DETERMINATION OF MARKET EFFICIENCY, VOLATILITY AND ASYMMETRIC EFFECT AT NAIROBI STOCK EXCHANGE

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DECLARATION AND RECOMMENDATION

DECLARATION

This Thesis is my original work and has not been presented to any other institution for award of any degree.

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RECOMMENDATION

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DEDICATION

To

My mum Angeline and late beloved dad Alfred.

ACKNOWLEDGEMENT

First I thank Almighty God for His great care, good health, strength and provision this far I have come. All majesty, glory and honor be unto you Jehovah God.

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ABSTRACT

Stock market efficiency is an important concept, especially in a growing economy such as the Kenyan's one in understanding market risk and return behavior for investors. Literature on Market efficiency and return-volatility behavior is plenty for a developed stock market. The aim of this study was to empirically determine the market efficiency, time-varying volatility effect, asymmetric and leverage effect of the Nairobi Stock Exchange (NSE). The study also involved the forecast performance of the GARCH, TGARCH and the EGARCH models. Secondary data of the daily NSE 20-share index for a period spanning from January 2001 to 2010 was used. The stock returns follow an ARMA (2,1) stochastic process with significant positive serial correlation. Market efficiency was determined basing on unit root tests, the Augmented Dickey-Fuller (ADF) test, the Phillip- Perron (PP) test and the Non-Parametric Runs test. The ADF test and PP test clearly gave evidence that the NSE index were non-stationary (random) at level and stationary (non-random) for the first and second differences. This implies that the NSE market is informationally inefficient at the weak-form level. This is also confirmed in the non-parametric run test. The results indicated volatility is a significant determinant of stock returns and persistence of shocks in the NSE market. The tendency for volatility response to shocks displayed a long trend, implying time-varying volatility in the NSE index stock returns. The Exponential GARCH (EGARCH) model and the Threshold GARCH (TGARCH) model using student's t-distribution were the best models to capture asymmetric effect of stock returns. Since the asymmetric parameter estimate (γ_1) was positive, it implied no leverage effect i.e. good news (positive shocks) had a higher impact on volatility than bad news (negative shocks). Addressing the forecast performance, EGARCH-M (1,1) emerged the best model using the t-distribution over the GARCH-M (1,1) and TGARCH-M (1,1) due to it's lower values of the RMSE, MAE and MAPE . Using R^2 (the coefficient of determination) in comparison, EGARCH-M (1,1) model still emerged the best model of choice over the rest due to it's higher R^2 value. The results obtained are useful in determining the form of market efficiency and improvement of the market by reducing thin trading, encourage equal distribution of resources by the government thus able to plan, predict and manage investments at NSE. Thus, the best models ARMA (2,1), GARCH-M (1,1), EGARCH-M (1,1) and TGARCH-M (1,1) are helpful to investors especially in measuring market risk, portfolio diversification by encouraging collection of investment assets with lower risk and hedging strategies at the NSE market.

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AR	Autoregressive
ARMA	Autoregressive Moving Average
ARCH	Autoregressive Conditional Heteroskedasticity
AIC	Akaike Information Criteria
ACF	Autocorrelation Function
ASEA	African Stock Exchange Association
CMA	Capital Market Authority
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GED	General Error Distribution
GJR	Glosten-Jagannathan-Runkle
IID	Independent Identically Distributed
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Maximum Log-Likelihood
MSE	Mean Square Error
NSE	Nairobi Stock Exchange
NASI	Nairobi All Share Index
NYSE	New York Stock Exchange
OLS	Ordinary Least Square
PACF	Partial Autocorrelation Function
PP	Phillip-Perron
QMLE	Quasi-Maximum Likelihood Estimator
RMSE	Root Mean Square Error
RCA	Random Coefficient Autoregressive
SBIC	Schwarz Bayesian Information Criteria
S & P	Standard and Poor
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
TIC	Theil Inequality Coefficient
WN	White Noise

CHAPTER ONE
INTRODUCTION

1.1 Background Information

Efficient markets are a necessary prerequisite if it is desired that funds should be allocated to the highest-valued projects. A stock market is termed to be efficient if the prices fully reflect all information in the market. Market efficiency however is important to the economy since it results to low transaction costs, thus enhancing trading of securities. It also leads to enough securities to efficiently allocate risk. Market efficiency and the risk-return behavior in a number of emerging stock market economies have been examined by Bekaert (1995); Choudhry (1996) ; Bekaert and Harvey (1997); Kim and Singal (1999). Market efficiency is categorized into three forms as weak, semi-strong and strong Fama (1970, 1991). These forms differ in terms of the types of information, which are used in developing trading strategies. The three forms of market efficiency can be distinguished in the following ways: weak-form efficiency where the prices of financial assets reflect all information contained in the past prices. Semi-strong-form efficiency postulates that prices reflect all the publicly available information. Strong-form efficiency posits that prices of financial assets reflect, in addition to information on past prices, public available information and private (inside) information. Study by Muhanji (2000), Dickson and Muragu (1994) found that NSE had a weak form of efficiency. The EGARCH model applied to the Kenyan and Nigerian Stock Market returns by Ogum *et al.* (2006), found that both the stock markets had a weak form of efficiency.

Volatility is a tendency of the assets prices fluctuating either up or down. Increased volatility is perceived as indicating a rise in financial risk which can adversely affect investor assets and wealth. It is observed that when stock market exhibit increased volatility there is a tendency on part of the investors to lose confidence in the market and they tend to exit the market. Stock return-volatility has received a great attention from both the academicians and practitioners because it can be used as a measure of risk in financial markets. Researchers such as Nelson (1991), Glosten *et al.*(1993), Bekaert and Wu (2000), Wu (2001), Brandt and Kang (2004) report negative and often significant relationship between the volatility and return. Chinese stock market forecast of volatility using the GARCH-type models was done by Hongyu and Zhichao (2006). Studies carried out in the African stock markets include, Frimpong and Oteng (2006) applied GARCH models to the Ghana Stock Exchange, Brooks *et al.* (1997)

examined the effect of political change in the South African Stock market. Volatility and volatility spillovers in emerging markets in Africa were investigated by Appiah and Pascetto (1998). Kenya's stock market has been under-researched as far as using non-linear time series models in determining the efficiency, volatility modelling and asymmetric effect is concerned.

Asymmetric effect is the impact of positive shocks (good news) on volatility. The Asymmetric effect shows that stock returns are negatively correlated with changes in return volatility (good news has higher impact on volatility than that of bad news) Black (1976). Leverage effect implies that bad news (negative shocks) has much stronger effect on volatility than good news (positive shocks) Black (1976). However, if the magnitude of volatility response to bad and good news has the same absolute value of correlation then bad and good news have asymmetric effect on stock volatility. The impact of negative shocks (bad news) and positive shocks (good news) on volatility measured by Engle and Ng (1993), reported an asymmetry in stock market volatility towards positive shocks as compared to negative shocks. The asymmetric effect is shown in the EGARCH model with the parameter estimate (γ) when it is positive and statistically different from zero. If the parameter is negative and statistically insignificant at 5% level of significance it indicates leverage effect. In the TGARCH model, when (γ) is less than zero indicates the same results as (γ) in the EGARCH model (asymmetric effect).

The Nairobi Stock Exchange (NSE) is part of the African Stock Exchange Association (ASEA) founded early 1990s. It's one of the most active capital market in Africa in view of its high returns on investment and a well-developed market structure (Ogum, 2005). The NSE market includes the following sectors: Agricultural, Commercial and Services, Financial and Investment, Industrial and Allied. The sectors are controlled and managed by the Capital Market Authority (CMA) established by the Act of the Kenyan parliament to promote, regulate and facilitate the development of an ordinary, fair and efficient Capital Markets in Kenya. The NSE market comprises of two main share index, namely NSE 20 share index and NSE All Share index which are mainly used to measure market performance. The stock market plays a major role to promote culture of thrift (saving) through facilitating the mobilization of capital for development. The NSE improves efficiency in mobilization of savings as capital is allocated to investments that bring the most value to the economy. It provides enterprises with a non-bank source of financing through the sale of shares to the public. It also provides not only the substitution but also diversification of risk to entrepreneurs as they raise capital through equity. The government uses the NSE as an alternative source of funds through taxes. However, if NSE is efficient, it is easier for the firms to raise capital as the market performs the price discovery process. It also determines the price at which market players are willing to exchange claims on firm's future cash flows.

1.2 Statement of the problem

Market inefficiency may slow down the flow of information on corporate performance for the participants, which creates difficulties for investors to allocate their money optimally among different types of investments. The resulting uncertainty may induce the investors to withdraw from the market or be discouraged from investing for the long-term. Previous studies clearly indicate NSE market data has been modeled using the linear models and ARCH models. However, using non-linear models in modeling the asymmetric effect and leverage effect has not been researched so far for Nairobi stock market. In addition, market efficiency and effect of past information has also been under-researched as far as using non-linear models is concerned.

This study empirically investigates the form of the market efficiency, time-varying risk-return volatility, asymmetric effect and the forecasting performance using the unit root tests namely ADF test, PP test and the Runs test and non-linear time series models namely GARCH, TGARCH and EGARCH for the NSE 20-share index.

1.3 Objectives

1.3.1 General objective

The main objective of the study was to determine the form of the market efficiency, time-varying volatility, asymmetric effect and forecast performance of the NSE using time series models.

1.3.2 Specific Objectives

1) To empirically investigate the form of market efficiency at Nairobi Stock Exchange using ADF test, PP test and the Runs test.
2) To empirically determine volatility at NSE using the EGARCH and TGARCH models.
3) To empirically determine the asymmetric and leverage effects in NSE using EGARCH and TGARCH models.
4) To empirically determine the best model to forecast volatility at NSE using the In-sample forecast and the three models namely GARCH, EGARCH and TGARCH.

1.4 Assumption

1) The data used was stationary.
2) Missing values on public holidays and weekends were ignored.

1.5 Justification

An efficient stock market is so important for utilizing scarce capital resources to achieve economic growth for any economy. NSE as an emerging capital market has faced challenges in its development and growth such as economic depression and political uncertainty, among others. This has resulted to inflation leading discouragement of the investors to invest. The daily NSE 20-Share index was found to have asymmetric effect by Ogum (2005) and Ogum et al (2006) when modeling using EGARCH (1,1) model. From the available literature, the NSE market has been researched as far as market efficiency, time-varying volatility, asymmetric effect and forecast performance using linear time series models is concerned. This study therefore empirically contributes to the literature available on the NSE stock market by investigating the form of market efficiency at NSE using the unit root tests namely, ADF test, Phillip-Perron test and the Non-Parametric Runs test. Using the non-parametric runs test to determine the form of market efficiency, randomness and predictability for the sequence of returns was tested. Time-varying risk-return volatility and forecast performance was analyzed by using the ARCH-type models. Lastly, the asymmetric effect and leverage effect for the daily NSE 20-share index was analyzed using the ARCH models namely, GARCH-M, EGARCH-M and TGARCH-M which has not been studied before. The EGARCH-M (1,1) and TGARCH-M (1,1) were the preferred models to describe the dependence in variance for NSE returns since they were able to capture the asymmetric effect. The daily NSE 20-share index was preferred since it measures the overall performance of 20 blue-chip companies and it's long time in the market.

1.6 Expected Outputs

1) Appropriate form of market efficiency for NSE market.
2) Appropriate volatility effect, the asymmetric and leverage effects in NSE market.
3) Award of a MSc. degree in statistics.
4) A paper is to be published in a refereed journal.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

Researchers have applied different models to the stock market data from time to time. The Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) allows the variance of the error term to vary over-time, in contrast to the classical regression model, which assumes a constant variance. Nonlinear Exponential GARCH (EGARCH) model proposed by Nelson (1991) to solve the problem of leverage effect based on a logarithmic expression of the conditional variability in the variable analysis. Threshold GARCH (TGARCH) which is considered to be the best model in estimating positive and negative shocks on volatility was introduced by Zakoian (1994). Engle and Ng (1993) measured the impact of new information on volatility and report an asymmetry (leverage effect) in stock market volatility towards good news (positive shocks) as compared to bad news (negative shocks) using the EGARCH model.

2.2 ARMA models

Autoregressive Moving Average (ARMA) model is a mixed model of Autoregressive (AR) model and Moving Average (MA) model. An ARMA model predicts the value of the target variable as a linear function of lag value (autoregressive part) and an effect from recent random shock values (moving average part). The Box and Jenkins (1994) ARMA models only works well with stationary time series.

ARMA model stationary process exhibits a wide range of autocorrelation functions which is used to determine the order of the model in financial time series analysis. A stationary solution (X_t) of the linear difference equations given as;

$$X_t - \phi_1 X_{t-1} - \dots - \phi_p X_{t-p} = \omega_t + \theta_1 \omega_{t-1} + \dots + \theta_q \omega_{t-q} \qquad 2.1$$

$$\phi(B) X_t = \theta(B) \omega_t$$

where $\omega_t \sim WN\left(0, \sigma^2\right)$.

A special case of the ARMA (p, q) model, the ARMA (1,1) which is a combination of AR(1) and MA(1) process defined as;

$$(1-\phi_1 B)W_t = (1-\theta_1 B)e_t \qquad 2.2$$

$$W_t - \phi_1 W_{t-1} = e_t - \theta_1 e_{t-1}$$

$$F_t = \phi_1 W_{t-1} - \theta_1 e_{t-1}$$

where W_t is a stationary time series, e_t is a white noise error component, and $F_t = W_t - e_t$ is the forecasting function.

2.3 ARCH models

Autoregressive conditional heteroscedasticity (ARCH) model, introduced by Engle (1982) modelled the United Kingdom inflation by allowing the variance of the error term to vary over-time. ARCH models are capable of modelling and capturing many of the stylized facts of the volatility behavior usually observed in financial time series including time varying volatility or volatility clustering (Zivot and Wang, 2005). This model allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. (Engle, 1982).

In contrast to the ARMA model which focuses on modelling the first moment (mean), the ARCH models specifically take the dependence of the conditional second moments (variance) in modelling consideration. This accommodates the increasingly important demand to explain and to model market efficiency and the asymmetric effect in the Stock market (Fan and Yao, 2003; Degiannakis and Xekalaki, 2004; Engle, 2004). An ARCH process can be defined in terms of the distribution of the errors of a dynamic linear regression model. The dependent variable y_t is assumed to be generated by

$$y_t = x_t' \xi + \varepsilon_t , \quad t = 1, \ldots, T \qquad 2.3$$

where x_t' a kx1 vector of exogenous variables, which may include lagged values of the dependent variable and ξ is a kx1 vector of regression parameters. The ARCH model characterizes the distribution of the stochastic error ε_t conditional on the realized values of the set of variables $\psi_{t-1} = \{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}\}$. Specifically, Engle's (1982) model assumes

$$\varepsilon_t / \psi_{t-1} \sim N(0, h_t)$$

where

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \qquad 2.4$$

with $\alpha_0 > 0$ and $\alpha_i \geq 0,\ i = 1,\ldots,q$ to ensure that the conditional variance is positive.

Engle (1983) found that a large lag q was required in the conditional variance function when applying the ARCH model to the relationship between the level (rank) and volatility of inflation of the United Kingdom. To reduce the computational burden, Engle (1982, 1983) parameterized the conditional variance as;

$$h_t = \alpha_0 + \alpha_1 \sum_{i=1}^{q} w_i \varepsilon_{t-i}^2 \qquad 2.5$$

where the weights $w_i = \dfrac{(q+1)-i}{0.5q(q+1)}$ decline linearly and are constructed so that $\sum_{i=1}^{q} w_i = 1$.

With this parameterization, a large lag can be specified and only two parameters are required in the conditional variance function.

Due to the relatively long lag length in the variance equation of ARCH models, the task of estimation of parameters subject to inequality in the variance equation is often called for to capture the time-varying volatility in stock returns.

2.4 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

To avoid the long lag of the ARCH (q) developed by Engle (1982), Bollerslev (1986), generalized the ARCH model, called the (GARCH), by including the lagged values of the conditional variance. GARCH model is one of the widely used ARCH-type models (Engle, 2004). Bollerslev (1986) proposed an extension of the conditional variance function (2.6) which he termed as the generalized ARCH (GARCH) and suggested that conditional variance be specified as,

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \ldots + \beta_p h_{t-p} \qquad 2.6$$

with the inequality condition $\alpha_0 > 0, \alpha_i \geq 0$ for i=1,…,q, $\beta_i \geq 0$ for i=1,…,p to ensure that conditional variance is strictly positive. A GARCH process with orders p and q is denoted as

GARCH (p,q) and this essentially generalizes the purely autoregressive ARCH model. The motivation for the GARCH process can be seen by expression (2.7) as

$$h_t = \alpha_0 + \alpha(B)\varepsilon_t^2 + \beta(B)h_t \qquad 2.7$$

where $\alpha(B) = \alpha_1 B + ... + \alpha_q B^q$ and $\beta(B) = \beta_1 B + ... + \beta_q B^q$ are polynomial in the backshift operator B. If the roots of $1 - \beta(Z)$ lie outside the unit circle, equation 2.7 is written as

$$h_t = \frac{\alpha_0}{1-\beta(1)} + \frac{\alpha(B)}{1-\beta(B)}\varepsilon_t^2 = \alpha_0^* + \sum_{i=1}^{\infty} \delta_i \varepsilon_{t-i}^2 \qquad 2.8$$

where $\alpha_0^* = \frac{\alpha_0}{[1-\beta(1)]}$ and the co-efficient δ_i is the co-efficient of B^i in the expression

$$\alpha(B)[1-\beta(B)]^{-1}$$

There exists some situations where the parameter estimates in GARCH (p,q) models are close to the unit root but not less than unit,

i.e. $\sum_{i=1}^{p} \alpha_i = \sum_{j=1}^{q} \beta_j = 1$, for the GARCH process.

This processes exhibit the persistence in variance/volatility where the current information remains important in forecasting the conditional variance.

Equation 2.8 shows that a GARCH (p,q) process is an infinite order ARCH with a rational lag structure imposed on the co-efficient so as to represent GARCH process in a high-order ARCH-process (Bera and Higgins, 1993; Engle, 2004; Degiannakis and Xekalaki, 2004). The simplest GARCH (1,1) is often found to be the most efficient in modeling time series Stock market data since GARCH (p,q) model, where (p + q >2), leads to increased estimation of risk when considering potential regime in the model.

In contrast to the empirical success, GARCH models have one major disadvantage, they are unable to model asymmetric effect or leverage effect due to the positive and negative shocks of the same magnitude resulting to the same amount of volatility.

A special case of the GARCH (p, q) models, the simple GARCH (1,1) model is given as,

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 \qquad 2.9$$

where

$$\omega > 0,\ \alpha_1 \geq 0,\ \beta_1 \geq 0$$

As seen from 2.8, the model is constructed with non-negative constraints for all alphas and betas. The parameters α_1 and β_1 determine the short-run dynamics of the resulting volatility time series. A large value of the GARCH lag coefficient β_1 indicates that shocks to conditional variance will take long time to die out. In other words it means the volatility is persistent. A large value of α_1 implies that the volatility will react quite intensely to movements in the market. If $\alpha_1+\beta_1$ is close to unity a shock at time t will persist for many periods in the future. A high sum value of ($\alpha_1+\beta_1$) therefore implies persistence. If $\alpha_1+\beta_1=1$, it implies that a shock will lead to a permanent change in all future values of σ_t.

2.5 The Exponential GARCH (EGARCH) model

The EGARCH model of Nelson (1991) is the first asymmetric GARCH model. This model looks at the conditional variance and tries to accommodate for the asymmetric relation between stock returns and volatility changes. The EGARCH model is also used to test the hypothesis that the variance of return was influenced differently by positive and negative excess returns. The model captures the leverage effect in the financial market that the main GARCH model is not able. The specification for the higher order conditional variance for the EGARCH model is given as,

$$Log\left(\sigma_t^2\right)=\omega_0+\sum_{j=1}^{p}\beta_j\log\left(\sigma_{t-j}^2\right)+\left(\sum_{i}^{q}\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|+\gamma_i\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \qquad 2.10$$

where $\varepsilon_t=\eta_t\sqrt{\sigma_t}$ and $\eta_t\sim$ i.i.d N (0,1).

The parameter (α_i) in equation (2.10) measures the impact of innovation at time t while parameter(β_j) is the auto-regressive term on lagged conditional volatility, reflecting the weight given to previous period's conditional volatility at time t. The presence of leverage and asymmetric effects is tested by the parameter (γ_i).

A special case of EGARCH (p,q) models, the EGARCH (1,1) model is given as,

$$Log\left(\sigma_t^2\right)=\omega_1+\beta_1\log\left(\sigma_{t-1}^2\right)+\alpha_1\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}-E\left\{\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\}\right]+\gamma_1\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \qquad 2.11$$

where,

$$E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right) = E\{|Z_{t-1}|\} = \sqrt{2/\pi}$$

with degrees of freedom $v > 2$.

The left-hand side of equation (2.11) is the log of the conditional variance, which implies that the asymmetric effect is exponential, rather than quadratic, and that forecasts of the conditional variance are generated to be non-negative. The presence of leverage effect can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

EGARCH model has several advantages compared to the GARCH model. In the EGARCH model σ_t^2 is logged which means that although the parameters are negative, σ_t^2 will be positive. This implies that the model needs no assumption of non-negative constraints as for the GARCH model. But a necessary assumption for the EGARCH model is the assumption of stationarity in the time series. The EGARCH model allows for asymmetries, which is defined as the parameter estimate γ. If the leverage term is negative, it implies a negative relationship between volatility and returns. In the EGARCH model the persistence is entirely captured by the β_1 term.

2.6 Threshold GARCH (TGARCH) model

The Threshold GARCH (TGARCH) model developed by Zakoian (1994) is similar to GJR ARCH, and the specification is one on conditional standard deviation instead of conditional variance.

$$h_t = \alpha_0 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- \qquad 2.12$$

where $\varepsilon_t = \eta_t \sqrt{h_t}$ and $I_t^- = 1$, if $\varepsilon_t < 0$ and zero otherwise. In the TGARCH model, $\varepsilon_{t-i} > 0$ indicates positive shocks (good news), and $\varepsilon_{t-i} < 0$ bad news, this has differential effect on the conditional variance. Good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility while if $\gamma_i \neq 0$, the news impact is asymmetric.

A special case of TGARCH (p, q) model, the TGARCH (1,1) is given by;

$$h_t = \alpha_0 + \beta_1 h_{t-1} + \alpha_1 \varepsilon_{t-1} + \gamma_1 \varepsilon_{t-1}^2 I_{t-1}^- \qquad 2.13$$

where I_t takes value 1 for $\varepsilon_t < 0$, and 0 otherwise. So 'good news' (positive shocks) and 'bad news' (negative shocks) have a different impact. Good news has an impact parameter estimate γ, while bad news has an impact of $\gamma + \theta$. If $\theta > 0$ there is asymmetry, while if $\theta = 0$ the news impact is symmetric. When the threshold term I_{t-k}^{-} is set to zero, then equation 2.13 becomes a GARCH (p,q) model.

CHAPTER THREE
METHODOLOGY

3.1 Determination of Market Efficiency

Secondary data from NSE 20-Share daily index for the period spanning from 1st January 2001 to 31st December 2010 was used. To test if the time series data is stationary, a unit root Philips-Peron test was utilized. Then, transformation of the time series daily index to daily returns was calculated by taking the first-order log difference.

The log return is defined as;

$$R_t = \log \frac{p_{t+1}}{p_t} = \log p_{t+1} - \log p_t \qquad 2.14$$

where R_t is the daily return and P_t , P_{t+1} are the daily index of an asset at two successive days, $t+1$ and t. The market efficiency was tested with reference to the unit root tests. First, the unit root tests were conducted to test for non-stationarity in the NSE index series as necessary condition for the form of market efficiency. Unit root tests are commonly used to test the stationary property of a time series data. The unit root test is designed to discover whether the series is difference-stationary (the null hypothesis) or trend-stationary (the alternative hypothesis). A series with unit root is said to be non-stationary indicating non random walk. Augmented Dickey-Fuller tests are the most widely applied tests for unit roots. This unit root test provides evidence on whether the stock prices in NSE stock market follow a random walk. Therefore, it is also a test of the weak-form market efficiency. In this study, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were employed.

Second, a non-parametric runs test was employed to examine whether successive returns series changes are independent or random. Accordingly, it tested whether returns in NSE market were predictable.

3.1.1 Augmented Dickey-Fuller (ADF) Test

The augmented Dickey-Fuller (ADF) test was used to test the existence of a unit root in the series of price changes in the stock index series. The ADF test assumes that y series follows an AR (p) process and add p lagged difference terms of the dependent variable y to the right side of the regression. ADF test utilized the following equations;

$$\Delta y_t = \beta y_{t-1} \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t \qquad 2.15$$

$$\Delta y_t = \alpha + \beta y_{t-1} \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t \qquad 2.16$$

$$\Delta y_t = \alpha + \lambda t + \beta y_{t-1} \sum_{j=1}^{p} \gamma_j \Delta y_{t-j} + \varepsilon_t \qquad 2.17$$

where, y_t is the price at time t, γ_j are coefficients to be estimated, p is the number of lagged terms and ε_t is white noise.

Equation (2.15) does not include intercept (drift) and trend terms, equation (2.16), includes constant term α and equation (2.17), includes constant term and trend term λt. The null hypothesis was that δ=0, that is, there was a unit root, the series was non-stationary. The alternative hypothesis was that δ<0. Failing to reject H_0 implied that the time series has the properties of a random walk.

3.1.2 Phillip-Perron(PP) Test

PP tests are proposed by Phillips and Perron (1988). These tests are similar to ADF tests. The difference between the PP and the ADF tests is in how they deal with serial correlation and heteroskedasticity in the errors. The idea of the Phillips-Perron tests is to run a non-augmented Dickey-Fuller regression, and then to adjust for the bias that might occur due to correlation in the innovation term. Phillips-Perron test is a non parametric test with the following specifications;

$$y_t = c_0 + \rho y_{t-1} + \ldots + \mu_t \qquad 2.18$$

where, y_t is the natural logarithm of the price index at time t, c is a constant and μ_t is pure white noise error term. The hypotheses Phillips-Perron (PP) test was represented as;

H_0: there is a unit root in the series

H_1: there is not any unit root in the series (stationary)

3.1.3 Runs test

The Runs test is a non-parametric test that is designed to examine whether successive price changes are independent. A run can be defined as a sequence of consecutive price changes with the same sign. The non-parametric run test is applicable as a test of randomness for the sequence of returns. Accordingly, it tested whether successive returns in NSE stock market index are predictable.

Here the hypothesis was presented as;

H_0: The return series of NSE follow a random walk (it is weak-form efficient) for the period of study.

H_1: The return series of NSE does not random follow a random walk (it is not weak-form efficient) for the period of study.

To perform this test, the premise that if a series of data is random, the observed number of runs in the series should be close to the expected number of runs was put into consideration. Let, n_a and n_b respectively represented observations above and below the sample mean, median and mode, and r represents the observed number of runs, with $n=n_a+n_b$.

$$Z(r) = r - \frac{E(r)}{\sigma(r)} \qquad 2.19$$

The expected number of runs was calculated by the formula;

$$E(r) = n + \frac{2n_a n_b}{n} \qquad 2.20$$

and the standard error by;

$$\sigma E(r) = \left[\frac{2n_a n_b(2n_a n_b - n)}{n^2(n-1)}\right]^{1/2} \qquad 2.21$$

3.2 Determination of Volatility

Appropriate GARCH (p,q) models were fitted to predict the time-varying volatility of daily returns in the NSE 20-share index. To confirm for volatility, first existence of the ARCH process in volatility clustering was tested by the size and significance of $\alpha_i > 0$. Next persistence of shocks to volatility was examined on the sum of parameters of ARMA component $\sigma_t^2, \alpha_i + \beta_j$. Values of the sum lower than unity indicated a tendency for the volatility response to decay over-time. Values of the sum equal or greater than unity implied indefinite or increasing volatility persistence to shocks over-time.

3.3 Estimation of Volatility Clustering

To examine if the daily returns series exhibited volatility clustering, first the correlation in the return series was checked by using autocorrelation function (ACF). If ACF exhibited correlation for the return series, then autocorrelation of the squared return for the NSE 20-share index was checked. Ljung-Box-Pierce Q-test was used to test for volatility clustering by first calculating the first-order autocorrelation coefficient in squared returns and then testing the hypothesis, that all the serial correlations of returns are simultaneously equal to zero.

The Ljung-Box-Pierce (Q) statistics (1978) was defined as;

$$Q = n(n+2)\sum_{K=1}^{l} \frac{r_k^2}{n-k} \qquad 2.22$$

where $n =$ sample size, $1 =$ the number of autocorrelation lags included in the statistics and r_k^2 was the squared sample autocorrelation at lag k. If the computed Q value exceeded the critical value from the Chi-square table given the level of significance, the null hypothesis that all γ_k are zero was rejected. If the null hypothesis was rejected it implied that volatility clustering is present in the return series.

3.4 Estimation of Asymmetric and Leverage effect

Asymmetric and leverage effect is performed by the empirical work of Black (1976), where the rise in volatility was observed as a response to ‘‘bad news (negative shocks)’’ and a fall as a response to ‘‘good news (positive shocks)’’. The TGARCH and EGARCH models captured the asymmetric effect and leverage effect. The presence of leverage effect was tested by the hypothesis that the parameter $\gamma < 0$ and asymmetric effect by the parameter $\gamma \neq 0$. If the magnitude of volatility response to bad and good news has the same absolute value of correlation, then bad and good news had asymmetric effect on stock volatility.

3.5 Determination of Forecast Performance

Literature based on forecast performance in Africa, showed that ordinary GARCH models are successful in estimating and forecasting volatility to simpler parsimonious models. The GARCH, EGARCH and TGARCH models were estimated for forecast performance of the NSE 20-share index returns series using the robust method of Bollerslev and Wooldridge (1992), the Quasi-Maximum Likelihood Estimator (QMLE) assuming the Gaussian standard normal distribution. The QMLE (or composite likelihood estimate) is an estimate of the parameter θ in a statistical model that come's about by maximizing a function that is related to the logarithm of the likelihood function. This technique adjusts for small deviations from normality. The Akaike Information Criteria and Maximum Log-Likelihood (ML) values and a set of model diagnostic tests (ARCH-LM test, and Q-statistics tests) were used to choose the model that describes the conditional variance of the NSE 20-share index. Common measures of forecast evaluation, the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and the Theil Inequality Coefficient (TIC) were used to show the performance of each model. The model that exhibited the lowest values of error measurements was considered the best.

The MAPE was used to measure accuracy in the fitted time series models the GARCH, EGARCH and TGARCH given as,

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad 2.23$$

where, A_t was the actual value and F_t the forecast value.

The MAE and RMSE were used to measure the average magnitude of the errors in a set of forecast for each of the three time series models. If RMSE calculated value is equal to MSE value, then all the errors are of the same magnitude. RMSE was given as,

$$RMSE = \sqrt{\frac{1}{n\sum_{t=1}^{n}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2}} \qquad 2.24$$

where, n is the sample size and σ_t^2 is the conditional variance.

The analysis was facilitated by use of computer packages E-views 6.0 and SPSS version 16.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Preliminary Analysis

In this study, the NSE 20-share daily index data was used for the period spanning from 1st January 2001 to 31st December 2010. The preliminary analysis was done by use of time plots for the NSE 20-share index.

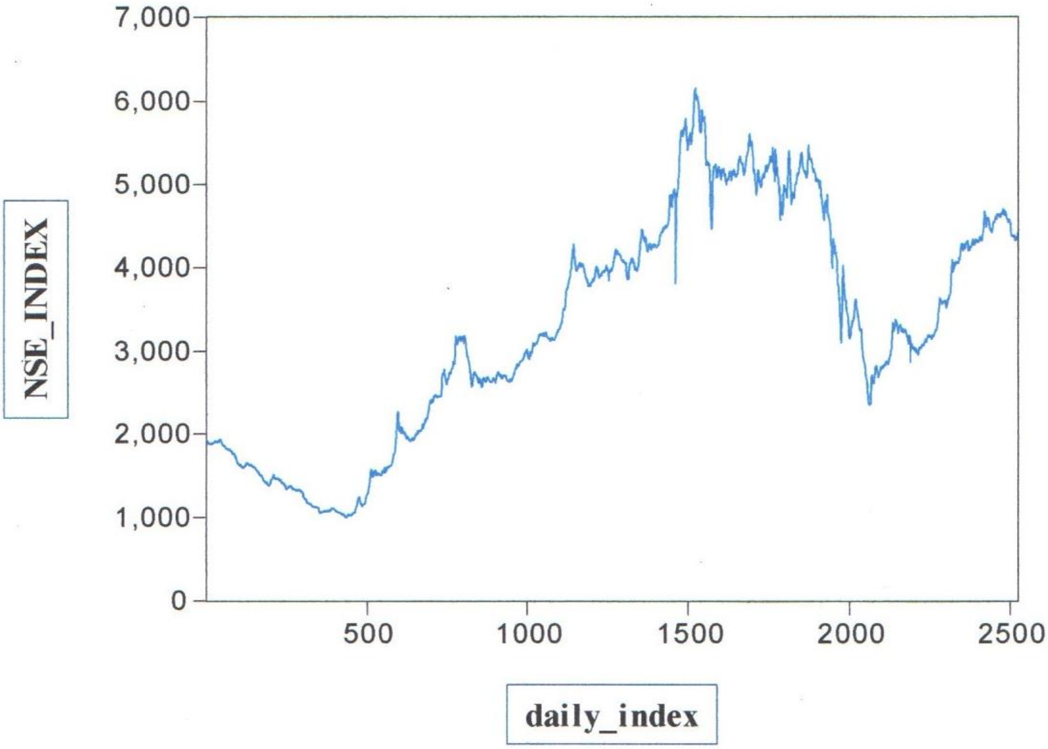

Figure 1: Time plot for daily NSE 20-share index

A visual inspection of the time plots clearly shows that the mean and variance are not constant, implying non-stationarity of the data. The pronounced trend (increasing or decreasing) appear to meander without a constant long-run mean or variance. The series was transformed by taking the first difference of the natural logarithms of the values in the series. The transformation was aimed at attaining stationarity of the NSE 20-share index with the equation given by $R_t = \log \frac{p_{t+1}}{p_t} = \log p_{t+1} - \log p_t$ where, R_t is the daily return and P_t , P_{t+1} are the daily indices of an asset at two successive days, $t+1$ and t. The sequence plot for the returns is presented as;

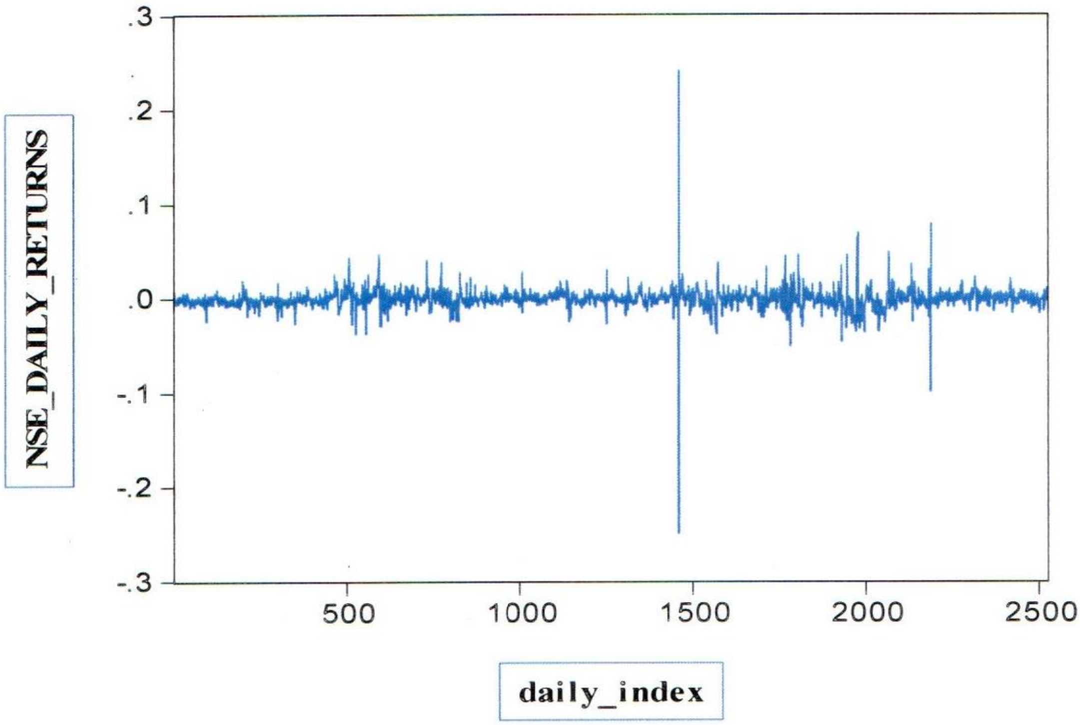

Figure 2: Time plot for the NSE 20-share index daily returns

A closer examination of the return series plot reveals the very well known characteristic of high frequency data. There is evidence of positive serial correlation in the amplitude of the returns. From Figure 2, it is clear that there are sub periods of higher volatility (and therefore are riskier) than others. This means that expected value of the magnitude of disturbance terms are greater at certain periods compared to others. Additionally, these riskier times seem to be concentrated and followed by periods of lower risk (lower volatility) that are again concentrated. This time-series model displays a successive disturbance, although uncorrelated its serially dependent. Thus, suggesting the utilization of a nonlinear model and preferably a non-normal distribution for modelling data.

Table 1 provides the statistical properties of NSE 20-share daily return index. The Jarque-Bera (JB) statistic was used to test whether or not the series was normally distributed. For a normally distributed series, S=0, K=3 and the null hypothesis of normality in distribution, the JB is equal to 0, (S=skewness coefficient and K=kurtosis coefficient). The Positive JB value

(2398642) indicated evidence against normality in the series. The returns are negatively Skewed (-0.188912) which indicated that large negative returns tend to be larger than the higher positive returns. The negative skewness also implied that the stock index returns are flatter to the left compared to the normal distribution. The high and positive kurtosis (154.0526) indicated a "peaked" leptokurtic distribution relative to the normal. However, negative skewness and high kurtosis indicated that there was strong departure from normality in the unconditional distribution of the returns. The Jarque-Bera test statistics rejects the hypothesis of a normal distribution of returns, at a significance level of 1%. Thus, from the results on Skewness, Kurtosis and Jarque-Bera test statistics, NSE stock returns are inefficient in the weak-form.

In general the NSE stock return has large difference between the maximum and minimum returns. The standard deviation in the daily returns is low compared to the daily index (1371.406), which indicates a low level of fluctuation of the daily returns. The mean return is positive and close to zero; a characteristic common in the financial return series. The series has heavy tails showing a strong departure from Gaussian (normal) assumption.

Table 1: Descriptive Statistics of the returns

Statistic	Returns
Mean	0.000335
Median	5.49E-05
Maximum	0.241348
Minimum	-0.248703
Std.Dev.	0.011801
Skewness	-0.188912
Kurtosis	154.0526
Jarque-Bera	2398642 (0.00)
Observations	2523

P-Value is given in brackets

4.2 Empirical Results and Discussions

4.2.1 ARMA models

Table 2 and 3 shows the empirical fittings of several ARMA (p,q) model to the daily return and the goodness of fit statistics respectively. The returns are calculated as the first-order log difference of NSE 20-share index. The series autocorrelation function (ACF) and partial autocorrelation function (PACF) of Q-statistics in Table 4 were not significant while for Q^2-statistics in Table 5 clearly showed signs of slow exponential decay after the first lag. The results indicated that stock return follows an ARMA (2,1) stochastic process with significant serial correlation. The AR (p) parameter ($|\theta| < 1$) in Table 2 and MA (q) parameter ($|\phi| < 1$) indicated stationarity and invertability of NSE stock returns respectively. Based on the Box-Jenkins selection method, ARMA (p,q) models were assessed using the Log-likelihood (LL), Schwarz Bayesian Information Criterion (SBIC) and Akaike Information Criterion (AIC) tests. The models that minimized the SBIC and AIC but maximized the Log-likelihood were considered to be the best. Results clearly indicated that stock returns followed significant ARMA (2,1) stationary trend process. Thus, the series under study exhibits ARCH effects like many financial time series data.

Table 2: Summary Results of ARMA (p,q) models

Model	Parameter	Estimates
ARMA(1,1)	C	0.000336 (0.3020)
	θ	0.728066 (0.00)
	ϕ	-0.618735(0.00)
ARMA(1,2)	C	0.000332 (0.2448)
	θ	0.056579 (0.0045)
	ϕ	0.165598 (0.00)
ARMA(2,1)	C	0.000333 (0.2609)
	θ	0.176616 (0.00)
	ϕ	0.053998 (0.0067)
ARMA(2,2)	C	0.000332 (0.2393)
	θ	0.180556 (0.0946)
	ϕ	0.000661 (0.9952)

P-Values are given in brackets

Table 3: The goodness of fit statistics for the ARMA models

Model	Statistics	
ARMA(1,1)	LL	7549.717
	SBC	-6.057072
	AIC	-6.064010
ARMA(1,2)	LL	7662.265
	SBC	-6.067023
	AIC	-6.073961
ARMA(2,1)	LL	7660.274
	SBC	-6.067850
	AIC	-6.074791
ARMA(2,2)	LL	7656.661
	SBC	-6.064984
	AIC	-6.071925

Table 4: Correlogram of Residuals for ARMA (2,1) model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.000	-0.000	0.0001	
| |	| |	2	0.000	0.000	0.0004	
|* |	|* |	3	0.080	0.080	16.154	0.000
| |	| |	4	0.006	0.006	16.255	0.000
| |	| |	5	-0.027	-0.028	18.164	0.000
| |	| |	6	-0.045	-0.052	23.359	0.000
| |	| |	7	-0.006	-0.007	23.444	0.000
| |	| |	8	0.006	0.011	23.540	0.001
| |	| |	9	0.011	0.019	23.824	0.001
| |	| |	10	0.031	0.032	26.244	0.001
| |	| |	11	0.012	0.008	26.628	0.002
| |	| |	12	0.003	-0.003	26.650	0.003

Sample: 4 2524
Included observations: 2521
Q-statistic probabilities adjusted for 2 ARMA term(s)

Table 5: Correlogram of Standardized Residuals Squared for ARMA (2,1) model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|**** |	|**** |	1	0.503	0.503	637.52	
| |	**| |	2	0.019	-0.312	638.47	
| |	|** |	3	0.013	0.233	638.90	0.000
| |	*| |	4	0.000	-0.183	638.90	0.000
| |	|* |	5	0.001	0.151	638.90	0.000
| |	*| |	6	0.001	-0.126	638.90	0.000
| |	|* |	7	0.003	0.112	638.92	0.000
| |	*| |	8	0.003	-0.095	638.95	0.000
| |	|* |	9	-0.000	0.081	638.95	0.000
| |	| |	10	0.003	-0.064	638.98	0.000
| |	| |	11	0.005	0.059	639.04	0.000
| |	| |	12	0.003	-0.050	639.05	0.000

Sample: 4 2524
Included observations: 2521
Q-statistic probabilities adjusted for 2 ARMA term(s)

Diagnostic checks are presented in Table 6. For ARMA (2,1), the Q-statistics of standardized residuals is not significant indicating the mean equation is correctly specified and Q-squared statistic was significant at 5% which implies that ARMA does not remove the volatility. The Jarque-Bera test rejected the normality assumption in the residuals, (for normality the Jarque-Bera statistics should not be significant).

Positive skewness indicates that the data is skewed to the right and the increased positive kurtosis indicates a "peaked" leptokurtic distribution. The Philips-Peron test is utilized to check for the stationarity of the stock returns, the P-value of the test is below 0.05, which implies that stock returns are now stationary.

Table 6: Diagnostic Tests for Standardized Residuals for ARMA(2,1) model

Statistics	ARMA (2,1)
Skewness	0.391749
Kurtosis	183.2439
JB	3412645 (0.00)
Q(36)	50.079 (0.037)
$Q^2(36)$	639.24 (0.00)
Phillip-Peron test	-47.47972 (0.0001)

P-Values are given in brackets

JB- Represents Jarque-Bera statistics for normality

Q (36) - Represents Ljung-Box Q statistics for the standardized residuals

Q^2(36) - Represents Ljung-Box Q statistics for squared standardized residuals

4.2.2 Market Efficiency

The ADF and PP tests were carried on the index, d(index) and d(index,2) using the package Eviews6 to empirically determine the form of market efficiency. The tests were performed in levels, first difference and second difference. The null hypothesis of a unit root is rejected at 5% level of significance.

Table 7, 8 and 9 reports the results of the ADF as well as the PP tests for NSE 20-share index at without intercept and trend, with intercept and with trend and intercept respectively. The results clearly show empirical evidence that the NSE index is non-stationary (random) at level and stationary (non-random) for the first and second differences. This implies that the NSE market is informationally inefficient at the weak-form level. Therefore, prudent investors realized abnormal returns by using historical sequences of stock prices and other market generated information. This arise from frictions or thinness in trading process, delay in operations and high transaction cost, limited provision of information of firms' performance to market participants, lack of professional financial analyst and brokerage analysis of the stock market returns for investors.

Table 7: ADF and PP Unit Root Test Results (Without Intercept and Trend)

Type of Test	Index Level	t-statistics	Critical value 1% level	Critical value 5% level	Critical value 10% level
ADF	INDEX	0.643997(0.8552)	-2.565879	-1.940949	-1.616615
ADF	D(INDEX)	-30.22853(0.000)	-2.565880	-1.940949	-1.616615
ADF	D(INDEX,2)	-61.15121(.0001)	-2.565880	-1.940949	-1.616615
PP	INDEX	0.633734(0.8531)	-2.565879	-1.940949	-1.616615
PP	D(INDEX)	-49.50625(.0001)	-2.565879	-1.940949	-1.616615
PP	D(INDEX,2)	-169.5439(.0001)	-2.565880	-1.940949	-1.616615

P-Values are given in brackets

Table 8: ADF and PP Unit Root Test Results (With Intercept)

Type of Test	Index Level	t-statistics	Critical value 1% level	Critical value 5% level	Critical value 10% level
ADF	INDEX	0.943654(0.7746)	-3.432748	-2.862485	-2.567318
ADF	D(INDEX)	-30.24160(0.000)	-3.432750	-2.862486	-2.567319
ADF	D(INDEX,2)	-61.13908(0.0001)	-3.432751	-2.862487	-2.567319
PP	INDEX	-0.949685(0.7726)	-3.432748	-2.862485	-2.567318
PP	D(INDEX)	-49.51923(0.0001)	-3.432749	-2.862486	-2.567319
PP	D(INDEX,2)	-169.5036(0.0001)	-3.432750	-2.862486	-2.567319

P-Values are given in brackets

Table 9: ADF and PP Unit Root Test Results (With Trend and Intercept)

Type of Test	Index Level	t-statistics	Critical value 1% level	Critical value 5% level	Critical value 10% level
ADF	INDEX	-1.185865(0.9122)	-3.961681	-3.411589	-3.127663
ADF	D(INDEX)	-30.23606(0.000)	-3.961684	-3.411590	-3.127664
ADF	D(INDEX,2)	-61.12695(0.000)	-3.961686	-3.411591	-3.127664
PP	INDEX	-1.196644(0.9101)	-3.961681	-3.411589	-3.127663
PP	D(INDEX)	-49.51000(0.000)	-3.961683	-3.411589	-3.127663
PP	D(INDEX,2)	-169.4635(0.0001)	-3.961684	-3.411590	-3.127664

P-Values are given in brackets

Using the non-parametric runs test to determine the form of market efficiency, randomness and predictability for the sequence of returns was tested. Table 10 display runs test results taking median as the base respectively. The estimated Z-values are significant at 1% level. SPSS16 software is used to obtain the runs test results below. The resulting negative Z values for NSE index and returns indicated positive serial correlation. The runs test show that the successive returns were not independent at 5% level (critical value of -1.96). This suggests that NSE market is weak-form inefficient.

Table 10: RUNS TEST with Median

	NSE INDEX	DIFF(NSE INDEX,1)	DIFF(NSE INDEX,2)
Test Value[a]	3197.95	0.11	-0.12
Cases < Test Value	1262	1261	1261
Cases >= Test Value	1262	1262	1261
Total Cases	2524	2523	2522
Number of Runs	20	939	1612
Z (r)	-49.493	-12.883	13.942
Asymp. Sig. (2-tailed)	0.000	0.000	0.000

a. Median

b. There are multiple modes. The mode with the largest data value is used.

Descriptive statistics are presented in Table 11. NSE stock return show large difference between the maximum and minimum returns. The standard deviation in the daily returns is low compared to the daily index which indicates a low level of fluctuation of the daily returns. The mean return is positive and close to zero especially in the second difference (0.0090); a characteristic common in the financial return series. NSE index is found to be at the highest-risk due to its highest standard deviation (1371.40569) unlike in NSE index returns (46.12550). The series has heavy tails showing a strong departure from Gaussian (normal) assumption.

Table 11: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
NSE INDEX	2524	1004.70	6161.46	3.2939E3	1371.40569
DIFF(NSE INDEX,1)	2523	-1077.39	1041.53	1.0015	46.12550
DIFF(NSE INDEX,2)	2522	-1077.39	2118.92	0.0090	64.79675
Valid N (list wise)	2522				

4.2.3 Time-varying, persistency and clustering of volatility

The empirical results of volatility and risk-returns are presented in Table 12 and 13 respectively. As the variance is expected to be positive, the coefficients (C, α_1 and β_1) in the variance equation are all positive and stationarity of the variance is preserved since the coefficients (α_1 and β_1) are less than one. High values of β_1 (0.563785, 0.676532) and Low values of α_1 (0.343366, 0.268657), showed highly persistent and less reactive in volatility. In other words, the market took more time to fully digest the price shocks than for other stocks. A large value of the GARCH lag coefficient β_1 indicated that shocks to conditional variance took long time to die out implying that the volatility was persistent. The sum of the parameters α_1 and β_1 was approximately equal to unity indicating that volatility shocks were quite persistent (volatility clustering) a tendency observed in high frequency financial data. The sum of the parameters $\alpha_1+\beta_1$ being close to unity (0.907151 or 0.945189) also implied shocks at time t persists for many periods in the future and indicated stationarity of the stock returns. Thus, the fitted GARCH-M (1,1) model is the best choice for this data which is consistent with the findings of Box and Jenkins (1994) , Ogum (2005) and Ogum et al. (2006).

Table 12: The Parametric Estimates for the Mean Equations ARMA (p,q)

Parameter	t-distribution
δ	2.330284(0.3189)
C	8.38E-05(0.6643)
θ	0.228208(0.00)
ϕ	0.291086(0.00)

P-Values are given in brackets

Table 13: The Parameter Estimates for the Variance Equation GARCH-M (1,1)

Parameter	t-distribution
C	1.02E-05(0.00)
α_1	0.343366(0.00)
β_1	0.563785(0.00)

P-Values are given in brackets

GARCH-in-mean (GARCH-M) models for different values of p and q were fitted to the NSE data using student's t-distribution. None of autocorrelation function (ACF) or the partial autocorrelation function (PACF) of the standardized residuals for the 12 lags was significant (Table 14). This implied that the mean and the variance equations are correctly specified. Diagnostic checks and goodness of fit statistics indicated that GARCH-M (1,1) model to be the best choice. This is consistent with most empirical studies involving the application of GARCH-M models in financial time series data, Box and Jenkins (1994) and Ogum (2005). In all the cases, the student's t-distribution provided a better model than the GED distribution. This could be due to the fact that financial data is highly leptokurtic with fat tails which are relatively better captured by the student's t-distribution. The fitted models were adequate since their standardized residuals were not significantly correlated basing on the Ljung-Box Q statistics. The model parameter estimates for the mean and variance equations are presented in Table 12 and 13 above.

Table 14: Correlogram of Standardized Residuals for the GARCH-M model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.003	-0.003	0.0220	
| |	| |	2	0.022	0.022	1.2690	
| |**	| |**	3	0.055	0.056	9.0219	0.003
| |	| |	4	0.019	0.019	9.9220	0.007
| |	| |	5	0.019	0.017	10.839	0.013
| |	| |	6	-0.014	-0.017	11.311	0.023
| |	| |	7	-0.012	-0.015	11.657	0.040
| |	| |	8	0.015	0.013	12.236	0.057
| |*	| |*	9	0.028	0.030	14.179	0.048
| |	| |	10	0.009	0.011	14.396	0.072
| |	| |	11	0.001	-0.001	14.398	0.109
| |	| |	12	-0.018	-0.022	15.221	0.124

Sample: 4 2524

Included observations: 2521

Q-statistic probabilities adjusted for 2 ARMA term(s)

Goodness of fit statistics for specific GARCH-M (p,q) models was tested by basing on the SBIC, AIC and the Log likelihood test as in Table 15 below. The models that minimized the SBIC and AIC but maximized the log likelihood were considered to be the best. Results clearly indicated that stock returns followed significant GARCH-M (1,1) model. Basing on the results, the distribution of choice was the student's t-distribution. The model adequacy was checked using the Ljung-Box Q statistics for residuals and squared residuals in which the null hypothesis of significant correlations was rejected implying that the fitted model was adequate. The standardized residuals are leptokurtic and the JB statistic strongly rejected the hypothesis of normal distribution. The Diagnostic tests are presented in Table 16.

Table 15: Goodness of fit statistics for the GARCH-M (1,1) model

	t-distribution
LL	8954.945
AIC	-7.097965
SBIC	-7.079457

Table 16: Diagnostic tests on the standardized residuals for the GARCH-M models

Statistics	GARCH-M (1,1) t-distribution
Skewness	-14.02079
Kurtosis	459.7093
JB	21992548 (0.00)
Q (36)	38.851 (0.260)
Q^2(36)	0.1240 (1.000)

P-Values are given in brackets

JB- Represents Jarque-Bera statistics for normality

Q (36) - Represents Ljung-Box Q statistics for the standardized residuals

Q^2 (36)- Represents Ljung-Box Q statistics for squared standardized residuals

In contrast to the empirical success, GARCH model is unsuitable for modeling the frequently observed asymmetric effect or leverage effect due to the positive and negative shocks. To capture these effects, asymmetric models, the Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) were fitted.

4.2.4 Asymmetric and Leverage effect

The EGARCH model proposed by Nelson (1991) was fitted to capture the asymmetric and leverage effect in the financial market that the main GARCH model was not able to capture. The presence of leverage effect was tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

The EGARCH-in mean (EGARCH-M) models for different values of p and q were fitted to the NSE data using student's t-distribution. Tables 18 and 19 presented the mean and variance equations respectively. The autocorrelation function (ACF) for the first 12 lags and the partial autocorrelation function (PACF) for Q-statistic in Table 19 clearly indicated no significance. Models that minimized the SBIC and AIC but maximized the log likelihood were considered to be the best. Results clearly indicated that stock returns followed EGARCH-M (1,1) model. Basing on our results, the distribution of choice for fitting asymmetric and leverage effect was the student's t distribution. The estimate of the risk-return parameter δ was positive and not statistically significant at 5% in the mean equation which clearly confirmed the hypothesis that in individual asset investment volatility is not a significant determinant of stock returns.

In the EGARCH-M (1,1) model, the parameter (γ_1) was positive and statistically different from zero indicating the existence of asymmetric effect. This result are consistent with the earlier findings of Ogum (2005) and Ogum *et al.*, (2006) on the Nairobi Stock Exchange who found the asymmetry parameter (γ_1) to be positive when modelling the daily NSE 20-share index using the EGARCH models. Since the asymmetric parameter estimate (γ_1) was positive, it implied no leverage effect i.e. good news (positive shocks) had a higher impact on volatility than bad news (negative shocks). This could be due to inefficiency in the NSE market in that companies tend to spread good news and hide that of bad news. Another reason could be due to delay in operations and high transaction costs that the Kenyan economy has been facing since post-election violence which had a strong effect on the NSE stock market. The squared error parameter (α_1) is positive and significant indicating the existence of ARCH process in the error term, thus suggests the tendency of the shocks to persist (volatility clustering). The sum of the parameters (α_1) and (β_1) is greater than one, thus the tendency for volatility response to shocks displayed a long trend, implying time-varying volatility in the NSE index stock returns.

Table 17: Correlogram of Standardized Residuals for the EGARCH-M model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.010	0.010	0.2684	
| |	| |	2	0.021	0.021	1.3481	
| |**	| |**	3	0.060	0.060	10.440	0.001
| |	| |	4	0.013	0.011	10.852	0.004
| |	| |	5	0.016	0.014	11.511	0.009
| |	| |	6	-0.017	-0.022	12.253	0.016
| |	| |	7	-0.011	-0.013	12.582	0.028
| |	| |	8	0.012	0.011	12.972	0.043
| |*	| |*	9	0.029	0.032	15.125	0.034
| |	| |	10	0.014	0.014	15.591	0.049
| |	| |	11	0.006	0.004	15.671	0.074
| |	| |*	12	-0.021	-0.026	16.825	0.078

Sample: 4 2524
Included observations: 2521
Q-statistic probabilities adjusted for 2 ARMA term(s)

Table 18: The parameter estimates for the mean equations ARMA (p,q)

Parameter	t-distribution
δ	0.821399 (0.800)
C	0.000194 (0.3369)
θ	0.228416 (0.00)
ϕ	0.292916 (0.00)

P-Values are given in brackets

Table 19: Parameter Estimates for the Variance Equation EGARCH-M(1,1)

Parameter	t-distribution
ω_1	-1.070225 (0.00)
α_1	0.306738 (0.00)
γ_1	0.048137 (0.0073)
β_1	0.912241 (0.00)

P-Values are given in brackets

Diagnostics and goodness of fit statistics for the EGARCH-M (1,1) model are presented in Tables 20 and 21 respectively. The Ljung-Box Q statistic of standardized residuals of order 36, Q (36), was significant and the squared standardized residuals, $Q^2(36)$, fail to reject the null hypothesis of the residuals being uncorrelated indicating that the mean and variance equations are correctly specified respectively, thus the fitted model is adequate. The Kurtosis in the EGARCH-M (1,1) model still showed positivity but reduced compared to the GARCH-M (1,1) model, while the negative value of the skewness indicated that the data is skewed to the left. This also meant that the left tail is long relative to the right tail. The JB statistics also strongly rejected the null hypothesis of normality in the standardized residuals.

Table 20: Goodness of fit statistics for the EGARCH-M (1,1) model

	t-distribution
LL	8943.504
AIC	-7.088064
SBIC	-7.067242

Table 21: Diagnostic tests on the standardized residuals for the EGARCH-M models

EGARCH-M (1,1)	
Statistics	t-distribution
Skewness	-10.17060
Kurtosis	303.1714
JB	9508019 (0.000)
Q (36)	42.496 (0.150)
Q^2 (36)	0.2039 (1.000)

P-Values are given in brackets

JB – Represents Jarque-Bera statistics for normality

Q (36) – Represents Ljung-Box Q statistics for the standardized residuals.

Q^2(36) – Represents Ljung-Box Q statistics for the squared standardized residuals

The Threshold GARCH (TGARCH) model by Zakoian (1994) was also used to determine the asymmetric and leverage effect. The model is based on the assumption that unexpected (unforeseen) changes in the returns of the index have different effects on the conditional variance of the stock market index returns. Specific TGARCH-M (p,q) models were fitted and diagnosed by using student's t-distribution. None of the ACF and PACF for the Q statistics is significant as indicated in Table 22 below. Student's t distribution was utilized in the diagnostic check for the TGARCH-M (1,1) model. This indicated that the student's t-distribution captured tail properties of the data. The mean and variance equation results for best model TGARCH-M (1,1) are presented in Tables 23 and 24 respectively. The risk-return parameter δ was positive and not significant at 5%, which implies the concept of diversification of investment assets that has collectively lower risk than individual asset is not put in consideration at the NSE stock market. Existence of ARCH process in the error term and the tendency of the shocks to persist was indicated by the positivity of the parameter (α) in the TGARCH-M (1,1) model. The sum of (α) and (β) parameters (0.891905 or 0.936111) was close to unity implying time-varying volatility in the NSE index.

Table 22: Correlogram of Standardized Residuals for TGARCH-M model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.002	-0.002	0.0133	
| |	| |	2	0.022	0.022	1.2859	
| |**	| |**	3	0.056	0.056	9.0748	0.003
| |	| |	4	0.019	0.019	9.9736	0.007
| |	| |	5	0.019	0.017	10.899	0.012
| |	| |	6	-0.014	-0.018	11.375	0.023
| |	| |	7	-0.012	-0.015	11.712	0.039
| |	| |	8	0.015	0.013	12.286	0.056
| |*	| |*	9	0.028	0.030	14.240	0.047
| |	| |	10	0.009	0.011	14.459	0.071
| |	| |	11	0.001	-0.001	14.461	0.107
| |	| |	12	-0.018	-0.022	15.251	0.123

Sample: 4 2524
Included observations: 2521
Q-statistic probabilities adjusted for 2 ARMA term(s)

Table 23: The parameter estimates for the mean equations ARMA(p,q)

Parameter	t-distribution
δ	2.316989 (0.3241)
C	6.59E-05 (0.7340)
θ	0.228807 (0.00)
ϕ	0.292065 (0.00)

P-Values are given in brackets

Table 24: Parameter Estimates for the Variance Equations TGARCH-M (1,1)

Parameter	t-distribution
C	1.03E-05 (0.00)
α_1	0.328246 (0.00)
γ_1	0.029196 (0.6533)
β_1	0.563659 (0.00)

P-Values are given in brackets

As discussed in the EGARCH-M (1,1) model, the presence of leverage effect was tested by the hypothesis that ($\gamma<0$) and the impact of asymmetric effect by ($\gamma\neq0$). In comparison with the TGARCH-M (1,1) model ($\gamma > 0$) indicating that the news (shocks) impact is asymmetric as in the EGARCH-M (1,1) model. The results indicated that the effect in the shape of news impact curve from the normal phenomena, negative shocks (bad news) followed by higher volatilities than that of positive shocks (good news). This is consistent with the findings of Ogum (2005) and Ogum *et al.*, (2006) who applied EGARCH models to the daily NSE 20-Share Index.

The diagnostics and goodness of fit statistics for the TGARCH-M (1,1) model are presented in Tables 25 and 26 respectively. The skewness in the TGARCH-M (1,1) model still showed negativity but had reduced compared to the previous model EGARCH-M. Unlike the skewness, kurtosis in TGARCH-M (1,1) model increased indicating a sharp peak as compared to the previous model. Ljung-Box Q statistics for (36) lags for the standardized residuals was significant and squared standardized residuals was not significant at 5%; this implied that the mean and variance equations are correctly specified thus the fitted model is adequate. The JB statistics also rejected the null hypothesis of normality in the standardized residuals.

Table 25: Goodness of fit statistics for the TGARCH-M (1,1) model

	TGARCH-M (1,1) t- distribution
LL	8955.103
AIC	-7.097266
SBIC	-7.076444

Table 26: Diagnostic tests on the standardized residuals for the TGARCH-M models

TGARCH-M (1,1)	
Statistics	t-distribution
Skewness	-13.99623
Kurtosis	458.6333
JB	21889139 (0.00)
Q (36)	38.931 (0.257)
Q^2 (36)	0.1260 (1.000)

P-Values are given in brackets

JB – Represents Jarque-Bera statistics for normality

Q (36) – Represents Ljung-Box Q statistics for the standardized residuals.

Q^2(36) – Represents Ljung-Box Q statistics for the squared standardized residuals

The results of estimation and statistical verification for the GARCH-M (1,1), EGARCH-M (1,1) and TGARCH-M (1,1) are shown in Table 27. The log-likelihood, AIC and SBIC tests were used to select the best model that fits the NSE 20-share index data. The higher the log-likelihood value the better the model was to fit the data, (Tooma 2005). According to (Shamir and Hassan 2005; Tooma 2005), log-likelihood value, AIC and SBIC gives the same indication about what model to prefer. The student's t-distribution for each model was used.

Table 27: Efficiency comparison between the ARCH-type models

	GARCH-M (1,1)	EGARCH-M(1,1)	TGARCH-M (1,1)
LL	8954.945	8943.504	8955.103
SBIC	-7.079457	-7.067242	-7.076444
AIC	-7.097965	-7.088064	-7.097266
Skewness	-14.02079	-10.17060	-13.99623
Kurtosis	459.7093	303.1714	458.6333

A close comparison of the values in the GARCH models, clearly indicated GARCH-M (1,1) model to be the preferred model due to it's maximum log likelihood value and minimum AIC and SBIC values. The GARCH-M (1,1) model is also justified by it's low negative value of the residual skewness and the positive high kurtosis value. Thus the best ARCH-type model that fits NSE stock returns data is GARCH-M (1,1) model which is consistent with the findings of Box and Jenkins (1994) , Ogum (2005) and Ogum et al. (2006).

The statistical results for both models appear to have very similar characteristics. They both display negative skewness, found to be deviating from normal, and display a degree of serial correlation. These stylized results are very similar to a number of previous empirical works. Fama (1976) showed that the distribution of both daily and monthly returns for the Dow Jones departs from normality, and are skewed, leptokurtic, and volatility clustered. Furthermore, Kim and Kon (1994) found the same for the S&P 500 and Mecagni and Shawky (1999) show similar results in the ESE. Finally NSE stock market weak-form inefficiency was similar to the findings of Harvey (1994) that display non-randomness stock price behavior and reject of the weak-form efficiency in the developing and emerging markets.

4.3 Forecasting

The models were also evaluated in terms of their forecasting ability of future returns. The common measure of forecast evaluation the RMSE, MAE, MAPE and TIC were used. In Table 28 the results of the dynamic in-sample forecast performance are shown using data from the beginning of the estimation sample to the end of the estimation. For every period, the previously forecasted values for dlog(index)(-1) were used in forming a forecast of the subsequent value of dlog(index). The model that exhibits the lowest values of the error measurements was considered to be the best. The results clearly indicated the asymmetric EGARCH-M (1,1) model outperformed all the other models. The symmetric GARCH-M (1,1) performed the least in forecasting the conditional volatility of the NSE 20-Share index returns. These results contradict the findings of Dimson and Marsh (1990) that relatively complex nonlinear models are inferior in forecasting to simpler parsimonious models. The Bias Proportion showed how far the mean of forecast is from the mean of the actual series while the covariance proportion measured the remaining unsystematic forecasting errors of the actual series. The large variance proportion (0.999408) indicated that the forecast tracked the seasonal (movements) variation in the NSE returns only at the beginning of the forecast sample and quickly flatten out to the mean forecast value.

Table 28: Dynamic Forecast Performance Estimated Models (In-Sample)

	GARCH-M (1,1)	EGARCH-M(1,1)	TGARCH-M (1,1)
Root Mean Square Error (RMSE)	0.011803	0.011803	0.011803
Mean Absolute Error (MAE)	0.006359	0.006356	0.006358
Mean Abs. Percent Error (MAPE)	130.8630	122.2630	128.5374
Theil Inequality Coefficient (TIC)	0.971616	0.977958	0.973270
Overal Rank	3	1	2
Bias Proportion	0.000000	0.000036	0.000001
Variance Proportion	0.988383	0.999408	0.998406
Covariance Proportion	0.001617	0.000556	0.001593
R^2	0.022967	0.187019	0.027379

Table 29 shows the results one-step ahead static in-sample forecast performance. The one-step a head static forecasts were more accurate than the dynamic forecasts since, for each period, the actual value of dlog(index)(-1) was used in forming the forecast of dlog(index). The asymmetric TGARCH-M (1,1) model exhibits the lowest values of the error measurements thus was considered the best choice with normal distribution. This is supported by its lowest R^2 value (-0.017020) compared to the others. The R-Squared (R^2) statistics measures the success of the regression in predicting the values of the dependent variable within the sample. It can be negative if the regression does not have an intercept or constant, if the regression contains coefficient restrictions, or if the estimation method is two-stage least squares or ARCH- type model. The asymmetric EGARCH-M performed the least unlike in the dynamic forecast where it performed the best. These findings also contradict the results of Dimson and Marsh (1990). The in-sample results display both leptokurtosis and asymmetric effect. Out-of-sample forecasts depict the asymmetric effects.

Table 29: Static Forecast Performance of Estimated Models (In-Sample)

	GARCH-M (1,1)	EGARCH-M(1,1)	TGARCH-M (1,1)
Root Mean Square Error (RMSE)	0.011750	0.011643	0.11748
Mean Absolute Error (MAE)	0.006349	0.006396	0.006350
Mean Abs. Percent Error (MAPE)	101.6865	169.4366	103.7375
Theil Inequality Coefficient (TIC)	0.947567	0.874460	0.942044
Overall Rank	2	3	1
Bias Proportion	0.000540	0.001324	0.000339
Variance Proportion	0.910678	0.813359	0.900930
Covariance Proportion	0.088782	0.185317	0.098731
R^2	-0.016172	0.024759	-0.017020

As noted for every period, the previously forecasted values for dlog(index)(-1) are used in forming a forecast of the subsequent values of dlog(index). Figure 3 and 4 presents the dynamic and static in-sample volatility forecast by examining the NSE index the first 2000 actual values of the sample versus the fitted (predicted) values.

The graphs for the period under analysis indicate that the interval estimate of returns made at a level of reliability is not constant in case of all the three models and take into account the changing variance of the variable in question. This means that, unlike classical approaches based on the assumption of a constant variance of random components, the EGARCH, GARCH and TGARCH models react to the actual changes in the volatility of the returns.

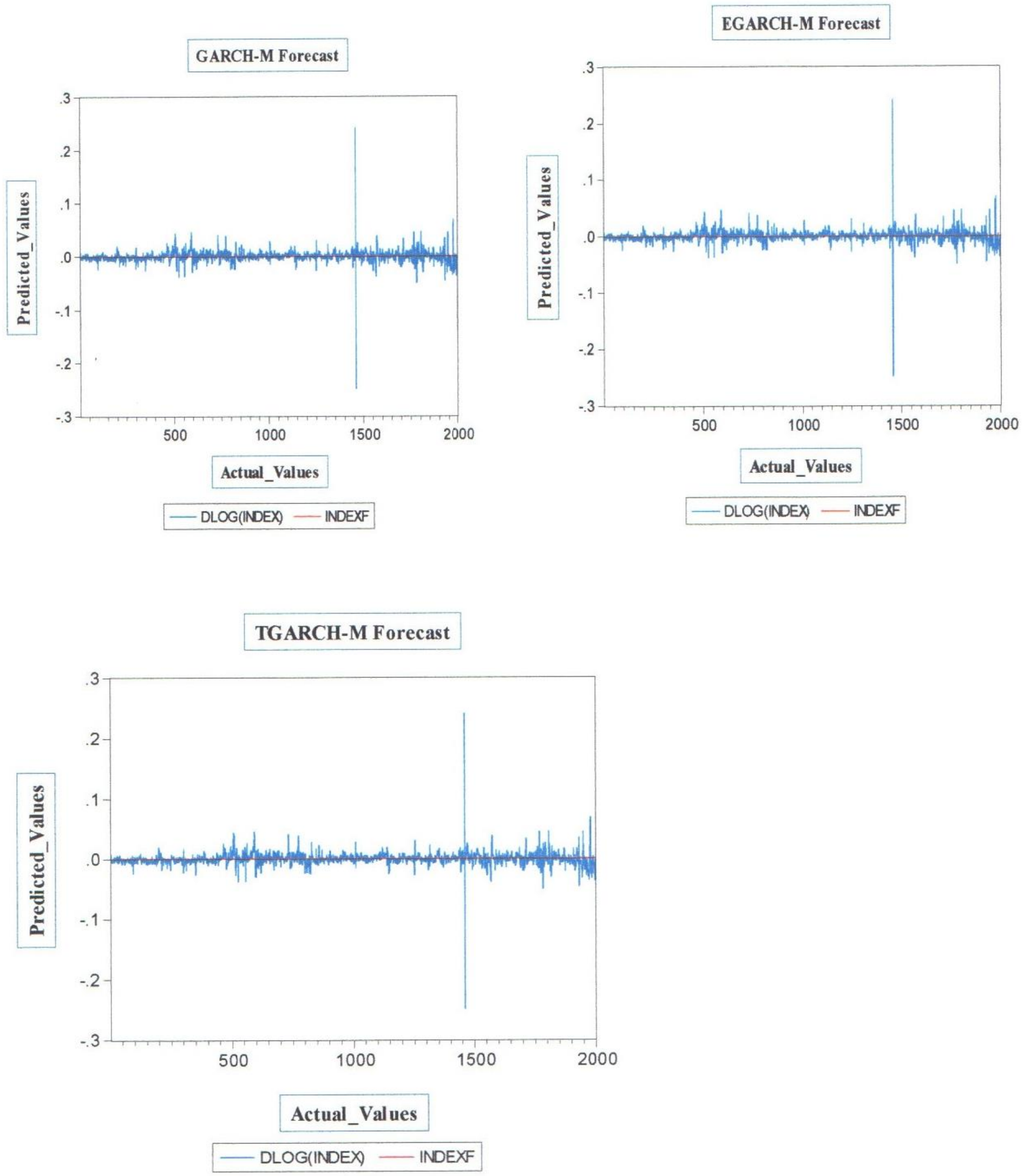

Figure 3: Dynamic Volatility In-Sample Forecast Graphs

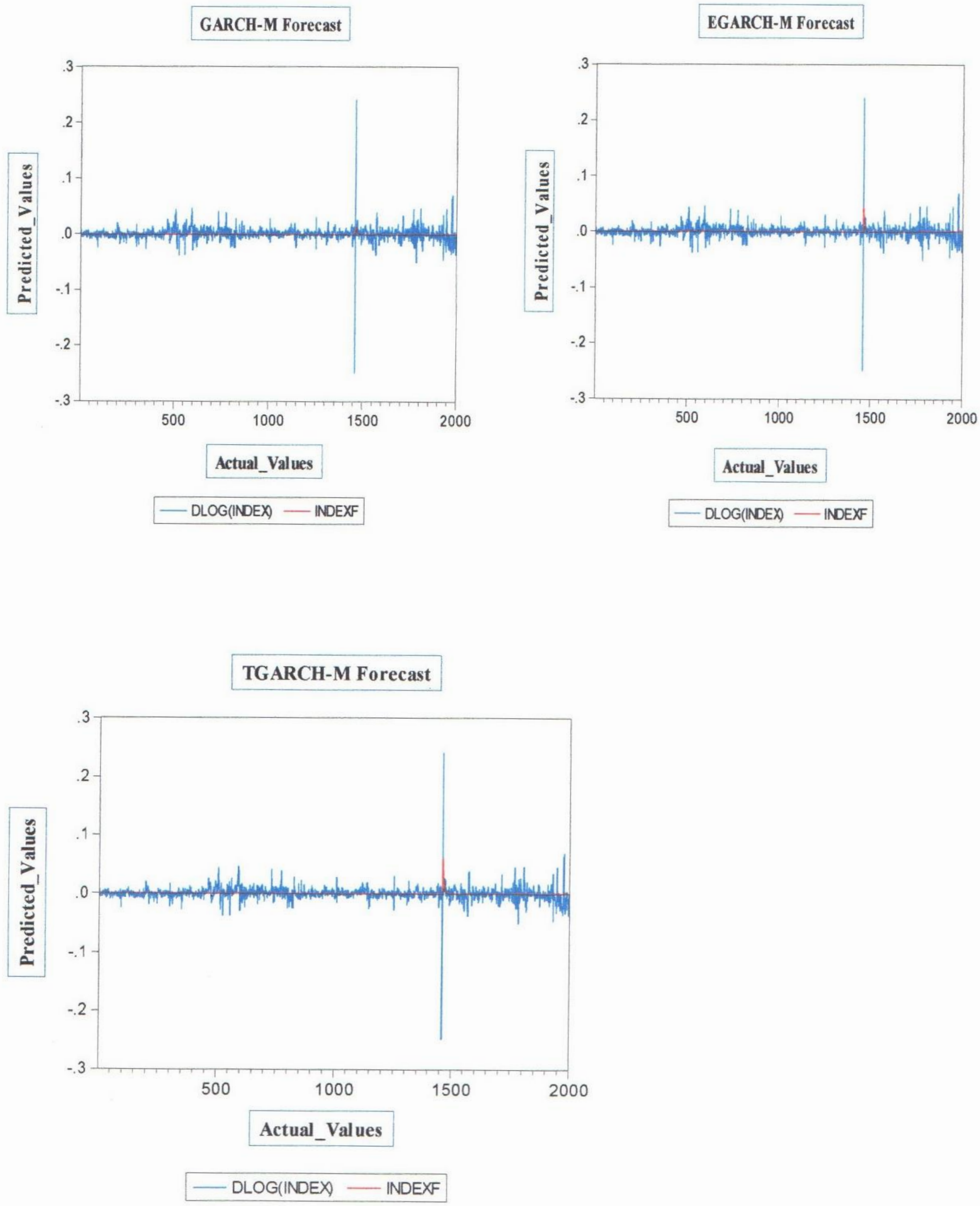

Figure 4: Static Volatility In-Sample Forecast Graphs

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary

In this study, the ARCH-in-mean models, Unit root tests and the Runs test were used to analyze the NSE 20-share index. The unit root test provides evidence on whether the stock prices in NSE stock market follow a random walk. Therefore, it is also a test of the weak-form market efficiency. The Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were employed. The ARCH-M models were used to determine time-varying volatility, asymmetric effect and the best model for forecasting the stock market volatility. A comprehensive summary is given below.

5.1.1 Market efficiency

To empirically determine the type of market efficiency at NSE, the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were used to test the existence of a unit root in the series of price changes in the stock market. Several orders of ARMA (p,q) were tested: (1,1), (1,2), (2,1) and (2,2). Employing the Box-Jenkins selection method using the AIC, LL and SBIC, the stock returns followed significant ARMA (2,1) stationary trend process. The ADF test and PP tests at without intercept and trend, with intercept and with trend and intercept clearly show empirical evidence that the NSE index are non-stationary (random) at level and stationary (non-random) for the first and second differences. This implies that the NSE market is informationally inefficient at the weak-form level.

Using the non-parametric runs test to determine the form of market efficiency, randomness and predictability for the sequence of returns was tested. The runs test show that the successive returns were not independent at 5% level (critical value of -1.96). This suggests that NSE stock market is weak-form inefficient.

5.1.2 Time-varying risk-return and volatility clustering

The risk-return parameter δ was positive and not statistically significant at 5% in all the three models which were not consistent with the portfolio theory, thus implying diversification of assets with lower risk in investment assets at NSE stock market is least considered. The asymmetry parameter γ_1 was positive in the EGARCH-M (1,1) and TGARCH-M (1,1) models which implied no leverage effect i.e. good news (positive shocks) had a higher impact on volatility than bad news (negative shocks) of the same magnitude. This could be due to inefficiency in the NSE market in that companies tend to spread good news and hide that of bad news (thin trading). This is in consistent with the findings of Ogum (2005) and Ogum et al., (2006).

5.1.3 Asymmetric and leverage effects

The ARCH-in-mean models namely GARCH-M, EGARCH-M and TGARCH-M were applied in this analysis of the stock market returns. Different p and q orders were fitted for each model in all cases: (1,1), (1,2), (2,1) and (2,2). The order (p,q) is equal to (1,1) was the best choice as is in consistent with GARCH model research results. A close comparison of the diagnostic and the goodness of fit statistics, the GARCH-M (1,1) outperformed the EGARCH-M and TGARCH-M models due to it's maximum log likelihood value and minimum AIC and SBIC value. The EGARCH-M (1,1) and TGARCH-M (1,1) were the preferred models to describe the dependence in variance for NSE returns since they were able to capture the asymmetric effect. However, none of the standardized residuals were significant in that they displayed non-normality in all cases.

5.1.4 Forecasting

Considering forecast performance, the asymmetric EGARCH-M (1,1) model with dynamic in-sample forecast emerged the best with student's t-distribution over the GARCH-M and TGARCH-M models due to it's lower values in RMSE, MAE and MAPE. Comparison using the R^2 also gave the same results in that the EGARCH-M (1,1) emerged the best due to it's highest value of R^2 (0.187010) unlike the TGARCH-M and GARCH-M.

5.2 Conclusions

Our results clearly display the sum of the coefficients on the lagged squared error and the lagged conditional variance was high and close unity for the GARCH-M (1,1), EGARCH-M(1,1) and TGARCH-M(1,1) model. This suggested a high degree of persistence in conditional volatility at the NSE market. The asymmetric models, the EGARCH-M and TGARCH-M outperformed the symmetric GARCH-M model when considering both modeling conditional volatility and in-sample forecasting of the conditional volatility.

In comparison, the asymmetric EGARCH-M (1,1) model outperformed the asymmetric TGARCH-M(1,1) and symmetric GARCH-M(1,1) model due to it's maximum log likelihood value, minimum AIC and SBIC value and the it's highest R^2 value in the dynamic in-sample forecast. In the one-step ahead static in-sample forecast, TGARCH-M (1,1) model emerged the best and the results display leptokurtosis and asymmetric effects. The TGARCH-M model shows asymmetric effect in that good news (positive shocks) has a higher impact on stock price than that of bad news (negative shocks).

The parametric and non-parametric tests previous results suggest that past movements in stock prices cannot be used to forecast their future movements. Therefore, NSE stock market does not follow a random walk and is informationally inefficient in the weak-form. This implies that prudent investors will realize abnormal returns by using historical data of stock prices and trading volume. However, this result contradicts the earlier studies on NSE for instance Ogum et al., (2006), Dickson and Muragu (1994) and Muhanji (2000) who found the NSE market to be weak-form efficient. This could arise from inconsistency in trading process and lack of professional financial analyst that can analyze stock market returns for investors at Nairobi Stock Exchange. In addition, the flow of information to market participants at NSE may not be efficient as in developed markets.

5.3 Recommendations and Further Research

When modeling the NSE daily index, the GARCH-M (1,1) emerged the best statistical model with student's t-distribution. However, in forecasting the NSE market future returns, the asymmetric models EGARCH-M (1,1) and TGARCH-M (1,1) with student's t-distribution and normal distribution respectively are recommended.

Further work is recommended in determination of the form of market efficiency by application of other prediction models like Power ARCH (PARCH), Component GARCH (CGARCH), Nonlinear GARCH (NAGARCH) and Integrated GARCH (IGARCH) and employing various distributions since Ogum et al. (2006) found NSE market to be of weak-form efficient using the EGARCH model and this study found the market to be inefficient at weak-form level by using both the Unit root tests and the Runs test.

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