distribution. The formulation for $g(Z_t)$ allows the sign and the magnitude of Z_t to have separate effects on the volatility. This is particularly useful in an asset pricing context.

Since $\log \sigma_t^2$ may be negative there are no (fewer) restrictions on the parameters.

Integrated Generalized Autoregressive Conditional Heteroskedasticity (IGARCH) is a restricted version of the GARCH model, where the persistent parameters sum up to one, and therefore there is a unit root in the GARCH process. The condition for this is

$$\sum_{i=1}^{p} \beta_i + \sum_{i=1}^{q} \alpha_i = 1 \quad \text{.......... 2.11}$$

ARCH models are rarely used nowadays to describe financial time series because of the fact that GARCH models perform better (Alexander, 2001).

2.2 GARCH Models

GARCH models have been found to perform well with stock market returns, exchange rates, Consumer price indices and many other variables. Existing literature suggests that GARCH models are better in describing returns series that have the changing variance level. They have been extensively researched on and tested statistically and empirically.

The Gaussian GARCH (1, 1) process, in particular, is widely used and highly regarded in practice as well as in the academic discourse. It is often preferred by financial modeling professionals because it provides a more real-world context than other forms when trying to predict the prices and rates of financial instruments. The model is the most celebrated among the ARCH family. GARCH (p, q) is a generalization of GARCH (1, 1).

The standard GARCH (1, 1) model is defined as:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad \text{2.12}$$

Where

- ε_t are returns with zero mean and unit variance
- ω, α_1 and β_1 are model coefficients, $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$ and

  $\varepsilon_t = u_t \sqrt{\sigma_t^2}$; $u_t \approx i.i.d$ N(0,1)

The GARCH (1, 1) model is equivalent to an infinite ARCH model with exponentially declining weights.

In practice, the standard GARCH (1, 1) has been found to be sufficient to capture the volatility clustering in the data. And according to most researches, it is rarely necessary to use more than a GARCH (1, 1) model for financial applications. In particular, according to Omar (2013), GARCH (1, 1) successfully captures thick tailed returns, and volatility clustering, and can readily be modified to allow for several other stylized facts, such as non-trading periods and predictable information releases.

In addition to the standard GARCH (1, 1), other lower order GARCH models have been found to fit well to stock returns, for instance GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2). These four GARCH models have been utilized in this thesis in order to determine the best fitting model for each data set and thereafter carry out forecasting of future prices.

2.3 Financial Time Series reviews.

There is plenty of literature on behavior of stock market returns, which date back to Mandelbrot (1963) and Fama (1965). These seminal studies provide evidence that time series of daily stock returns exhibit some autocorrelation for short lags. However, due to the small magnitudes of the autocorrelations, it is not possible to form profitable trading rules. Low statistical significance of the autocorrelation estimates lead to the assumption of serially uncorrelated stock returns.

Financial time series data often exhibit some common characteristics. Fan and Yao (2003) summarizes the most important features of financial time series as: The series tend to have leptokurtic distribution, i.e. they have heavy tailed distribution with high probability of extreme values. In addition, changes in stock prices tend to be negatively correlated with changes in volatility, that is; volatility is higher after negative shocks than after positive shocks of the same magnitude. This is referred to as the leverage effect.

The sample autocorrelations of the data are small whereas the sample autocorrelations of the absolute and squared values are significantly different from zero even for large lags. This behaviour suggests some kind of long range dependence in the data. The distribution of log returns over large periods of time (such as a month, a half a year, a year) is closer to a normal distribution than for hourly or daily log-returns. Finally, the variances change over time and large (small) changes of either sign tend to be followed by large (small) changes of either sign (Mandelbrot, 1963). This characteristic is known as volatility clustering. These are facts characterizing many economic and financial variables, they are commonly referred to as ‘stylized facts.’

Since the introduction of ARCH and GARCH models, there has been a significant amount of research on volatility of stock markets of many countries, developed and emerging markets alike. For instance, Gary and Mingyuon (2004) applied the GARCH model to the Shanghai Stock Exchange, Magnus and Fosu (2006) utilized GARCH models in modeling and forecasting Ghana Stock Exchange returns, Onwekwe et al., (2011) applied GARCH models to Nigerian Stock returns, Islam (2013) applied GARCH models to four Asian markets while Bertram (2004) modeled Australian Stock Exchange using ARCH models. Other studies on these stock markets include Hongyu and Zhichao (2006) who forecasted the volatility of the Chinese stock market using the GARCH-type models and Ngailo (2011), utilized GARCH models on the inflation rates of Tanzania, just to name but a few.

A few papers have also attempted to apply GARCH models to Nairobi Securities Exchange, among them; Ogum et al., (2006) applied the EGARCH model to the Kenyan and Nigerian Stock Market returns, Maana et al., (2010) applied GARCH model to the Volatility of exchange rates in the Kenyan market, Omar (2013) applied GARCH in modeling of foreign exchange and share prices for specific companies listed in the Nairobi Securities Exchange for the period 2001-2010 and more recently Wagalla et al.,(2011) applied ARCH type models in modeling volatility of weekly returns of the Nairobi Securities exchange.

The simplest GARCH (1, 1) is often found to be the benchmark of financial time series modeling because such simplicity does not significantly affect the preciseness of the outcome for instance, Omar (2011) used GARCH to model share prices and foreign exchange in Kenya and confirmed the empirical evidence in Bollerslev (1992), that GARCH (1, 1) is usually adequate in describing financial time series. Maana et al., (2010) also applied GARCH in their research on volatility of exchange rates in the Kenyan market and concluded that GARCH (1, 1) was applicable in the estimation of volatility in the Kenya foreign exchange market data for the period 1993-2006. Ngailo (2011) applied GARCH models to Tanzania Inflation rates and the standard GARCH (1, 1) was found to be the best for modeling and forecasting future prices. Magnus and Fosu (2006) while modeling Ghana Stock Exchange also found out that GARCH (1, 1) was able to model and forecast conditional volatility of Databank Stock index better than other competing models.

In practice, GARCH (1, 1) comprising of only 3 parameters (ω, α_1 and β_1) in the conditional variance equation has been found to be sufficient to capture the volatility clustering in the data.

For a long time, the focus of financial time series modeling has been on the ARCH model and its various extensions, thereby ignoring the effect of data frequency on forecasting performance using the ARCH-type models. As a matter of fact, the subject of data frequency for financial modeling and forecasting has received little attention. There are few studies that have considered the issue of time points and their ability to forecast future values, for instance, Green (2011) used Box Jenkins ARIMA model to compare first day of the month and 15th day of the month as well as weekly stock prices of eight companies, the results revealed that six out of the eight chosen companies were better predicted by data sampled weekly as compared to the 1st day of the month and 15th day of the month. The present study therefore aimed at finding the time points or the sampling intervals from daily, weekly and monthly share prices that gives the best forecasts for the sectors listed in the NSE as represented by the three chosen companies using the GARCH models.

The GARCH models according to Wagalla et al., (2011) are more appropriate for the stock market data since they are able to capture the stylized facts exhibited by the NSE.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The study focused on modeling the daily, weekly and monthly share prices for the three chosen companies namely, National Bank of Kenya, East African Portland Cement and Kenya Airways from Nairobi Securities Exchange.

The companies selected have been trading in the NSE for the period of study and are representative of the three sectors namely, Finance & Investment, Industrial & Allied and Commercial & Services categorized in the NSE.

Kenya Airways was incorporated in 1977 following the breakup of the then East African Airlines. Since its inception, the airline has grown its destination network and currently flies to 31 international and domestic destinations. The company was listed in the NSE in 1996 and its stock is widely held both by foreign and local investors.

The NBK is a large financial services provider in Kenya, serving individuals, small-to-medium sized enterprises (SMEs) and large corporations. As of December 2011, NBK's asset base was valued at approximately US$821 million (KES: 68.7 billion), with shareholders' equity valued at about US$125 million (KES: 10.5 billion). In April 2011, The NBK was ranked number eight, by assets, among the forty-four licensed commercial banks in the country. It was established in 1968 as a 100% government-owned financial institution. In 1994, the Kenyan Government reduced its shareholding to 68% by selling

32% shareholding to the public. The government further divested from NBK over the years, until its present shareholding of 22.5%, as of October 2010.

The East African Portland Cement Company Ltd. is a manufacturer and seller of cement. It was founded in February 1933 and is headquartered in Athi River, Kenya. It is the second largest cement producer in Kenya and its operations are predominantly within the country.

For over 70 years, East African Portland Cement Limited has been Kenya's leading cement manufacturer. By providing the ‘lifeblood’ of the country’s construction industry, East African Portland Cement has played a central role in the nation building.

Blue Triangle Cement, the company's flagship brand, is well known all over Kenya as a symbol of quality and reliability. The company's products have been used in projects in areas such as housing, road construction, education, health, tourism, transport and communication, as well as hydro-electric power across the country.

3.2 Data

Three data sets from three companies were considered in this research. The first data set was the daily closing stock price from the selected companies collected over the period 3rd June, 2006 to 31st Jan, 2012. The stock prices were obtained from the NSE historical price database.

The five-year study period was chosen to ensure that likelihood function is well defined and that the models properly converge, a few years of data are needed but not too many that current market conditions are not reflected. If we take a too short period data, then parameter estimates may not be robust. (Chand et al., (2012)

3.3 Data Analysis

Box and Jenkins (1976) approach of ARIMA model building was utilized that is model identification, estimation and diagnostic testing. In the model identification stage, exploratory analyses were done to determine the characteristics of the data sets but model order was however not considered because the models used were already predetermined as the lower GARCH models, then the data was fit to the respective models identified by estimation and finally diagnostic testing was done to rule out any model misspecification that could have occurred. Forecasting, which was the main aim of this thesis, was also done using the models chosen, and the time points evaluated. All the analyses were done using R software version 3.1.0.

3.3.1 Exploratory Data analysis

In order to explore the three datasets in details, and be able to get clues on the likely nature or characteristics of the series, a number of important preliminary investigations and descriptive statistics were computed, these were Skewness, Kurtosis, Jarque-Bera, mean, maximum, minimum and standard deviation.

Skewness is a measure of symmetry. Positive skewness of a variable under consideration implies that its distribution has a long right tail. On the other hand, negative skewness shows that the distribution of a variable under consideration has a long left tail.

For univariate data sets x_1, $x_2 \ldots x_n$, skewness is given by

Skewness

$$= \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{(n-1)s^3} \quad \text{...} 3.1$$

Where, $\bar{x}$ is the mean, s is the standard deviation, and n is the number of observations.

The Kurtosis is a measurement of whether the data is peaked or not relative to the normal distribution, and it determines the shape of a probability distribution. A positive kurtosis that is higher than three shows that the distribution has higher, acute peaks around the mean and has fat tails (Leptokurtic). While, a distribution with negative kurtosis shows it has lower, wider peaks around the mean and thinner tails. For a univariate data x_1, $x_2,\ldots,x_n$, the formula is given by:

Kurtosis

$$= \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{(n-1)s^4} \quad \text{..} 3.2$$

The Kurtosis for standard normal distribution is three. So, Excess Kurtosis is given by

Excesskurtosis

$$= \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{(n-1)s^4} - 3 \quad \text{...} 3.3$$

The Jarque-Bera test was an alternative way to test normality. It is a type of Lagrange multiplier test that was developed to test normality. The Jarque-Bera statistics is calculated from skewness and kurtosis, and it follows a chi square distribution with two degrees of freedom as shown below:

Jarque-Berra

$$= n * \left[\frac{skewness^2}{6} + \frac{(kurtosis - 3)^2}{24} \right] \sim \chi^2_{(2)} \text{...} 3.4$$

The null hypothesis of the normality is rejected if the value for Jarque-Bera statistic is greater than the critical value. The Jarque-Berra statistic is also rejected if the p value is less than the significant values at the given level of significance

Measures of central tendencies and dispersion such as Means, maximum, minimum and the standard deviation were used. The standard deviation in particular was an indication of volatility of the share prices. The mean and standard deviation are given by the formulas;

Mean

$$= \bar{x} = \sum_{i=1}^{n} \frac{x_i}{n} \text{...} 3.5$$

Standard deviation

$$= s = \sqrt{\left[\sum_{i=n}^{n} \frac{(x_i - \bar{x})^2}{n-1} \right]} \text{..} 3.6$$

Time plots were also used in order to get clear visual characteristics of the series; such as if the series has noticeable patterns, for instance Kirchler and Huber (2007) mentioned that volatility clustering manifests itself as periods of tranquility interrupted by periods of turmoil. So the visual inspection of the time plots of returns were used to determine whether or not the data exhibited volatility clustering or not.

Transformation of the series into returns was done using the operation;

$$r_t = \ln\left[\frac{p_t}{p_{t-1}}\right] \qquad 3.7$$

where P_t and P_{t-1} are current and previous closing share prices for times $t = 1, 2, 3 \cdots$

The transformed series is now referred to as returns and are expected to be stationary. To confirm the stationarity of the returns, Augmented Dickey–Fuller test (ADF) for unit roots was utilized. ADF test is a test for unit roots in time series. Presence of unit roots is an indication of stationarity. ADF tests the hypothesis that the series is non-stationary against an alternative hypothesis that the series is stationary. It is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there are no unit roots at some level of confidence. The hypothesis is also rejected if the p values are found to be smaller than the level of significance used in the investigation.

Acceptance of the null hypothesis would imply that the series is non stationary, thus further differencing would be needed to make the data sets stationary. This is done to ensure that the stationarity condition has been achieved before proceeding further to estimate and fit time series models. Stationarity is desired in time series because it ensures that the time series models can be used to examine the dynamic behavior of volatility of returns over time.

Sample autocorrelation function (ACF) plots were then used to ascertained the serial dependence for observations x_1, x_2,…x_n at varying time lags. It is rarely necessary to test correlations to lags greater than 20, so they were tested at lags 10, 15 and 20.

ACF is given by

$$ACF(h) = \rho(h) = \frac{\gamma(h)}{\gamma(0)}, \qquad 3.8$$

ACF plots are plots of the correlations at the varying lags against the time lags h = 0, 1, n-1 and where $\gamma(h)$ the sample autocovariance is function (ACVF) given by:

$$ACVF(h) = \gamma(h) = \frac{1}{n}\sum_{t=1}^{n-h}(x_{t+h} - \bar{x})(x_t - \bar{x}) \qquad 3.9$$

The autocorrelations should be near zero for all the time lags if the time series is an outcome of a completely random phenomenon, otherwise, one or more of the autocorrelations will be significantly non-zero.

ACF plots of squared returns against time lags were also examined, and if the plots exhibit significant correlation and die out slowly the results indicate that the variance of returns is conditional on its past history and may change over time.

Presence of GARCH effects in the returns were then checked using Ljung Box test on the returns. Ljung Box and Lagrange multiplier (ARCH LM) as suggested by Engle (1982) are the conventional ways of testing ARCH effects. ARCH LM Test is a Lagrange Multiplier test for GARCH effects up to order 12 in the residuals.

The ARCH effect applies the white-noise test on the time series squared:

$$y_t = x^2_t \qquad 3.10$$

The test hypothesis for the ARCH effect:

$$H_O : \rho_1 = \rho_2 = ... = \rho_m = 0$$

Where:

ρ is the population autocorrelation function for the squared time series (i.e. $y_t = x^2_t$) and

m is the maximum number of lags included in the ARCH effect test.

The Ljung-Box text was formally applied on the returns series to check for the presence of GARCH effects. The Ljung-Box modified Q^* statistic is computed as:

$$Q^*(m) = n(n+2)\sum_{j=1}^{m}\frac{\hat{p}_j^2}{n-1} \qquad 3.11$$

Where:

- m is the maximum number of lags included in the ARCH effect test,
- $\hat{p}_j$ is the sample autocorrelation at lag j for the squared residuals

$Q^*(m)$ has an asymptotic chi-square distribution with m degrees of freedom.

$$Q^*(m) \sim \chi^2_{(m)}$$

Where $\chi^2_{(m)}$ **is** a Chi-square probability distribution function and m is is the degrees of freedom for the Chi-square distribution.

The computed p-value is compared with the significance level used in the investigation, and the hypothesis of no GARCH effects was rejected if the p value is found to be less than 0.05.

In practice, the choice of m affects test performance of the statistic $Q^*(m)$. If T is the length of the observed time series, choosing m = ln (n) is recommended (Tsay, 2010).

If there are no GARCH effects in the returns then the GARCH model is unnecessary and misspecified (Zivot & Gary, 2006) but if the GARCH effects are found to be significant then the specification of the appropriate models will be done using Model selection criterion such as Akaike Information Criterion and the Bayesian Information Criterion (AIC& BIC).

Akaike Information Criterion (AIC) is a measure of the relative quality of a statistical model for a given set of data; as such it provides a model for model selection. For any statistical model, AIC is given by

AIC = 2k-2 ln (L)……………………………………......……………………….....…….3.12

Where k is the number of parameters in the model and L is the maximized value of the likelihood for the model.

Bayesian Information Criterion (BIC), on the other hand is also a criterion for model selection among a finite set of models. It is based on the likelihood function and is closely related to AIC. BIC is given by

BIC=-2ln(L)+kln (n)………………………………………………………..……………3.13

Where k is the number of parameters in the model, L is the maximized value of the likelihood for the model and n is the sample size.

3.3.2 Model Estimation, Selection and fitting

After exploring the characteristics and distributional properties of the data sets and confirming the presence of GARCH effects in the returns, the GARCH models were then estimated for the respective series. The lower orders GARCH models were utilized in this study because of their simplicity and the ability to capture the stylized features exhibited by financial time series.

GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) parameters for the three companies for all the returns were estimated using robust method of Bollerslev-Woodridge's Quasi Maximum Likelihood Estimator (QMLE) assuming the Gaussian standard normal distribution. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were thereafter compared for each data set to determine the most appropriate model; given a set of competing models for the data, the preferred model is the one with the minimum AIC and BIC values.

3.3.3 Diagnostic testing

Adequacy of the models was checked to ensure detection of possible model misspecification. This is done by analyzing the residuals (fitting error) from the fitted models. Residuals are the difference between the observed values and the estimated values. Ljung Box test and ARCH LM tests were used on squared residuals to establish the presence of autocorrelation and GARCH effects. P values less than 5% for the test statistics suggest rejection of the no autocorrelation and no GARCH effects null hypotheses respectively.

3.4 Forecasting and forecasting performance

In time series, forecasting is a mathematical way of estimating future values using present and historical values of the series (Aidoo, 2010). Forecasting as described by Box and Jenkins (1976) provides basis for economic and business planning, inventory and production control and optimization of industrial process. Predicting future values using the constructed models is one of the main objectives of time series analysis.

3.4.1 Forecasting evaluation

Forecasting of future share prices was done using the fitted models of each data set and the forecasting performance of each time points evaluated and compared using common statistical error functions which measure forecasting accuracy. The intention was to find a time point that gives the best forecasting power. These measures are Mean Absolute Percentage error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) which are given by:

MAPE

$$=\frac{100}{K}\sum_{t=n+1}^{n+K}\left|\frac{\hat{\sigma}_t-\sigma_t}{\sigma_t}\right| \text{......} 3.14$$

MAE

$$=\frac{\sum_{t=n+1}^{n+K}\left|\hat{\sigma}_t-\sigma_t\right|}{K} \text{......} 3.15$$

RSME

$$=\sqrt{\frac{\sum_{t=n+1}^{n+K}\left(\hat{\sigma}_t-\sigma_t\right)^2}{K}} \text{......} 3.16$$

Where n is the sample size, K is the number of steps ahead, $\hat{\sigma}_t$ and σ_t are the square root of the conditional forecasted volatility and the realized volatility respectively.

The time point which yields the lowest mean error values of the forecast evaluation statistics is considered better than the rest

CHAPTER FOUR

RESULTS AND INTERPRETATION

4.1 Introduction

The findings and results of data analysis, model estimation and evaluation, as well as diagnostic tests and forecasting are presented in this chapter in figures and tables.

4.2 Exploratory Data Analysis

4.4.2 Daily series

The time plots of the daily closing prices of the companies whose share prices were analyzed are presented in Figure 1 below.

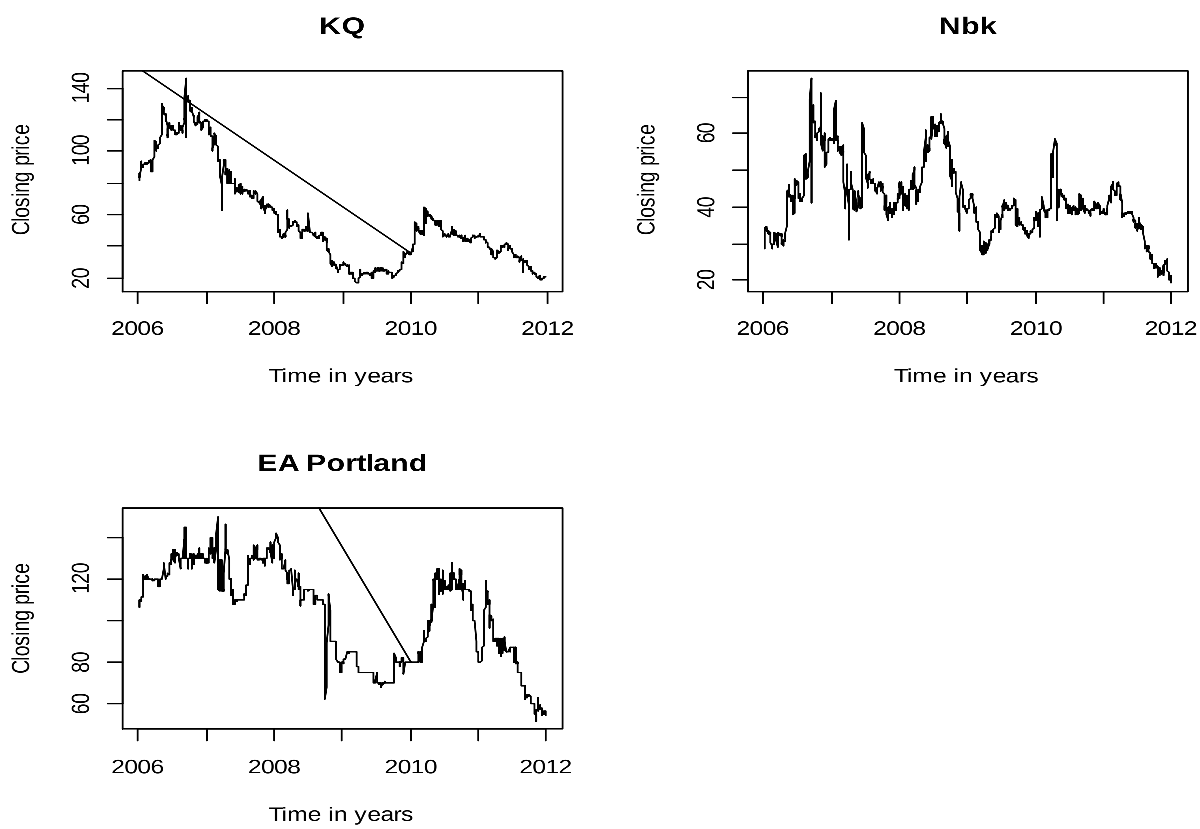

Figure 1: Time plots for the daily series

From the time plots in Figure 1, the swings are evident and its clear that the stock prices are very irregular with varied degree of flactuations.The mean and variance are not constant impling that the series are non stationary. Consequently, transformation was done using equation 19, and the returns series plotted against time points.

The plots of daily returns are presented in Fig 2.

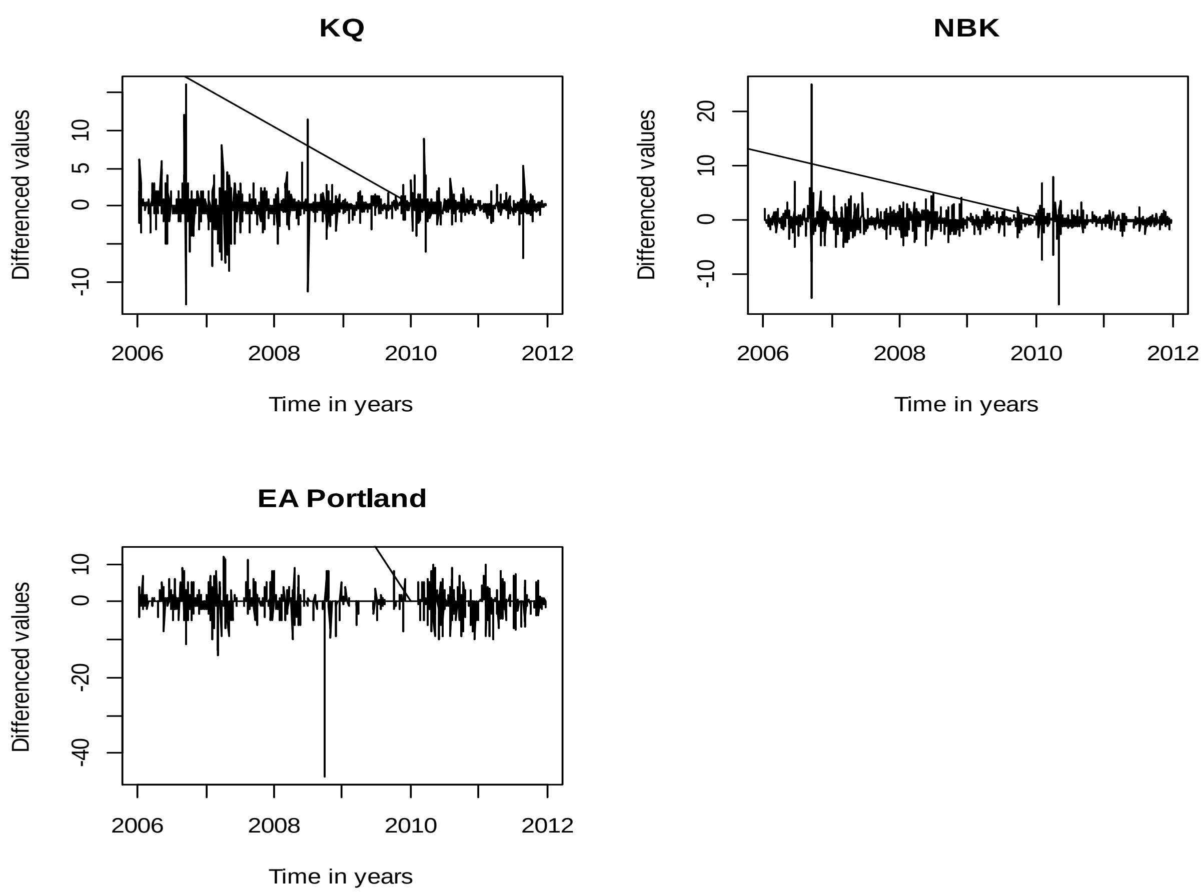

Figure 2: Time plots of daily returns

Unlike the plots of closing prices, the plots of returns are trendless and amplitude of returns varies over time. They tend to fluctuate around zero and periods of relative calmness interspersed by periods of turmoil. Table 1 below presents the descriptive statistics of the daily returns.

Table 1: Descriptive statistics for the daily returns

Compa	Min	Max	Mean	Std	Skew	Kurt	Jarque/Berra
KQ	-0.255	0.209	-0.0009	0.028	-0.196	13.459	11383.880(<2.2e-16)
NBK	-0.346	0.476	-0.0002	0.034	0.873	37.324	87741.240(<2.2e-16)
EA Port	-0.555	0.108	-0.0005	0.027	-5.874	121.509	936435.500(<2.2e-16)

The means for the three sets of returns are all negative and the difference between the minimum and maximum returns are high. NBK exhibits the highest volatility with standard deviation of 0.034 while East African Portland cement was the least volatile with a standard deviation of 0.027. KQ has positive skewness while NBK and EA Portland both have a negative skewness. Kurtosis for all the returns are greater than three thus clearly indicating deviation from the normal distribution. Moreover, the Jarque-Bera tests rejects null hypothesis for all the returns in the three cases because of the small p values as indicated in brackets. These tests confirm that the returns are not normally distributed.

Table 2: Unit root testing for daily return and closing prices

Company	Daily returns		Prices	
	ADF	**P-value**	**ADF**	**P-value**
KQ	-11.1087	0.01	-1.7900	0.6671
NBK	-34.0284	0.01	-3.6687	0.0607
EA Port	-40.1553	0.01	-3.0446	0.1361

Table 2 presents the stationary checks for the raw data and the returns using ADF test statistics. The ADF values are more negative for returns series than for closing prices, p values are also conspicuously smaller for the returns series than for the raw series.

The autocorrelation of returns and squared returns were done to ascertain serial dependence in the data. Figure 3 below shows that the ACF plots of the daily returns.

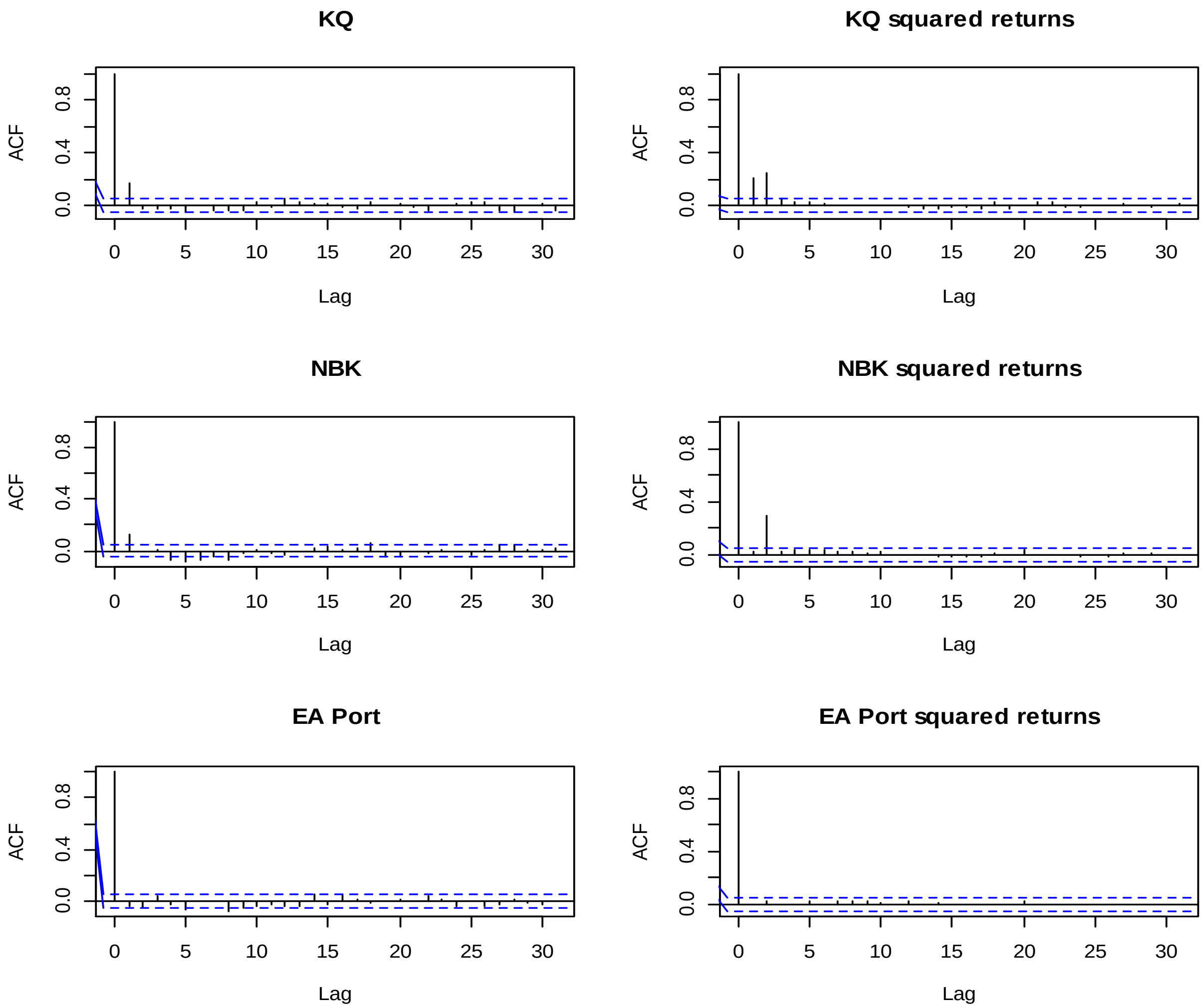

Figure 3: ACF of returns and squared returns for the daily returns

The Ljung Box test statistics for daily returns for lags 10, 15 and 20 are provided in Table 3.

Table 3: Ljung Box test for daily returns

Company	Lag					
	10		15		20	
	Statistic	p value	Statistic	p value	Statistic	p value
KQ	**52.765**	<2.2e-16)	60.064	<2.2e-16	62.257	<2.2e-16
NBK	**61.189**	<2.2e-16)	65.534	<2.2e-16	76.844	<2.2e-16
EA Port	**28.378**	<2.2e-16)	38.489	<2.2e-16	43.14	<2.2e-16

The p values for all the returns are all less than 0.05, implying a rejection of the no autocorrelation null hypothesis at 5% level of significance.

4.2.2 Weekly series

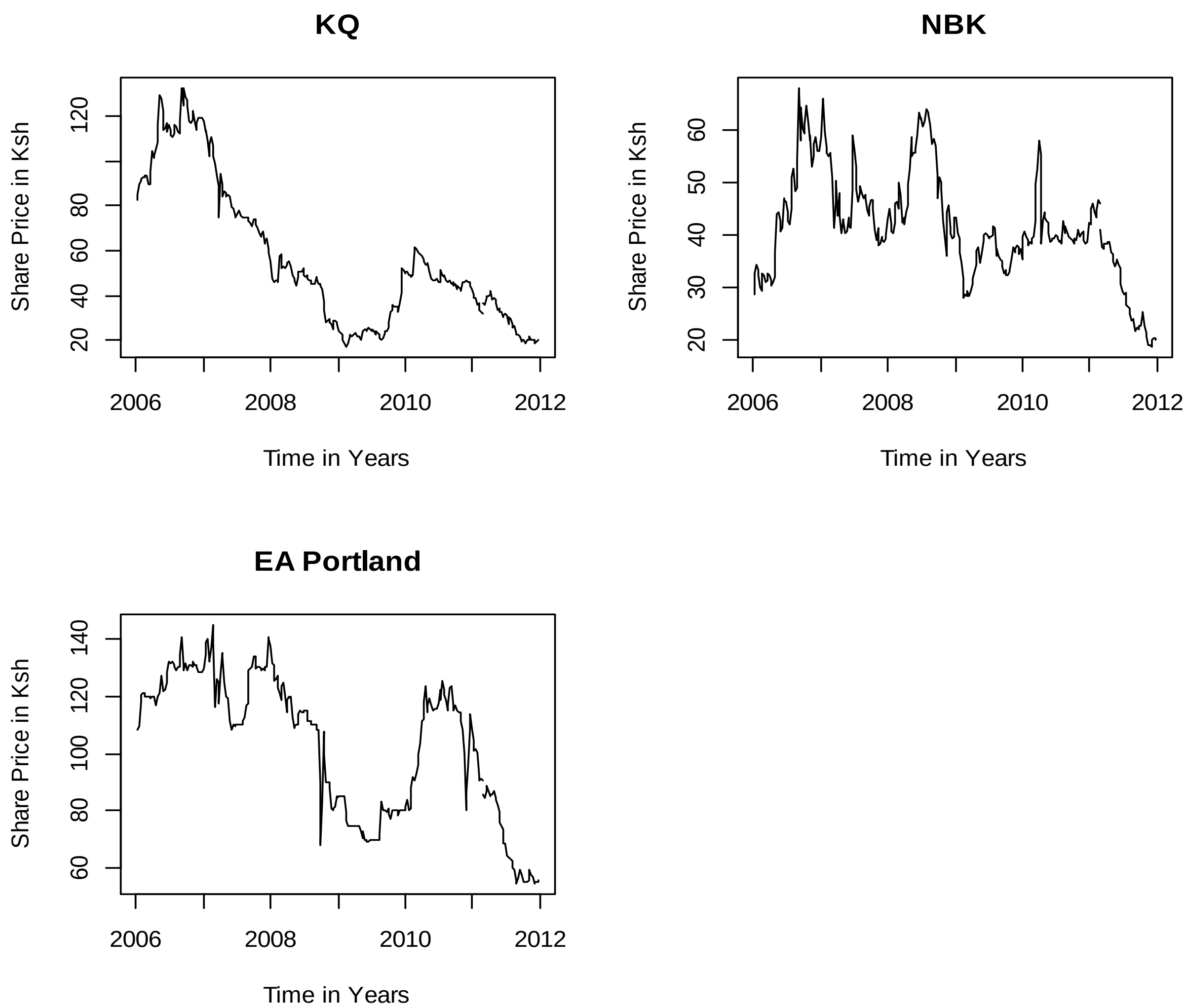

Figure 4: Time plots of weekly series.

Visual inspection of Figure 4 above, shows that the weekly prices are quite irregular and that, fluctuations are frequent, suggesting that the mean and variance are not constant and hence non stationary. Transformation was done and the time plots plotted.

The resulting time plots are as shown in Figure 5 below.

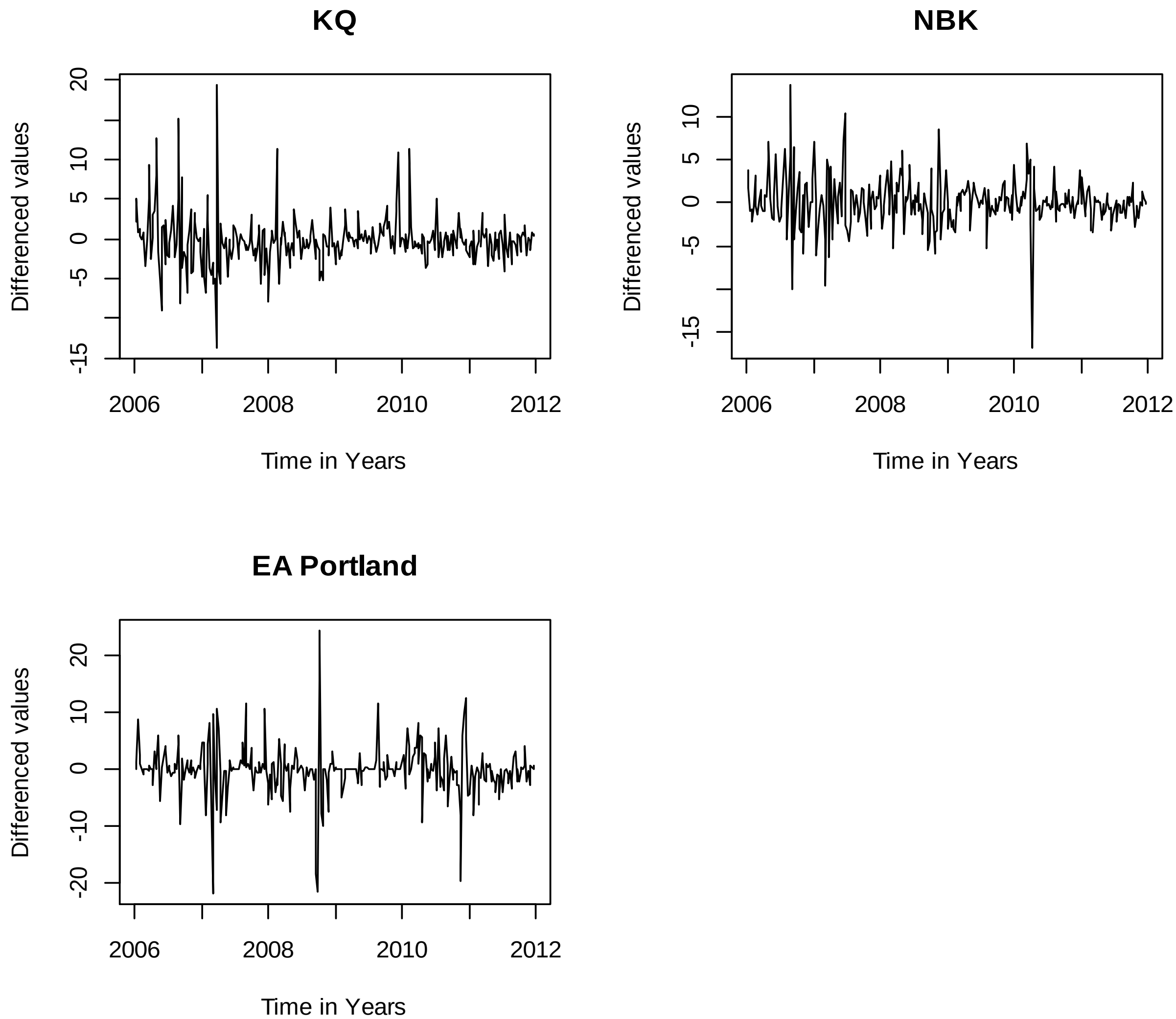

Figure 5: Time plots of weekly returns

The weekly returns in Figure 5 appear in clusters, with varying amplitude but generally vary around zero. This suggests that the returns are now stationary. The plots are marked by periods of relative calmness interposed with turmoil. This phenomenon is referred as volatility clustering and it is very conspicuous in all the returns plots.

Descriptive statistics were carried out to further explore the distribution characteristics of weekly returns and the results are presented in Table 4.

Table 4: Descriptive statistics for weekly returns

Comp	Min	Max	Mean	Stdv	Skew	Kurt	Jarque/Berra
KQ	-0.1693	0.2331	-0.0045	0.0556	0.8504	3.5984	210.9605 (<2.2e-16)
NBK	-0.3637	0.2244	-0.0011	0.0624	-0.2168	4.3222	251.4412(<2.2e-16)
EA Port	-0.2758	0.2554	-0.0021	0.0445	-0.3579	11.7112	1824.407(<2.2e-16)

The means for the three sets of returns are all negative and the difference between the minimum and maximum returns are high. NBK exhibited the highest volatility with standard deviation of 0.0624 while East African Portland cement was the least volatile with a standard deviation of 0.0445. KQ has positive skewness while NBK and EA Portland both have a negative skewness. Kurtosis for all the returns are greater than three thus clearly indicating deviation from the normal distribution. Moreover, the Jarque-Bera tests rejects null hypothesis for all the returns in the three cases because of the small p values as indicated in brackets. These tests confirm that the returns are not normally distributed. In order to test whether the returns are stationary or not, ADF tests were done and the results are shown in Table 5 below.

Table 5: ADF test for weekly series and returns

Company	Weekly returns		Weekly prices	
	ADF	**P-value**	**ADF**	**P-value**
KQ	-6.5658	0.01	-1.6314	0.7318
NBK	-6.2064	0.01	-3.2398	0.0816
EA Port	-7.3272	0.01	-2.4041	0.4060

The ADF values are more negative for returns series than for the weekly prices. The p values were also significantly smaller for the returns series than for the raw series. These p values are also less than 0.05, suggesting the rejection of non-stationary null hypothesis at 95% confidence level.

To test the presence of GARCH and serial dependence in the returns, Ljung-Box test and autocorrelation plots of returns were used respectively. The results are presents in Table 6 and Figure 6 respectively.

The Ljung Box test statistics for weekly returns for lags 10, 15 and 20 are provided in Table 6.

Table 6: Ljung Box test for weekly returns

Company	Lag					
	10		**15**		**20**	
	Statistic	**P value**	**Statistic**	**P value**	**Statistic**	**P value**
KQ	12.0948	0.2788	19.3479	0.1984	23.2288	0.2777
NBK	31.3988	0.0005	35.3701	0.0022	40.7585	0.0040
EA Port	19.7058	0.0322	25.2052	0.0473	3.4914	0.9989

Weekly returns for NBK are all significant at the lags tested, while EA Port's returns fail to be significant at lag 20. KQ's returns all fail to be significant FOR GARCH effects at lags 10, 15 and 20.

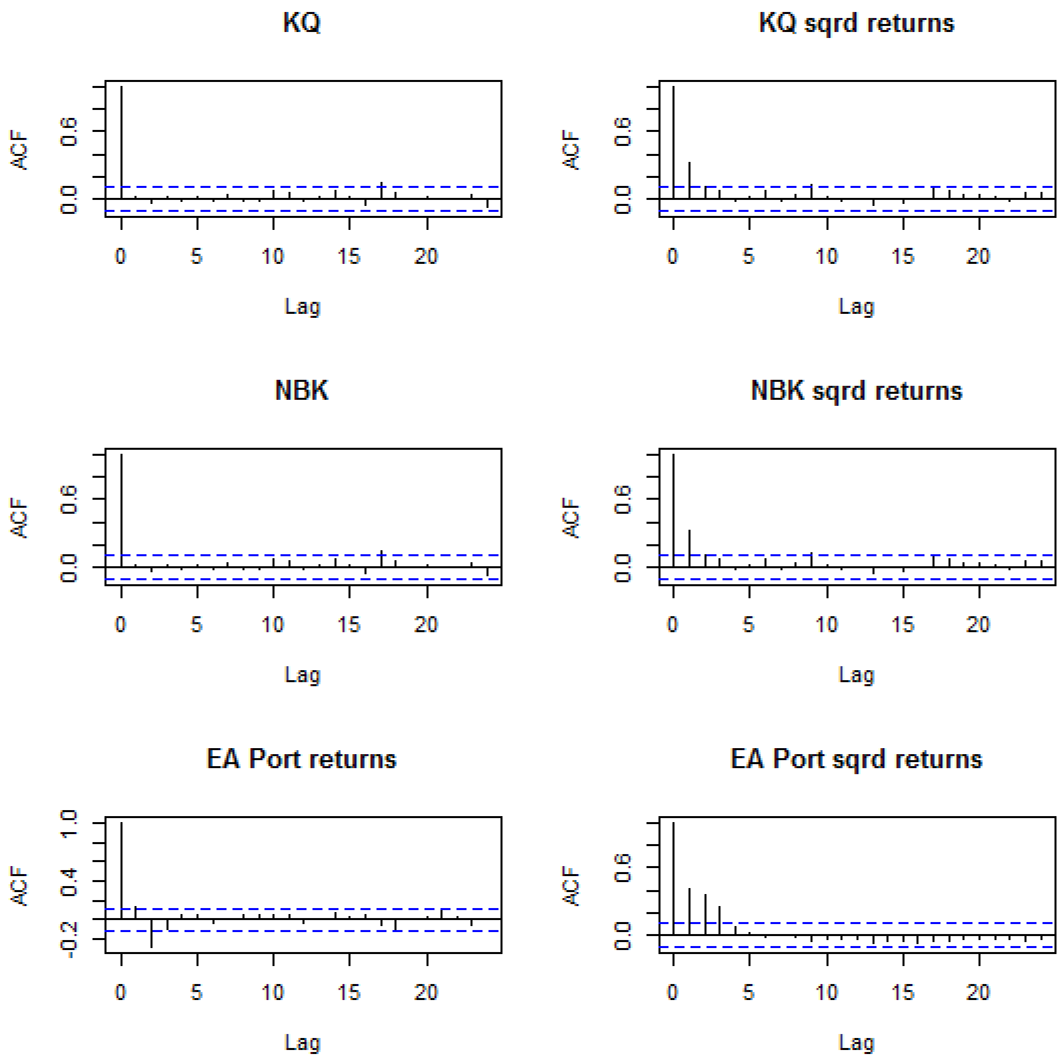

Figure 6: ACF plots of weekly returns and squared returns.

4.2.3 Monthly series.

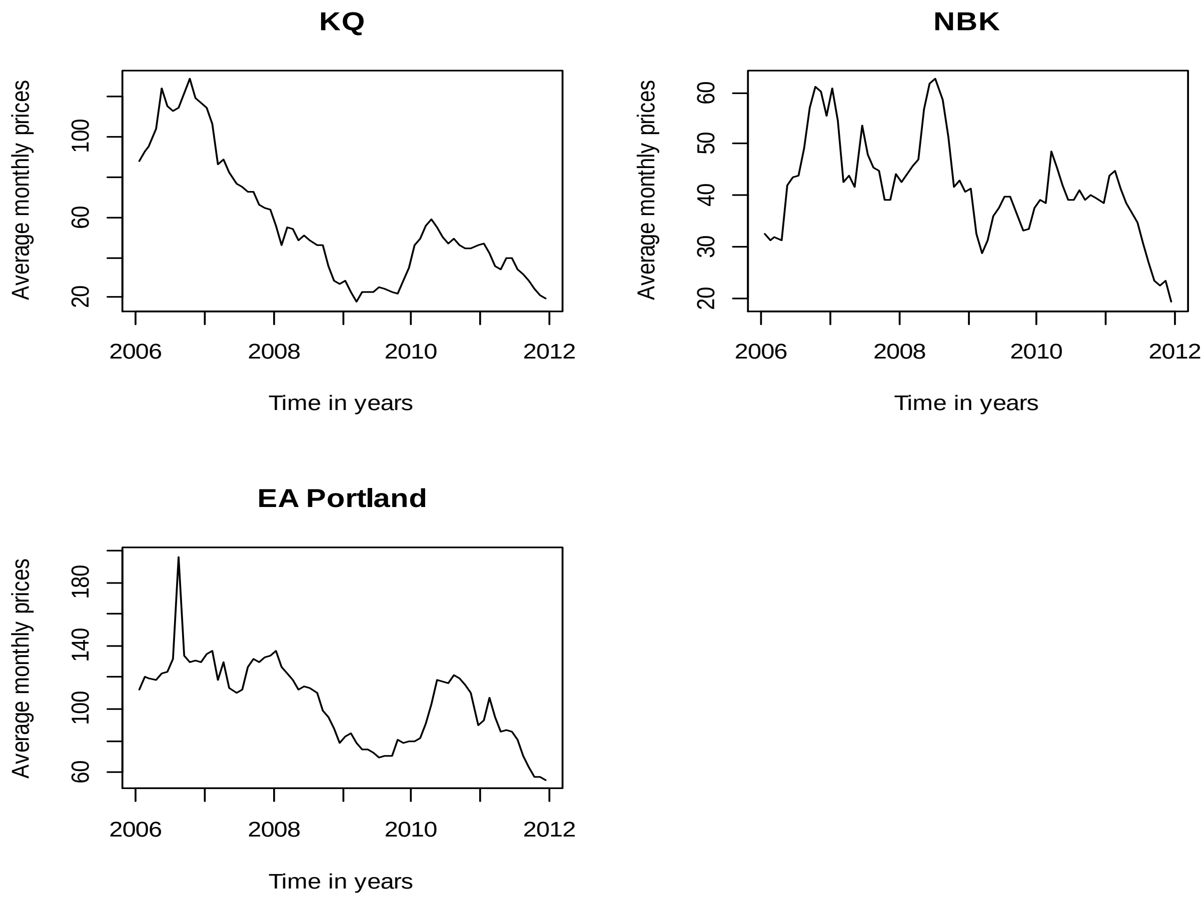

Figure 7: Time plots of monthly series

The time plots of monthly series in Figure 7 show no distinct pattern, the prices are varied and irregular suggesting that the series are non-stationary. Transformation of prices to returns was done and the time plots for the returns are as shown in Figure 8.

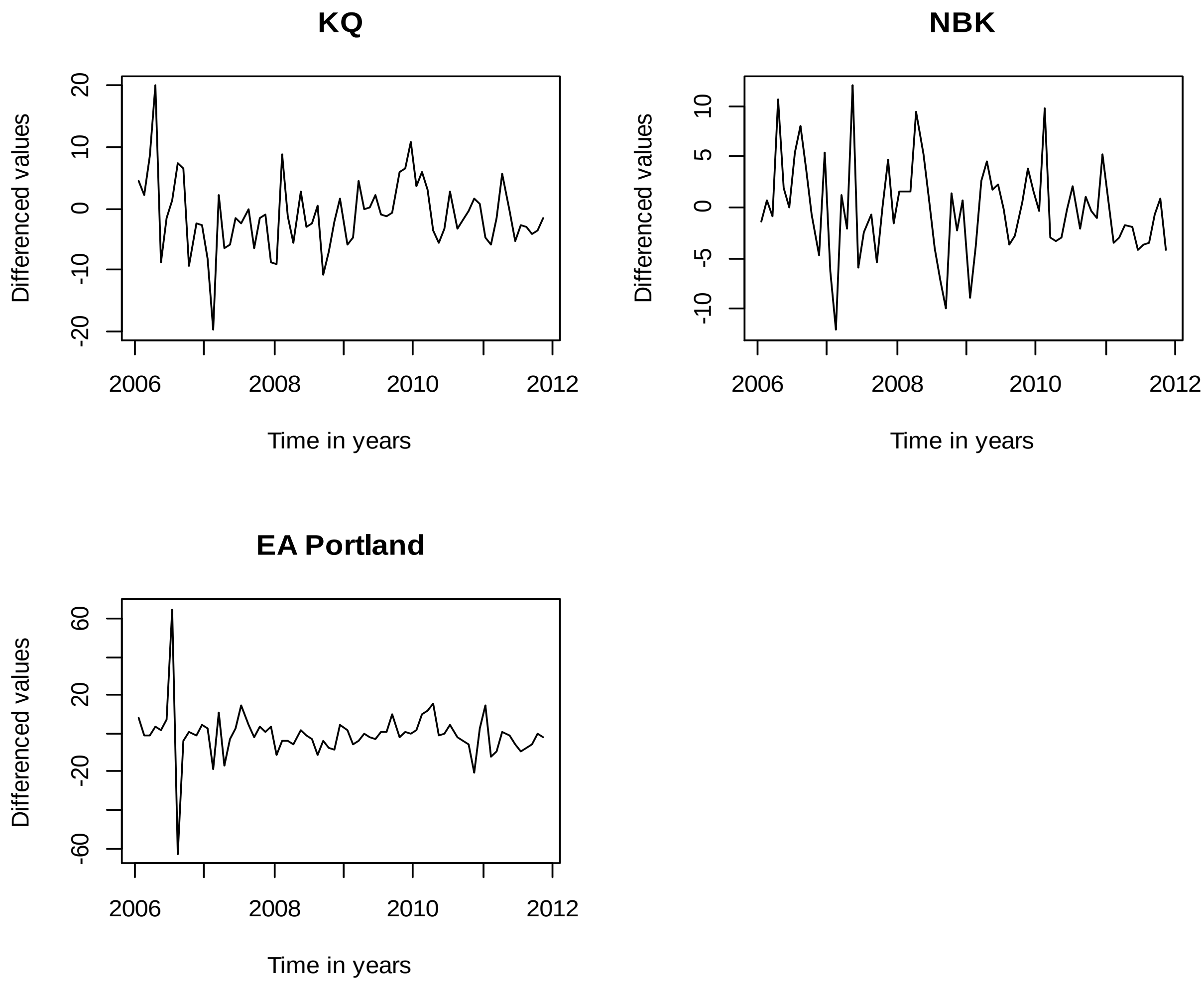

Figure 8: Time plots of monthly returns

Unlike the plots of average monthly prices, the plots of returns in Figure 8 are trendless and amplitude of returns varies over time. They tend to fluctuate around zero, implying a constant mean and variance. The returns are highly varied for all the returns except for East African Portland Cement which exhibits fewer sharp fluctuations.

Descriptive analysis of the three data sets was done and summarized in Table 7 below:

Table 7: Descriptive statistics for monthly returns

Company	Min	Max	Mean	Stdv	skew	Kurt	Jarque/Berra
KQ	-0.263	0.273	-0.0212	0.1124	0.3665	3.2247	1.9572 (0.3758)
NBK	-0.25	0.296	-0.0074	0.0113	0.2878	3.4860	2.0394 (0.3607)
EA Port	-0.385	0.399	-0.0099	0.0958	0.2383	5.9277	113.8534(<2.2e-16)

The means for the three sets of returns are all negative and the difference between the minimum and maximum returns are high. KQ exhibited the highest volatility with standard deviation of 0.1124 while NBK was the least volatile with a standard deviation of 0. 0113.They all have positive skewness implying a right tail, thus asymmetric. Kurtosis for all the returns are greater than three thus clearly indicating deviation from the normal distribution. The Jarque-Bera tests, however accept the null hypothesis for normality for KQ and NBK, but fails significantly for EA Port.

ADF tests were done to determine the existence of unit roots and the results were summarized in Table 8 below.

Table 8: ADF test for monthly series and returns

Company	Monthly returns		Monthly prices	
	ADF	P-value	ADF	P-value
KQ	-6.0401	0.01	-1.3135	0.8548
NBK	-7.0793	0.01	-2.4568	0.3893
EA Port	-9.1448	0.01	-3.0643	0.1420

The ADF values are more negative for returns series than for the closing prices. The p values were also significantly smaller for the returns series than for the raw series. The returns series have p values that are all smaller than 0.05, thus significant for existence of unit roots at 95% confidence level.

The Ljung-Box test and autocorrelation plots of returns were used to test the presence of GARCH effects and the serial dependence in the returns respectively and squared returns, the results are presented in Table 9 and Figure 9 below.

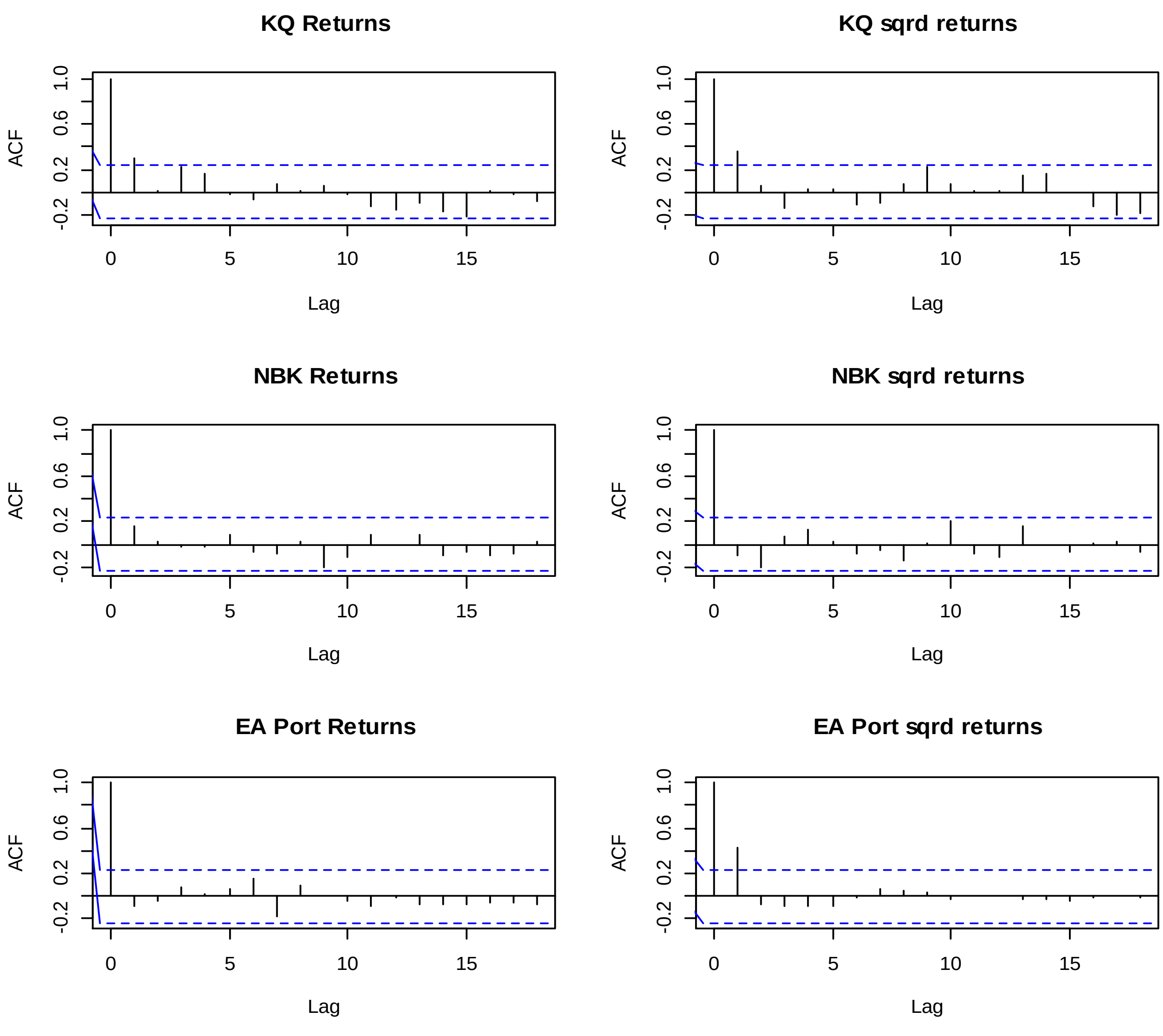

Figure 9: ACF plots of monthly returns and squared returns

Table 9: Ljung Box test for monthly returns

Company	**Lag**					
	10		**15**		**20**	
	Statistic	**p value**	**Statistic**	**p value**	**Statistic**	**p value**
KQ	12.5228	0.2516	20.8314	0.1423	21.3069	0.3793
NBK	7.1604	0.7102	9.0673	0.8740	13.9134	0.8349
EA Port	6.1396	0.8034	7.7050	0.9351	9.3570	0.9784

None of the p values for all the monthly returns were all greater than 0.05 at lags 10, 15 and 20.

4.3 Model Estimation and Evaluation.

After carrying out exploratory analysis on the three sets of data, and the returns found to exhibit the stylized characteristics of financial time series and GARCH effects found to be significant (except for monthly returns). Estimation and specification of GARCH models was in order.

The GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) parameters for the three companies for all the returns were estimated using robust method of Bollerslev-Woodridge's Quasi Maximum Likelihood Estimator (QMLE) assuming the Gaussian standard normal distribution. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were compared to determine the most appropriate model; models with smaller AIC and BIC are preferred. The results of AIC and BIC parameter estimation for the models under consideration were summarized in Table 10.

Table 10: AIC & BIC values for the GARCH Models

	Models	KQ		NBK		EA PORT	
Criteria		**AIC**	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Daily Returns series	GARCH (1, 1)	-4.5905	-4.5764	-4.3071	-4.2929	-4.4169	-4.4028
	GARCH (1, 2)	-4.5891	-4.5714	-4.3058	-4.2881	-4.4159	-4.3982
	GARCH (2, 1)	-4.5895	-4.5718	-4.3073	-4.2996	-4.4156	-4.3975
	GARCH (2, 2)	-4.5881	-4.5669	-1.5025	-1.3113	-4.4145	-4.3933
Weekly returns series	GARCH (1, 1)	-2.9680	-2.9707	-2.7888	-2.7409	-3.7978	-3.7499
	GARCH (1, 2)	-2.9771	-2.9772	-2.7847	-2.7249	-3.7915	-3.7317
	GARCH (2, 1)	-2.9609	-2.9711	-2.7905	-2.7307	-3.7915	-3.7317
	GARCH (2, 2)	-2.9707	-2.8989	-2.7845	-2.7127	-3.7851	-3.7134
Monthly returns series	GARCH (1, 1)	-1.5403	-1.4128	-1.5584	-1.4309	-1.9665	-1.839
	GARCH (1, 2)	-1.5101	-1.3507	-1.5307	-1.3713	-1.9382	-1.7788
	GARCH (2, 1)	-1.5101	-1.3507	-1.5307	-1.3713	-1.9382	-1.7788
	GARCH (2, 2)	-1.4819	-1.2907	-1.5025	-1.3113	-1.9123	-1.7188

From Table 10 above, KQ, EA Port daily returns and all the monthly returns had Minimum AIC and BIC values for GARCH (1,1) model, while NBK daily and weekly returns had the smallest AIC and BIC values for GARCH (2,1) and KQ weekly had the smallest AIC and BIC values for GARCH(1,2)

Parameter estimation for the chosen models was done and summarized in Tables 11, 12, 13 and 14

Table 11: Estimation of GARCH (1, 1) models

Daily returns

Parameters	KQ		EA Port	
	Estimate	**P value**	**Estimate**	**P value**
ω	0.0002	0.0059	0.0002	0.0553
α_1	0.4016	0.0042	0.0425	0.0452
β_1	0.3795	0.0004	0.6871	0.0003

Weekly returns

	EA Portland	
	Estimate	**P value**
ω	0.0007	0.0101
α_1	0.5048	0.0403
β_1	0.1115	0.3848

Monthly returns

	KQ		NBK		EA Port	
	Estimate	**P value**	**Estimate**	**P value**	**Estimate**	**P value**
ω	0.008	0.0084	0.0002	1.0000	0.0035	0.0426
α_1	0.3408	0.1272	0.0000	1.0000	0.9999	0.1577
β_1	0.0000	0.9999	0.9968	0.0001	0.0000	1.0000

Table 12: GARCH (1, 2) model for KQ weekly

Parameters	Estimates	P values
ω	0.0006	0.4987
α_1	0.2365	0.0584
β_1	0.2027	0.4585
β_2	0.3955	0.0234

The p values were greater than 0.05 for all the parameters except for β_2

Table 13: GARCH (2, 1) models for NBK daily and weekly returns

	NBK Daily		NBK weekly	
Parameters	**Estimate**	**P value**	**Estimate**	**P value**
ω	0.0001	0.0016	0.0019	0.811
α_1	0.3914	0.0018	0.3164	0.3144
α_2	0.0921	0.5232	0.2834	0.8650
β_1	0.5413	<2e-16	0.0000	1.0000

The sum of α_1, α_2 and β_1 for NBK GARCH (2, 1) model add up to 1.0248, this is a violation of the stationarity condition which requires that the sum of all parameters should be 1. GARCH (1, 1) model was therefore fit to the data and the parameters and their respective p values are as shown in Table 14.

Table 14: GARCH (1, 1) model for NBK daily

Parameters	**estimates**	**P values**
ω	0.0001	0.0149
α_1	0.4461	0.0000
β_1	0.5885	<2e-16

The parameter estimates for NBK GARCH (1, 1) model are all significant at 5% level of significance

4.4 Diagnostic testing.

Adequacy of the models was checked to ensure detection of possible model misspecification. This was done by analyzing the residuals of the fitted models. Ljung Box and ARCH-LM tests were carried out on squared residuals for all the returns series up to lag 20 and the results summarized in Tables 15, 16 and 17.

Table 15: LJUNG-BOX & ARCH LM tests for KQ returns

Returns	Q(m)	Statistic	P value
Daily	Q(10)	0.45827	0.99956
	Q(15)	1.11349	0.99995
	Q(20)	3.79738	0.99997
	ARCH LM Test	0.47587	0.99999
Weekly	Q(10)	8.2182	0.6075
	Q(15)	16.6508	0.7769
	Q(20)	13.2146	0.8679
	ARCH LM Test	8.3747	0.7552
Monthly	Q(10)	7.1494	0.7113
	Q(15)	13.5108	0.5629
	Q(20)	16.7804	0.6672
	ARCH LM Test	6.1043	0.9107

The p values for Ljung Box and ARCH LM are all greater than 0.05.

Table 16: LJUNG-BOX & ARCH LM tests for NBK returns

Returns	Q(m)	Statistic	P value
Daily	Q(10)	3.1416	0.9779
	Q(15)	3.8849	0.9981
	Q(20)	65.1961	0.0001
	ARCH LM Test	3.35022	0.9925
Weekly	Q(10)	3.4039	0.9703
	Q(15)	5.6408	0.9852
	Q(20)	9.1819	0.9807
	ARCH LM Test	3.5118	0.9907

Monthly	Q(10)	11.4782	0.3215
	Q(15)	16.3971	0.3562
	Q(20)	17.2118	0.6392
	ARCH LM Test	12.138	0.4347

The p values for Ljung Box and ARCH LM are all greater than 0.05 except for NBK which is 0.0001 at lag 20.

Table 17: LJUNG & ARCH LM tests EA Port returns

Returns	Q(m)	Statistic	P value
Daily	Q(10)	0.1401	0.9999
	Q(15)	0.23639	0.9999
	Q(20)	1.11025	0.9999
	ARCH LM Test	0.2044	0.9999
Weekly	Q(10)	2.7882	0.9859
	Q(15)	3.4914	0.9989
	Q(20)	5.6806	0.9993
	ARCH LM Test	3.1972	0.9939
Monthly	Q(10)	2.5047	0.9908
	Q(15)	3.2935	0.9993
	Q(20)	4.0888	0.9999
	ARCH LM Test	6.4986	0.8889

The p values for Ljung Box and ARCH LM tests are all greater than 0.05

4.5 Forecasting and Forecasting Evaluation

4.5.1 Forecasting

Forecasting was done and the time points were evaluated in terms of their forecasting ability of future returns. The mean errors measures for each of the data set were calculated and summarized in Table 18 below.

Table 18: Forecasting performance based on MAE, RMSE and MAPE

	KQ			NBK			EA Port		
	MAE	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**	**MAE**	**RMSE**	**MAPE**
Daily	0.8980	1.6488	1.6663	0.8629	1.5628	2.0205	1.1273	2.6702	1.0810
Weekly	1.9778	3.1753	3.7798	1.8918	2.8350	4.4067	2.4821	4.3726	2.4729
Monthly	4.3425	5.7990	8.8383	8.3366	4.4673	8.0333	6.7900	12.7036	6.1590

CHAPTER FIVE

DISCUSSION

5.1 Introduction

Three time points for three companies were investigated and several tests carried out to investigate the exploratory and descriptive characteristics of the returns. This chapter is organized as exploratory analysis, model estimation and evaluation, diagnostic testing and forecasting

5.2 Exploratory Data Analysis

From the time plots of all the data sets (raw series) Figures 1, 4 and 7, the swings are evident and its clear that the stock prices are very irregular with varied degree of flactuations. There are no distinct patterns exhibited. This suggests that the mean and variance are not constant impling that the series are non stationary. Unstable series such as these could be use for for model fitting and further statistical inferences because of their grave implications (Gujarati, 2004). Transformation of the raw series was therefore done by differencing in order to make the series stationary.

After differencing the raw series and plotting done on the resulting series, the time plots were presented in Figures 2, 5 and 8. These time plots plots provided visual representation of the returns. Unlike the time plots for the raw series, the plots for returns are trendless and their amplitudes vary over time. They tend to flactuate around zero, implying a constant mean and stabilized variance. Engle (2001) interpreted this as the presence of ARCH effects. The plots are marked by periods of calmness interposed with turmoil. This phenomenon is referred as volatility clustering because the returns appear in form of cluster and it is very conspicuous in all the returns plots.

Descriptive statistics on the data sets were also carried out and presented in Tables 1, 4 and 7. Generally, the difference between the maximum and minimum returns was large, which is a common feature of index returns, and as expected for time series of returns, the mean is quite close to zero for all the returns series. The standard deviation for all the returns are also high indicating a high level of fluctuations of returns, for instance, for the daily series, NBK was the most volatile with a standard deviation of 0.034 while East African Portland Cement was the least volatile with a standard deviation of 0.027. The kurtosis of all the three data sets exceeded the normal value of 3, indicating evidence of fat tails (leptokurtic) and sharp peaks around the mean, the monthly returns series however, had conspicuously lower kurtosis values as compared to other returns. This implies that their distributions were quite close to normal distributions. This is in line with the literature available. Positive and negative skewness were also observable in all the returns, this means that the right and the left tail is particularly extreme respectively, and an indication of lack of symmetry. The Jarque-Berra test also led to the same rejection of normality in all the return series at 5% level of significance, except for KQ and NBK monthly returns.

To check for stationarity of the series, before and after differencing, ADF tests were used, and the results summarized in Tables 2, 5 and 8. From the results, the unit roots were found to be more negative for the raw series than the returns series, and the p values are less than 5% significance level for all the returns series, which leads to the rejection of the no unit roots null hypothesis. This implies that unit roots were detected in returns series but failed significantly for the closing prices. This further, shows that unlike the raw series, the returns are stationary and could be used for time series modeling in order to examine volatility of share prices over time.

Stationarity is desired in time series because it ensures that the time series models can be used to examine the dynamic behavior of volatility of returns over time, and hence the stability of the models to be fitted to the data is ensured.

The above mentioned tests confirmed that the characteristics of the NSE returns were consistent with other financial time series, i.e. the stylized facts of financial time series such as, high kurtosis, with flat heavy tails and skewed distributions, as well as the volatility clustering as observed in the time plots of returns series.

Autocorrelation plots were further inspected to ascertain the presence of autocorrelation and from Figures 3, 6 and 9. ACF plots show no indication of correlation characteristics of returns because some time lags had non-zero values (except for lag 0 which is always 1). The autocorrelations should be near zero for all the time lags if the time series is an outcome of a completely random phenomenon, otherwise, one or more of the autocorrelations will be significantly non-zero (Ngailo, 2011). The ACF of squared returns, however, show significant correlation and die out slowly indicating that the variance of returns is conditional on its past history and may change over time.

The Ljung-Box test were then utilized to ascertain the presence of GARCH effects and from Tables 3 and 6, the test rejects the null hypothesis of no GARCH effects in the returns series at 5% level of significance as evidenced by the small p values for daily and weekly returns. The test however, fails for all the monthly returns as shown in Table 9. This suggests the presence of GARCH effects in the daily and weekly returns but fails to detect GARCH effects in the monthly returns.

5.3 Model estimation and Evaluation

From the exploratory analysis, the three sets of data were found to be leptokurtic, exhibited volatility clustering. GARCH effects were however found to be significant for daily and weekly returns series, but failed significantly in the monthly returns. Estimation and specification of GARCH models for all the returns series were however done because according to Hojatalla and Ramanarayanan (2010) this condition is necessary but not necessarily sufficient because the estimate meets the general requirement of a GARCH model.

The GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) parameters for the three companies for all the returns were estimated using robust method of Bollerslev-Woodridge’s Quasi Maximum Likelihood Estimator (QMLE) assuming the Gaussian standard normal distribution. Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values were compared to determine the most appropriate model; models with smaller AIC and BIC are preferred. The results of AIC and BIC parameter estimation for the models under consideration were summarized in Table 10.

From the comparison of AIC and BIC models in Table 10, GARCH (1, 1) model most returns series i.e. KQ daily and monthly returns, NBK monthly and all the returns series for East African Portland cement because they all have AIC and BIC values that are smallest as compared to the other models. GARCH (1, 2) has the smallest Akaike

Information Criteria value for KQ weekly and GARCH (2, 1) for NBK daily and weekly, suggesting a better fit that other competing models.

Another candidate model fitted to the data and tested was the GARCH (2, 2). The analysis showed that the GARCH (2, 2) was less preferred for any data set, this implies that it does not capture well the volatility clustering and leptokurtic characteristics of the stock returns as compared to the other competing models. This model was therefore not fitted to any series.

The parameter estimates for each of the GARCH (1, 1) models in Table 11 show that the coefficients of the conditional variance equation α_1 and β_1 are all positive and significant at 5%, levels, except for some weekly and all monthly returns. This implies a strong support for GARCH. The sum of α_1 and β_1 are quite close to unity for most series, except for KQ monthly which was quite low. The sum $\alpha_1+\beta_1$ is an indication of volatility persistence. A high persistence implies that volatility is likely to die slowly; new shock will affect the returns for a longer period. In such markets, old information is more important than recent information and such information decays very slowly. (Ngailo, 2011).

GARCH (1, 2) for KQ weekly returns was favoured by AIC and BIC, thus it can be considered a better model for KQ weekly returns as compared to other competing models. The parameters of the model were all positive and insignificant at 5% level of significance except for β_2.

Parameters estimates for GARCH (2, 1) for NBK daily and weekly are all positive and significant at the given levels of significance. Although GARCH (2, 1) for NBK daily has been favoured by AIC, the sum of parameters is greater than one, violating the variance stationarity condition. GARCH (1, 1) also violates this condition but comparing their log likelihood, 3244.053 verses 3242.947 respectively (check Appendix 1), GARCH (1, 1) is more preferred because it has smaller log likelihood and it is also simpler; a simpler model requires less parameters. The GARCH (1, 1) parameter estimates for NBK daily are all positive and significant at 5% level of significance. The sum $\alpha_1+\beta_1$ is greater than one, suggesting an explosive volatility. This implies that the daily share prices for NBK were highly volatile. High volatility implies that, if there is a new shock it will have implication on returns for a longer period.

5.4 Diagnostic testing

Using squared residuals based on the estimated models of KQ, NBK and EAPort daily, weekly and monthly data sets, the Ljung Box test and the ARCH tests in Tables 15, 16 and 17 indicate acceptance of the null hypothesis because of the large p-values (they are all greater than 0.05, except for EA Port squared residuals at lag 20). The ARCH LM test fails to reject the no GARCH effects in the residuals (no heteroscedasticity), and the Ljung Box test also fails to reject the null hypothesis of no correlation for all the data sets. This implies that there is no autocorrelation left in the residuals and that there is no heteroskedasticity in the fitted models. This suggests that the GARCH models considered were all adequate and fit for describing the volatility of NSE and thus appropriate to forecast future volatilities for the companies under investigation.

5.5 Forecasting and forecasting performance

Forecasting performance of the different sampling intervals was established by ranking the mean errors with respect to the time points for all the companies under investigation. The time point that gave the lowest values of the error measurements was considered to be the best one. The results in Table 18 show that the daily returns outperformed all the other time points, this is because its smallest error measurements for all the measures utilized as compared to the weekly and monthly returns i.e. daily series for each of the data sets gave the smallest mean squares, followed by weekly and then monthly series. This implies that the higher the frequency of data used (smaller sampling intervals), the better the forecasts produced. Better forecasts translate to better risk management and better option pricing for the stock market products.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This thesis examined the forecasting performance of share prices for Kenya Airways, National Bank of Kenya and East African Portland cement at different time points i.e. daily, weekly and monthly using GARCH models, with the aim of finding out which amongst them provides better forecasts in order to guide trading operations of the Nairobi Securities exchange. The thesis objectives were greatly achieved.

GARCH models were estimated and fitted because the exploratory analyses confirmed the leptokurtic, volatility clustering and asymmetric properties of financial time series in the NSE data. More importantly, GARCH effects were confirmed to be present except for all the monthly return series.

GARCH (1, 1) models performed better for most series, particularly the monthly series and daily series for the companies considered while, GARCH (1, 2) and GARCH (2, 1) were favoured by KQ and NBK weekly series respectively. This supports several other researches which confirmed that the simplest GARCH (1, 1) model captures all the stylized characteristics of financial time series and can consequently be used to estimate and describe the characteristics of financial time series. GARCH (2, 2) performed poorly for all the returns and was therefore not utilized to fit any data set.

The study revealed that there is no clear difference between the sectors investigated as shown by the fact that no model was particularly favoured by one sector as compared to the others. While considering the represented companies, volatilities were quite different, for instance KQ was highly volatile around 2007/ 2008, EA Port was highly volatile in 2008/2009 and NBK around 2010/2011 (Fig. 5). The difference in volatility is probably because of the varied extraneous factors that affect different sectors independently.

Comparing the different time points examined for each company, the study found out that there is a strong evidence of data sampled daily performing better than weekly and monthly intervals. The outcome of the study therefore suggests that in order to obtain accurate volatility forecasts for the sectors investigated in this thesis, investors and other stock market participants ought to closely watch the share prices, at a higher frequency. This will enable them make better investment decisions and hence increased gains not only for individuals but also for the country.

6.2 Recommendations

Volatility modeling and subsequent forecasting was done based on past historical information, with the assumption that the past and the present have rich information about the future. GARCH models considered performed quite well, particularly the standard GARCH (1, 1). High persistence were however, experienced for most return series and this would suggest the utilization of Integrated GARCH (IGARCH) models

It would also be beneficial to consider other GARCH extensions and other companies' share prices in the same sectors investigated in this study so as to compare and contrast the outcomes, in order to reinforce the findings of the present study.

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APPENDICES

GARCH MODEL FITTING, WITH SOME SELECTED COMPUTER OUTPUTS.

APPENDIX I: GARCH (1, 1)

Daily series

KQ

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = kqdailyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(1, 1)

<environment: 0x05038da0>

[data = kqdailyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

mu	omega	alpha1	beta1
-0.00078085	0.00021026	0.39837677	0.37850578

Std. Errors: robust Error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)	
mu	-7.809e-04	7.981e-04	-0.978	0.327853	
omega	2.103e-04	7.644e-05	2.751	0.005948	**
alpha1	3.984e-01	1.390e-01	2.865	0.004165	**
beta1	3.785e-01	1.068e-01	3.545	0.000392	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:

3451.486 normalized: 2.297926

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	25112.88	0
Shapiro-Wilk Test	R	W	0.860034	0
Ljung-Box Test	R	Q(10)	29.57746	0.001004072
Ljung-Box Test	R	Q(15)	38.80359	0.0006856011
Ljung-Box Test	R	Q(20)	45.16143	0.00104918
Ljung-Box Test	R^2	Q(10)	0.4582735	0.9999956
Ljung-Box Test	R^2	Q(15)	1.11349	0.9999995
Ljung-Box Test	R^2	Q(20)	3.797376	0.9999697
LM Arch Test	R	TR^2	0.4758715	0.9999998

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-4.590527	-4.576373	-4.590541	-4.585254

NBK

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = Nbkdailyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(1, 1) [data = Nbkdailyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

```
        mu       omega      alpha1       beta1
1.1359e-04  9.0281e-05  4.4610e-01  5.8850e-01
Std. Errors:
 robust Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     1.136e-04   8.895e-04    0.128   0.8984
omega  9.028e-05   3.710e-05    2.434   0.0149 *
alpha1 4.461e-01   1.076e-01    4.148 3.36e-05 ***
beta1  5.885e-01   6.836e-02    8.609  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:
 3242.947    normalized:  2.156215

Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  10653.89  0
 Shapiro-Wilk Test  R    W      0.9121289 0
 Ljung-Box Test     R    Q(10)  37.1506   5.32968e-05
 Ljung-Box Test     R    Q(15)  40.45544  0.0003869615
 Ljung-Box Test     R    Q(20)  50.72512  0.0001742514
 Ljung-Box Test     R^2  Q(10)  3.141634  0.9778916
 Ljung-Box Test     R^2  Q(15)  3.884908  0.9980904
 Ljung-Box Test     R^2  Q(20)  65.19609  1.086026e-06
 LM Arch Test       R    TR^2   3.350224  0.9925257

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-4.307110 -4.292972 -4.307124 -4.301844
```

EA Port

```
Title: GARCH Modelling
Call: garchFit(formula = formula ~ garch(1, 1), data = EAPortdailyreturns, cond.dist =
"QMLE")

Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x02bddda0>
 [data = EAPortdailyreturns]
Conditional Distribution:
 QMLE
Coefficient(s):
        mu       omega      alpha1       beta1
-0.00090186   0.00019795   0.04253449   0.68708000
Std. Errors:
 robust Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.0009019   0.0005678   -1.588   0.1122
omega   0.0001980   0.0001033    1.917   0.0553 .
alpha1  0.0425345   0.0566152    0.751   0.4525
beta1   0.6870800   0.1647806    4.170 3.05e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:
 3325.568    normalized:  2.211149

Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  1590110   0
```

Shapiro-Wilk Test R W 0.5423572 0
Ljung-Box Test R Q(10) 16.78292 0.07930753
Ljung-Box Test R Q(15) 23.82283 0.06816387
Ljung-Box Test R Q(20) 28.44635 0.09924718
Ljung-Box Test R^2 Q(10) 0.140103 1
Ljung-Box Test R^2 Q(15) 0.2363888 1
Ljung-Box Test R^2 Q(20) 1.11025 1
LM Arch Test R TR^2 0.2044358 1

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-4.416978	-4.402840	-4.416992	-4.411712

Weekly series

KQ

Title: GARCH Modelling
Call: garchFit(formula = formula ~ garch(1, 1), data = kqweeklyreturns, cond.dist = "QMLE")

Mean and Variance Equation:
data ~ garch(1, 1)
<environment: 0x0ab94628>
[data = kqweeklyreturns]
Conditional Distribution:
QMLE
Coefficient(s):

mu	omega	alpha1	beta1
-0.00313563	0.00036163	0.15428066	0.74577787

Std. Errors: robust

```
Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -0.0031356   0.0030132   -1.041   0.2981
omega   0.0003616   0.0003474    1.041   0.2979
alpha1  0.1542807   0.0845213    1.825   0.0679 .
beta1   0.7457779   0.1428462    5.221 1.78e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Log Likelihood: 468.4997    normalized:  1.496804

Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  124.7705  0
 Shapiro-Wilk Test  R    W      0.9425982 1.130441e-09
 Ljung-Box Test     R    Q(10)  12.09481  0.2787611
 Ljung-Box Test     R    Q(15)  19.34796  0.1983969
 Ljung-Box Test     R    Q(20)  23.22882  0.2776991
 Ljung-Box Test     R^2  Q(10)  10.89133  0.3660467
 Ljung-Box Test     R^2  Q(15)  13.74173  0.5452002
 Ljung-Box Test     R^2  Q(20)  16.67555  0.6739302
 LM Arch Test       R    TR^2   10.56791  0.5662655

Information Criterion Statistics:
      AIC       BIC       SIC      HQIC
-2.968049 -2.920175 -2.968371 -2.948917
```

NBK

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = Nbkweeklyreturns, cond.dist = "QMLE")

```
Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x0a405934>
 [data = Nbkweeklyreturns]
Conditional Distribution:
 QMLE
Coefficient(s):
        mu       omega      alpha1       beta1
-0.0018153   0.0010617   0.3184978   0.4465084

Std. Errors: robust Error Analysis:
         Estimate  Std. Error  t value Pr(>|t|)
mu     -0.0018153   0.0032996   -0.550   0.5822
omega   0.0010617   0.0005599    1.896   0.0579 .
alpha1  0.3184978   0.1248147    2.552   0.0107 *
beta1   0.4465084   0.1858076    2.403   0.0163 *
---
Log Likelihood: 440.4437    normalized:  1.407168

Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  116.0948  0
 Shapiro-Wilk Test  R    W      0.9618953 2.66408e-07
 Ljung-Box Test     R    Q(10)  31.39878  0.0005040306
 Ljung-Box Test     R    Q(15)  35.37012  0.002177386
 Ljung-Box Test     R    Q(20)  40.75847  0.004000465
 Ljung-Box Test     R^2  Q(10)  2.642913  0.9886255
 Ljung-Box Test     R^2  Q(15)  4.576061  0.9951479
 Ljung-Box Test     R^2  Q(20)  7.905248  0.9924763
 LM Arch Test       R    TR^2   2.779018  0.9969132
```

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-2.788778	-2.740903	-2.789099	-2.769646

EA Portland

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = EAPortweeklyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(1, 1)

<environment: 0x04f85358>

[data = EAPortweeklyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

mu	omega	alpha1	beta1
-0.00299397	0.00072585	0.50481249	0.11154317

Std. Errors: robust Error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)	
mu	-0.0029940	0.0016841	-1.778	0.0754	.
omega	0.0007259	0.0002822	2.572	0.0101	*
alpha1	0.5048125	0.2461806	2.051	0.0403	*
beta1	0.1115432	0.1283327	0.869	0.3848	

Log Likelihood:

598.3528   normalized: 1.91167

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	756.081	0

Shapiro-Wilk Test R W 0.8801474 6.317427e-15
Ljung-Box Test R Q(10) 19.7058 0.03216143
Ljung-Box Test R Q(15) 25.20516 0.04725503
Ljung-Box Test R Q(20) 29.00357 0.08768903
Ljung-Box Test R^2 Q(10) 2.788152 0.9859793
Ljung-Box Test R^2 Q(15) 3.491368 0.9989849
Ljung-Box Test R^2 Q(20) 5.680614 0.9992652
LM Arch Test R TR^2 3.197212 0.9939843

Information Criterion Statistics:
AIC BIC SIC HQIC
-3.797782 -3.749907 -3.798103 -3.778650

Monthly series

KQ

Title: GARCH Modelling
Call: garchFit(formula = formula ~ garch(1, 1), data = kqmonthlyreturns, cond.dist = "QMLE")
Mean and Variance Equation:
data ~ garch(1, 1)
<environment: 0x0abe25e8>
[data = kqmonthlyreturns]
Conditional Distribution:
QMLE
Coefficient(s):
mu omega alpha1 beta1
-0.02716128 0.00804663 0.34083804 0.00000001
Std. Errors:
robust

Error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)	
mu	-2.716e-02	1.442e-02	-1.883	0.05967	.
omega	8.047e-03	3.054e-03	2.635	0.00842	**
alpha1	3.408e-01	2.235e-01	1.525	0.12718	
beta1	1.000e-08	2.759e-01	0.000	1.00000	

Log Likelihood:

58.6799 normalized: 0.8264774

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	0.7958027	0.6717283
Shapiro-Wilk Test	R	W	0.9905073	0.8737696
Ljung-Box Test	R	Q(10)	10.44899	0.4020232
Ljung-Box Test	R	Q(15)	18.01141	0.2620661
Ljung-Box Test	R	Q(20)	18.89296	0.5287935
Ljung-Box Test	R^2	Q(10)	7.149414	0.7112681
Ljung-Box Test	R^2	Q(15)	13.51076	0.5629099
Ljung-Box Test	R^2	Q(20)	16.78038	0.667185
LM Arch Test	R	TR^2	6.104337	0.9107313

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-1.540279	-1.412804	-1.546187	-1.489586

NBK

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = Nbkmonthlyreturns, cond.dist = "QMLE")

```
Mean and Variance Equation:
 data ~ garch(1, 1)
<environment: 0x0a343a3c>
 [data = Nbkmonthlyreturns]
Conditional Distribution:
 QMLE
Coefficient(s):
        mu       omega      alpha1       beta1
-9.1408e-03   1.1255e-08   1.0000e-08   9.9678e-01

Std. Errors: robust Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     -9.141e-03   1.523e-02   -0.600    0.548
omega   1.125e-08   1.571e-04    0.000    1.000
alpha1  1.000e-08   1.021e-01    0.000    1.000
beta1   9.968e-01   1.110e-01    8.977   <2e-16 ***

Log Likelihood:
 59.32457    normalized:  0.8355574

Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  1.333649  0.513336
 Shapiro-Wilk Test  R    W      0.9830886 0.4552591
 Ljung-Box Test     R    Q(10)  7.769196  0.65137
 Ljung-Box Test     R    Q(15)  9.868474  0.8279307
 Ljung-Box Test     R    Q(20)  16.50056  0.6851254
 Ljung-Box Test     R^2  Q(10)  11.47817  0.3214962
 Ljung-Box Test     R^2  Q(15)  16.39706  0.3561648
 Ljung-Box Test     R^2  Q(20)  17.21183  0.6391791
 LM Arch Test       R    TR^2   12.13803  0.4346591
```

Information Criterion Statistics:

AIC BIC SIC HQIC

-1.558439 -1.430964 -1.564347 -1.507746

EA Portland

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 1), data = EAPortmonthlyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(1, 1)

<environment: 0x0502e4f8>

[data = EAPortmonthlyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

mu	omega	alpha1	beta1
-0.02157635	0.00350550	0.99999999	0.00000001

Std. Errors: robust error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)	
mu	-2.158e-02	1.156e-02	-1.866	0.0621	.
omega	3.506e-03	1.729e-03	2.027	0.0426	*
alpha1	1.000e+00	7.078e-01	1.413	0.1577	
beta1	1.000e-08	9.619e-02	0.000	1.0000	

Log Likelihood:

73.81073 normalized: 1.039588

Standardised Residuals Tests:

Statistic p-Value

Jarque-Bera Test	R	Chi^2	43.69286	3.252494e-10
Shapiro-Wilk Test	R	W	0.9327251	0.0009119002
Ljung-Box Test	R	Q(10)	5.425078	0.8610363
Ljung-Box Test	R	Q(15)	9.487319	0.8506914
Ljung-Box Test	R	Q(20)	13.6377	0.84838
Ljung-Box Test	R^2	Q(10)	2.504651	0.9908078
Ljung-Box Test	R^2	Q(15)	3.293456	0.9992864
Ljung-Box Test	R^2	Q(20)	4.088825	0.9999443
LM Arch Test	R	TR^2	6.498626	0.8888937

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-1.966500	-1.839025	-1.972408	-1.915807

APPENDIX II: GARCH (1, 2)

KQ

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(1, 2), data = kqweeklyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(1, 2)

[data = kqweeklyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

mu	omega	alpha1	beta1	beta2
-0.00416358	0.00058743	0.23652492	0.20271835	0.39554245

Std. Errors: robust error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)	
mu	-0.0041636	0.0036371	-1.145	0.2523	
omega	0.0005874	0.0008684	0.676	0.4987	
alpha1	0.2365249	0.1249524	1.893	0.0584	.
beta1	0.2027183	0.2734499	0.741	0.4585	
beta2	0.3955425	0.1744602	2.267	0.0234	*

Log Likelihood:

470.9142   normalized: 1.504518

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	132.3431	0
Shapiro-Wilk Test	R	W	0.9450349	2.103627e-09
Ljung-Box Test	R	Q(10)	11.79112	0.2992796

Ljung-Box Test	R	Q(15)	19.59086	0.1881958
Ljung-Box Test	R	Q(20)	23.09316	0.2842434
Ljung-Box Test	R^2	Q(10)	8.21865	0.607489
Ljung-Box Test	R^2	Q(15)	10.65076	0.7769359
Ljung-Box Test	R^2	Q(20)	13.21457	0.8679889
LM Arch Test	R	TR^2	8.374658	0.7552098

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-2.977087	-2.971244	-2.977587	-2.953172

APPENDIX III: GARCH (2, 1)

NBK WEEKLY

Title: GARCH Modelling

Call: garchFit(formula = formula ~ garch(2, 1), data = Nbkweeklyreturns, cond.dist = "QMLE")

Mean and Variance Equation:

data ~ garch(2, 1)

[data = Nbkweeklyreturns]

Conditional Distribution:

QMLE

Coefficient(s):

mu	omega	alpha1	alpha2	beta1
-0.00166418	0.00197255	0.31641695	0.28336722	0.00000001

Std. Errors:

robust error Analysis:

	Estimate	Std. Error	t value	Pr(>|t|)
mu	-1.664e-03	3.755e-03	-0.443	0.658
omega	1.973e-03	8.260e-03	0.239	0.811
alpha1	3.164e-01	3.144e-01	1.006	0.314
alpha2	2.834e-01	1.664e+00	0.170	0.865
beta1	1.000e-08	3.472e+00	0.000	1.000

Log Likelihood:

441.7137 normalized: 1.411226

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	102.2326	0

Shapiro-Wilk Test	R	W	0.962599	3.343167e-07
Ljung-Box Test	R	Q(10)	34.03165	0.0001824322
Ljung-Box Test	R	Q(15)	37.79183	0.0009684386
Ljung-Box Test	R	Q(20)	43.50281	0.001753391
Ljung-Box Test	R^2	Q(10)	3.40394	0.9702598
Ljung-Box Test	R^2	Q(15)	5.640835	0.9851701
Ljung-Box Test	R^2	Q(20)	9.181895	0.9807031
LM Arch Test	R	TR^2	3.511799	0.9907255

Information Criterion Statistics:

AIC	BIC	SIC	HQIC
-2.790503	-2.730659	-2.791003	-2.766588