

**MODELING AND FORECASTING STOCK MARKET VOLATILITY
AT NAIROBI SECURITIES EXCHANGE**

BY

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DECLARATION

This research project is my original work and has not been presented for a degree in any other university.

Signature.....

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This research project has been submitted for examination with my approval as the University Supervisor.

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DEDICATION

From the valleys Denbecha and Woldia to the heart of Addis, thank you
mom and dad.

Dedicated To:

Tsege Mekonnen and Worku Mekoya

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ABBREVIATIONS

ADF:	Augmented Ducky Fuller Test
ARCH:	Autoregressive Conditional Heteroskedasticity
BG:	Breusch and Godfrey (BG) test of autocorrelation
EMH:	Efficient Market Hypothesis
EGARCH:	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GARCH:	Generalized Autoregressive Conditional Heteroskedasticity
GARCH M:	Generalized Autoregressive Conditional Heteroskedasticity in Mean
GJR GARCH:	Glosten, Jagannathan and Runkle Generalized Autoregressive Conditional Heteroskedasticity
JB:	Jarque Bera test
Ksh:	Kenyan Shilling
NASI:	Nairobi All Share Index
NSE:	Nairobi Securities Exchange
NSE 20 Shares Index:	Nairobi Stock Index 20 Shares
OLS:	Ordinary Least Square
USD:	United States Dollar

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ABSTRACT

The purpose of this study was to model and forecast the stock market volatility at Nairobi Securities Exchange since modeling and forecasting stock market volatility has been the subject of vast theoretical and empirical inquiry. The NSE 20 Share Index was used to generate the daily returns for the market. The study covered ten years of stock market indices and the series of returns (R_t) were generated using the natural logarithm of (P_t/P_{t-1}) . The study used both symmetric and asymmetric GARCH family specifications to model volatility at NSE. The stock market is inefficient in its weak form. The NSE 20 Share Index return was leptokurtosis and skewed to the left, hence it was not normally distributed. It also exhibited serial correlation. The unit root test showed that daily returns are integrated order of one, $I(1)$, which implies that the daily returns are mean reverting in their first difference form. The study indicates that the variance of the returns was not constant. It was time varying, which can be specified as a process of conditional heteroskedasticity. From the parameters estimated using GARCH, GJR GARCH, EGARCH and GARCH M model the returns in stock market exhibit volatility persistency and clustering effect, leverage effect and asymmetric response to external shocks. Further the market is not efficient in pricing risk. Therefore, from the empirical evidence of this study it was possible to deduce that the NSE is not efficient in its weak form and exhibits the stylized facts of financial markets.

Keywords: EMH, GARCH, NSE, Stock Market Volatility.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Modeling and forecasting stock market volatility has been the subject of vast theoretical and empirical inquiry. Many of the applications of volatility require the estimation or forecast of a volatility parameter (Brooks, 2004).

The stock returns volatility has generated heated debates and interests among economists, stock market analysts, government regulatory and policy makers. This interests and debates stem in part from the implication for market efficiency, stock market bubbling, market crash and recession in the financial sectors of the economy (Nyong, 2005).

Volatility as a measure of the intensity of unpredictable changes in asset returns and it is commonly time varying as recognized by Poon and Granger (2003) among others, so that it is possible to think of volatility as a random variable that follows a stochastic process. The task of any volatility model is to describe the historical pattern of volatility and possibly use this to forecast future volatility. An important characteristic of financial stock markets is that the periods of high volatility tend to be more persistent than periods of lower volatilities. Another stylized fact in financial data is that the stock return series exhibit non-normality and excess of kurtosis (Knight and Satchell, 2007).

Most of the traditional time series econometric tools are concerned with modeling the conditional mean of a random variable. However, many of interesting economic theories are designed to work with the conditional variance, or volatility, of a process. Some important empirical applications of the Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982) and generalized by Bollerslev (1986) in GARCH model and its various extensions are used to forecast volatility in stock return series Bollerslev, Chou and Kroner (1992), Bollerslev, Engle and Nelson (1994) and Kroner and Ng (1998).

Therefore, volatility modeling, forecasting and correlation are the crucial factors in risk management and measurement of financial market vulnerability. Further, investor's

ability to appropriately estimate the variability in the asset price movements and relationship among the assets greatly depends on forecasting volatility.

1.1.1. Stock Market Volatility

Volatility, as a measure of percentage change in stock returns is one of the central variables in mainstream financial economics. In fact, much empirical work has been done in this area. And the observed realized daily or monthly returns are not normally distributed as the theory assumes, rather they show fat tails (leptokurtosis) and excess skewedness, which a normal distribution cannot explain (Papa, 2004). Further it is well documented that stock market volatility is asymmetric, clustered, and persistent and has a long term memory.

If the distribution or the variability of returns is known, then it would be possible to forecast returns with higher accuracy. But the question arises that how volatility of stock markets is known, is it constant over time or stochastic or more importantly are the daily or monthly stock returns are normally distributed? Practitioners of the investment industry are very astute, have a sense of the problematic aspects of returns predictability and spend much time and effort in forecasting returns. One of the main conclusions of this sector and also a consensus within the academia is that stock prices are not predictable in the short to medium term and a lot of variability and uncertainty persists.

The first stochastic volatility models, where the market volatility is no longer a constant, but itself follows a stochastic process, normally an Orstein Uhlenbeck process, which excludes negative value and accounts for some mean reverting in the volatility process. Second is what is called the jump process (Poisson counting process). For the plain vanilla Black and Scholes model, the underlying price process is assumed to be a geometrical Brownian motion with constant drift and constant volatility. The jump diffusion process is a special case of the much more general Levy process. Both stochastic volatility and jump process, somewhat improve the pricing capability of the Black and Scholes formula, but empirical research reveals that they do not completely solve the volatility smile issue (Papa, 2004). In addition the relation between implied volatility and realized (historical) volatility is a keen area in finance.

1.1.2. Modeling and Forecasting Stock Market Volatility

Over the last few years, modeling and forecasting volatility of financial time series (asset returns) has become a fertile area of research in finance, and has been receiving considerable attention from academics and practitioners (Knight and Satchell, 2007). This is because volatility is an important concept for many economic and financial applications, like portfolio optimization, risk management, asset pricing and serves as a measure of uncertainty about future price or return changes on assets

A special feature of volatility, which according to Tsay (2010) is the conditional variance of the underlying asset returns, is not directly observable. Consequently, financial analysts are especially keen to obtain good estimates of this conditional variance in order to improve portfolio allocation, risk management or valuation of financial derivatives. Since the 1980s a number of models has been developed that are especially suited to estimate the conditional volatility of financial assets.

To model conditional variance, ARCH model was introduced by Engle (1982). A useful univariant of ARCH model was proposed by Bollerslev (1986) through the Generalized ARCH (GARCH) models which provide a parsimonious alternative to a higher order ARCH model. Though, these models were not able to appropriately address the asymmetric effect often observed in the dynamic of financial variables. And to allow for the possibility to model the different impact on conditional variance of bad news and good news, Nelson (1991) introduced the Exponential GARCH (EGARCH) models.

Since then, there have been a great number of empirical applications of modeling the conditional variance (volatility) of financial time series by employing different specifications of these models and their many extensions.

1.1.3. Over View of Nairobi Securities Exchange

In Kenya, dealing in shares and stocks started in the 1920's though it was in 1954 the Nairobi Stock Exchange was constituted as a voluntary association of stockbrokers registered under the Societies Act. In 2001, basic reformation of the capital market took place and divides the market in to four independent market segments. And recently in July 2011, the Nairobi Stock Exchange Limited changed its name to the Nairobi

Securities Exchange Limited. To incorporate and support the trading, clearing and settlement of equities, debt, derivatives and other associated instruments.

The exchange has two main market indices. The NSE 20 Share Index which is based on a geometric mean of average prices of the twenty constituent companies which are equally weighted. And an all inclusive NSE All Share Index (NASI) which is market capitalization weighted.

Currently, as of July 26th 2013 the NSE 20 Share Index closed at 4,801.63 with a market capitalization of Ksh 1,739.44 Billion and 8,723,200 shares traded since the beginning of the year. Since 2005 the participation of institutional investors in the capital market has increased from 38.89 percentages to 89.01 percentages at the end of the year 2012 living 10.99 percentage to individual investors. On the other hand the participation of foreign investor increased from 3.17 percentages in 2006 to 49.17 percentage at the end of 2012 (ASEA, 2013).

In 2012 the exchange listed 60 companies with a market capitalization of USD 15.9 billion which was 42.05 percent of the country's GDP. The equity value traded for the year 2012 reached to USD 1.084 billion with 342, 235 number of transaction. The sectoral shares of Telecommunication and Technology, Banking and Insurance, Energy and Petroleum and Commercial and Commercial Services were the most active in the market (ASEA, 2013).

1.1.4. Stock Market Volatility at Nairobi Securities Exchange

The volatility pattern exhibited by the stock market during the years of 1998 and 2007 exhibits a decline from a relative high value in 1998 to an all-time low which was experienced in late 2002. The market index from that point exhibits a steady growth to that of 2007 peak.

Through this period volatility was found to be persistent with long memory. Where a decline in the percentage return is followed by another percentage decline in return and vice versa. But it not clear whether the negative external shock is more persistent than the positive resulting asymmetric volatility trend.

Returns that are observed in the markets by Achia, Wangombe and Anyika (2012) are positive except between 1998 and 2001. And the result also reveals that the negative and positive skewness in the above markets explains that the returns from the market do not exhibit normal distribution. The non normal distribution assumption is also supported by the value of Kurtosis in each fragmented period and the return between 1998 and 2007 which shows that the returns in the market exhibits Kurtosis greater than 3, this finding was also supported by Wagala, Nassiuma and Islam (2011).

1.2. Research Problem

Poon and Granger (2003) present a persuasive case for why the forecasting of volatility is a critical activity in financial markets; it has a very wide sphere of influence including investment, security valuation, risk management, and monetary policy making. Specifically, the emphasis is on the importance of volatility forecasting is in pricing of options, underlined by the massive growth in the trading of derivative securities in recent times and financial risk management in the global banking sector in particular and the financial sector in general.

Volatility as a proxy for investment risk which exhibit persistency implies that the risk return trade off changes in a predictable way over the business cycle Shwert (1989). And if volatility on returns could be forecasted based on publicly available information this would have an important implication for portfolio selection and for the smooth functioning of the financial system. Further beyond having efficient estimator for the market dynamics it gives a means to handle potential shocks and variances.

This begs the obvious question of how to effectively model and forecast volatility and is it possible to clearly identify a preferred technique? Various methods by which such forecasts can be achieved have been developed in the literature and applied in practice. Such techniques range from the extremely simplistic models that use random walk assumptions through to the relatively complex conditional heteroskedastic models of the ARCH family.

In the finance literature of Kenya, generally the existing evidence concerning the modeling and forecasting of the volatility of the stock market is limited. Achia, Wangombe and Anyika (2012) in their study to model the volatility of NSE 20 share

index with response to information change proxied by political conditions of the country between 1998 and 2007, divide the time series with election seasons. Sifunjo and Mwasaru (2012) and Nyamute (1998) studied the volatility of the Kenya stock market with response to foreign exchange rate and financial variables like interest rate, money supply, inflation rate and foreign exchange rate respectively. Further, Wagala, Nassiuma and Islam (2011) based their volatility model on weekly returns of selected listed firms which has less frequency than the daily returns and less statistically representative of the stock market.

Notably, most of the papers in modeling volatility are relatively narrow and often restricted with exogenous variables. Their research did not include the investigation of financial time series data time clustering effects and volatility persistency, predictability and leverage effects. Hence, volatility modeling and forecasting has been under researched in the Kenya capital market in general and Nairobi Securities Exchange in particular leaving a room for further studies.

Therefore, the research questions are:

- What is the nature and degree of volatility at Nairobi Securities Exchange?
- Is it possible to model and forecast stock market volatility at Nairobi Securities Exchange? And how to model it?

1.3. Objective of the Study

The objective of this study was to model and forecast the stock market volatility at Nairobi Securities Exchange.

1.4. Value of the Study

The study seeks to extend and supplement the existing empirical evidence on the characteristics of financial time series data at NSE. It will provide a base point to assess investment risk to practitioners, that is, brokers, dealers and specialists. It will be instrumental to individual and institutional investor's decision making process so that they will trade their risk with informed judgment of the market.

It will be valuable to policy makers and executioners like the Capital Market Authority and Central Bank of Kenya and the NSE board in their endeavor to regulate and stabilize the market. It will enhance their understanding about the nature and degree of volatility of returns at the NSE.

Last but not least the study will contribute to the financial literature on NSE volatility modeling and forecasting. It will also serve as a base for further rigorous studies and application of advanced econometric tools in finance academic research.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

This chapter will discuss the various theoretical foundations and models that will provide explanation regarding the concept of volatility modeling and forecast with empirical studies that have been done. The chapter is organized in such a way that the fundamentals theories will be discussed first followed by stylized facts and empirical evidences from local and international perspective finally conclusion will be drawn.

2.2. Theoretical Literature

2.2.1. Random Walk Theory

The idea of stock prices following a random walk is connected to that of the EMH. The premise is that investors react instantaneously to any informational advantages they have thereby eliminating profit opportunities. Dupernex (2007) cited in Lo and McKinley (1999) that prices always fully reflect the information available and no profit can be made from information based trading. And this leads to a random walk where the more efficient the market, the more random the sequence of price changes. However, it should be noted that the EMH and random walks do not amount to the same thing. A random walk of stock prices does not imply that the stock market is efficient with rational investors.

A random walk is defined by the fact that price changes are independent of each other. Or if the safety in numbers is true, then today's change in price is caused only by today's unexpected news, that is yesterday's news is no longer important, and today's return is unrelated to yesterday's return; the returns are independent. If then, returns are independent and then they are random variables and follow a random walk (Edgar E. 1996). Technically the Random Walk with a drift (δ) as an individual stochastic series X_t that behaves can be defined as:

$$X_t = \alpha + X_{t-1} + \varepsilon_{t+1} \quad \varepsilon_{t+1} \sim \text{iid} (0, \delta^2_t)$$

The drift is a simple idea. It is merely a weighted average of the probabilities of each price the stock price could possibly move to in the next period (Brealey and Meyers, 2005).

However, even though it is useful, the model is quite restrictive as it assumes that there is no probabilistic independence between consecutive price increments. Market efficiency does not necessarily imply a random walk, but a random walk does imply market efficiency. Therefore, the assumption that returns are normally distributed is not necessarily implied by efficient markets. However, there is a very deeply rooted assumption of independence. Most tests of the EMH also test the random walk version. In addition, the EMH in any version says that past information does not affect market activity or return, once the information is generally known (Edgar, 1996).

2.2.2. Chaos Theory

Chaos is a bounded deterministic system with a positive Lyapunov exponent. A more intuitive definition came from the Royal Society of London in 1986, where chaos is stochastic behavior occurring in a deterministic system. A chaotic system will show random results to a repeated experiment on such a deterministic system. This may be counterintuitive to the common sense given that knowledge of a system's current state and evolutionary path should lead to predictions of all future states in the absence of random variables (Kuchta, 2012).

A defining characteristic of chaotic systems is that they have sensitive dependence to initial conditions. Any degree of uncertainty in the initial data, as often occurs in measuring, will grow as the system evolves (Kuchta, 2012). Moreover, the errors will propagate in unpredictable ways, making forecasting impossible. Therefore, a chaotic system has both local randomness and global determinism and these systems can be manmade or natural and can occur in social structures and in human beings (Cohen, 1997).

The independence of higher moments gives random walk theory the attribute that price movements will not follow any trends. In this specification, the independence of today's information and tomorrow's prices implies efficient markets. If the Efficient Market Hypothesis holds, then profits in asset markets exhibiting random properties can be

observed, and test for the randomness of chaos and nonlinearity can be conducted (Barnett and Apostolos, 1998).

If there is nonlinearity or chaos, then the exciting possibility of forecasting asset prices exists. However, if we can predict next period's prices, then it must not be independent of the current information set, and last period's price was not the best estimate. Predictability will reject the Efficient Market Hypothesis which is how the test for chaos originally came (Persaran, 1992).

2.2.3. Martingale Process

It is a more flexible model than the random walk. It is devised to improve the random walk model as it can be generated within a reasonably broad class of optimizing models (LeRoy, 1989). Dupernex (2007) cited in (Elton et al, 2002) that a martingale is a stochastic variable X_t which has the property that given the information set Ω_t , there is no way an investor can use Ω_t to profit beyond the level which is consistent with the risk inherent in the security. The martingale is superior to the random walk because stock prices are known to go through periods of high and low turbulence. This behavior could be represented by a model in which successive conditional variances of stock prices (but not their successive levels) are positively auto correlated (LeRoy, 1989). This could be done with a martingale, but not with a random walk.

2.3. Empirical Literature

2.3.1. Volatility in Financial Time Series: Stylized Facts

Financial time series is concerned with a sequence of observations on financial data obtained in a fixed period of time. According to Tsay financial time series data analysis is different from other time series analysis because the financial theory and its empirical time series contain an element of complex dynamic system with a high volatility and a great amount of noise (Tsay, 2010). Yonis cited in Cont (2000) that the uncertainty and noise makes the series to exhibit some statistical regularity, which is known as stylized facts. Stylized facts are empirical observations that are so consistence and have been made in so many contexts that they are accepted as truth. Stylized facts are obtained by

taking a common denominator among the properties observed in studies of different markets and instruments.

Therefore, the patterns that the financial time series follows and which are also crucial for correct model specification, estimation and forecast are:

1. ***Fat Tails:*** The distribution of financial time series like stock returns, exhibit fatter tails than those of normal distribution, that is, they exhibit excess kurtosis.
2. ***Volatility Clustering:*** The second stylized fact is the clustering of periods of volatility, that is, large movements followed by further large movements and vice versa. This is an indication of shock persistence. Correlograms and corresponding Box-Ljung statistics show significant correlation which exist at extended lag length (Knight and Satchell, 2007).
3. ***Leverage Effects:*** Price movements are negatively correlated with volatility. Knight and Satchell (2007) cited in Black (1976) this is true for stock returns however Black argued that the measured effect of stock price changes on volatility was too large to be explained solely by leverage effect. Nelson (1991) also suggested that volatility does not keep constant and returns stay closer.
4. ***Long Memory:*** Especially in high frequency data. Volatility is highly persistent. And there is evidence of near unit root behavior in the conditional variance process. These observations lead to two propositions for modeling persistence: the unit root or the long memory process. The ARCH and Stochastic Volatility (SV) models use the latter idea for modeling persistence (Knight and Satchell, 2007).
5. ***Co-movement in Volatility:*** When financial time series is looked across different markets like exchange rates for different currencies, it is observed that big movements in one currency being matched by big movements in another. This suggests the importance of multivariate models in modeling cross correlations in different markets (Nelson, 1991).
6. ***Skewness:*** The effect of skewness may be positive or negative, which describes their departure from symmetry.

7. ***Long-range dependence in the data:*** 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 behavior suggests that there is some kind of long range dependence in the data.

Therefore, to get reliable forecasts of future volatilities it is crucial to account for the stylized facts.

2.3.2. Stock Market Volatility Modeling and Forecast

For market performance, the stability of stock returns ought to be a major concern. This of course is linked to the efficiency of the market. In Austria, Spain, Italy and Japan, Cheung and Lai (1995) established empirically strong evidence of market inefficiency in their stock returns. In a similar manner, Forgha (2012) provided empirical evidence on the efficiency and volatility of stock returns in five stock markets in Africa namely, Cameroon, Nigeria, South Africa, Egypt and Kenya. And he established that markets are proven to be inefficient based on GARCH-M, ADF and the Variance Ratio tests. And Nyong (2005) based on stock returns in three emerging markets: Nigeria, South Africa and Brazil reject the random walk hypothesis designed to explain markets efficiency.

Forecasting stock market return volatility has great importance for both investors, traders and researchers, because predicting volatility might enable one to take risk minimized decisions including portfolio selection and option pricing. Recent financial turbulence once again proved the importance of reasonable measurement of uncertainty in financial markets. This uncertainty is usually known as volatility which has crucial significance to financial decision makers as well as policy makers (Asarkaya, 2005).

Forecasting volatility has attracted the interest of many academicians; hence various models ranging from simplest models such as random walk to the more complex conditional heteroskedastic models of the ARCH family have been used to forecast volatility. Over the past two decades, there have been many applications of ARCH and GARCH models to stock indices returns. More recently, asymmetric volatility models have been proposed to incorporate more effect. Through the years different variations of the GARCH model has been used to forecast volatility. These models include E-

GARCH, GJR-GARCH, GARCH-M, T-GARCH, VS-GARCH, QGARCH and many more.

Therefore, there is the general consensus that the appropriate approach to examine the efficiency and the volatility of stock returns is the ARCH developed by Engel (1982). The ARCH approach and its various modifications have been shown to provide a good fit to many financial return time series than other forecasting methods such as Random Walk (RW), Historical Mean (HM), Moving Average (MA) and Exponential Smoothing (ES) (Poon and Granger 2003; Taylor 1992; Engel and Bollersler 1986; Nelson 1991). This is because changes in the variability of returns over time are expected to impact on the risk or profit of an investment (Nyong, 2005).

The empirical successes and acceptance of the GARCH models in fitting volatility of stock returns notwithstanding, Udo (2000) warned that one should not be over optimistic about its forecasting results especially regarding the out of sample forecasting performance. This assertion seems to agree with empirical evidence by Zivot (2008) that the GARCH models do not forecast very well. Udo (2000) and Zivot (2008) conjectures provide an indication that no single model is clearly superior. The above recognition, perhaps, may have constrained the likes of Engel (1982) and Gujarati (2004) to admit that modeling is a probabilistic process. Consequently, some models tend to perform better in some periods and worse in other periods

2.3.3. Stock Market Volatility and Forecast at Nairobi Securities Exchange

For emerging African markets, Ogum, Beer and Nouyrigat (2005) investigate the market volatility using Nigeria and Kenya stock return series. Results of the exponential GARCH model indicate that asymmetric volatility found in developed markets are also present in Nigerian Stock Exchange, but Kenya shows evidence of significant and positive asymmetric volatility. Also, they show that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the Nigerian Stock Exchange return series exhibit a significant and positive time-varying risk premium.

By using asymmetric GARCH models Alagidede and Panagiotidis (2009) investigate the extent of volatility on the largest African stock markets (namely Egypt, Morocco, Nigeria, Kenya, South Africa, Tunisia and Zimbabwe). They find that these markets are highly volatile; however investors are usually compensated by a higher risk premium. Surprisingly, a higher level of volatility is found in markets that are less liberalized and less open to foreign investors.

Achia, Wangombe and Anyika (2012) measured the volatility NSE 20 share index between 1998 and 2007 by the absolute change in the rate of return and showed the positive serial correlation in the markets as expected. While imposing exogenous variable they also tested the market for EMH and their results indicate that the hypothesis is not satisfied as in their paper both the ARIMA (1, 1, 1) and the GARCH (1, 1) models are fit to the data. The random walk process that holds EMH is rejected.

By using NSE 20 share index from 1992 to 2003 to generate the daily returns, Muriu (2003) showed that the equity returns exhibit negative skewness, excess kurtosis and deviation from normality hence returns are predictable and therefore rejecting the weak form efficiency. And the asymmetric GARCH test showed leverage effect with volatility clustering. Persistence of conditional volatility as measured by the sum of alpha and beta is less than unity, an indication that it is stationary (mean reverting) and therefore not explosive. Stochastic process was also indicated by the ARCH-LM test than the chaos process. While Muriu (2003) volatility modeling was rigorous her study did not include volatility forecast estimation and evaluation for the market index.

Wagala, Nassiuma and Islam (2011) used the weekly average prices of three selected firms and the NSE 20 share index weekly average ranging from 1996 and 2010 to determine the most efficient model from the symmetric and the asymmetric models. And their results show that the Integrated GARCH (IGARCH) models with student's t distribution are the best models for modeling volatility in the Nairobi Stock Market data. Since their study base on weekly average index while the daily return can be observed, given that high frequency data are preferable for such type of financial time series analysis. Therefore, the weekly index imposes unnecessary generalization over the daily

returns. Further the study of individual asset along market aggregate index like NSE 20 share index may require multivariate analysis rather than univariate analysis.

Other studies which have been done by Sifunjo and Mwasaru (2012) and Nyamute (1998) can also be considered as volatility modeling with exogenously imposed variables. Causal relationship between the stock market and the currency market in was observed by Sifunjo and Mwasaru (2012) by concluding volatility spill over from the currency market to the stock exchange market.

2.4. Summary of the Literature Review

The classical EMH which followed the random walk assumption has been empirically tested for both developed and developing countries financial markets and the evidence failed to accept EMH. From the rejection of EMH the test for Chaos and non linearity in returns in the financial market give the possibility of forecasting asset prices. Further the Martingale process allowed for the financial time series data to be modeled in a successive conditional variance of the asset prices.

The empirical evidence generated from the financial markets suggested for stylizes of the behavior of the financial time series data's. This stylized facts established excess skewness and leptokurtosis distribution. Further the volatility of stock market returns have a tendency to cluster, persist and generate a leverage effect.

In modeling and forecasting stock market volatility the ARCH family models has been used by various studies. Empirical evidences generated from the developed capital markets used both symmetric and asymmetric GARCH extensions while the existing literature on developing countries volatility modeling and forecasting has not yet implemented those models and lack rigorous empirical evidences.

In conclusion, the developing countries financial market in general and African countries in particular has been under researched as far as volatility modeling is concerned. From the available literature, the NSE just like other African equity markets has been under researched which leaves a gap to be filled.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. Introduction

The following chapter discusses the research design which will be implemented, the population, sample size and the type of data which will be used. Further this chapter explains how the data will be analyzed and conclusion will be derived.

3.2. Research Design

Empirical research design was applied in this research since it is the most relevant form for time series data analysis. It also allows the behavior of the time series data, which will be sampled at a regular interval, to be studied before a particular model can be applied to analyze the data.

Therefore, the empirical methodology helps to avoid the possibility of generating wrong results and conclusions. Further the nature of the data analysis will be determined by the actual behavior of the financial data rather than a preconceived notion.

3.3. Population and Sample Design

In order to measure the daily returns of the Nairobi Securities Exchange the daily index of the stock market proxied by NSE 20 share index were observed. And from the observed index the financial time series data for the exchange will be generated on a daily basis. The index is useful in determining the performance of the NSE by measuring the general price movement in the major 20 shares of listed firms of the stock exchange.

The daily NSE 20 share index was obtained from NSE covering for the period nine years from July 1st 2004 to June 30th 2013.

And the daily returns, R_t , was calculated as:

$$R_t = \ln(P_t/P_{t-1})$$

Given that P_t will be observed as the daily NSE 20 share index.

3.4. Data Analysis

In order to model and forecast the volatility of the NSE 20 share index various tests and advanced econometric tools were employed on the daily returns by using Eviews 5 statistical software. Further the research will include descriptive analysis of the daily returns which will be presented by explaining all moments (Mean, Std. Div., Skewness and Kurtosis) of the distribution and graphical representation of volatility in the market.

The specific tests which will be engaged in this study are presented below.

3.4.1. Stock Market Analysis

The market efficiency was analyzed using the parametric tests since their use are tied with the assumption of a correctly specified model. Therefore, these tests were used to estimate the parameters and for testing hypotheses about the parameters on the assumption that the models are correctly specified. Then if the EMH is rejected it could be the case that the market is truly inefficient not due to a miss specified equilibrium model.

3.4.1.1. Test for Normality

The EMH implies that returns are normally distributed with zero Skewness and Kurtosis three. But financial time series data exhibit Skewness different from zero and Kurtosis greater than three. Therefore, Jarque Bera (JB) test of normality was employed. The JB test of normality is an asymptotic, or it is a test of goodness to fit to normal distribution for a large sample size, test. It is also based on the OLS residuals and uses the chi-square distribution with 2 degree of freedom Gujarati (2004).

H₀: The error terms are normally distributed.

H₁: The error terms are not normally distributed.

If the Null hypothesis is rejected, then the market is not efficient in its weak form and the returns are not normally distributed.

3.4.1.2. Test for Serial Correlation

The most common problem with a time series data's and specifically with financial time series data is serial correlation. Serial correlation violates Gauss Markov assumption that the error terms are not correlated with each other across time. And the error terms are not correlated with the independent variables. For an OLS to be best linear unbiased estimate the serial correlation must be corrected.

Following Gujarati (2004) to avoid some of the pitfalls of the DurbinWatson d test of autocorrelation, the Breusch and Godfrey (BG) test of autocorrelation was used. Which allow a sense for nonstochastic regressors, such as the lagged values of the regressand and higher order autoregressive scheme.

3.4.1.3. Stationary Test

Rejecting normality and detecting serial correlation in the error term suggests the presence of a trend in the data. A unit root test can be used to check whether trending data should be first differenced or regressed on deterministic function of time to achieve stationarity in the data.

Since the error terms are correlated the Augmented Dickey Fuller (ADF) test was used than the Dickey Fuller test itself.

Gujarati (2004) ADF follows the process of:

$$\Delta R_t = \beta_1 + \beta_2 t + \delta R_{t-1} + \alpha_i \sum \Delta R_{t-i} + \varepsilon_t$$

The Summation (\sum) runs from $i=1$ to m .

If $\delta = 0$, R_t is stationary around the deterministic trend β_1 that is evidence for efficient market but if $\delta \neq 0$, then R_t is non stationary, hence shows no tendency to return to the equilibrium value of the random shock in the market.

3.4.1.4. Test for ARCH Effect

A model that can capture the conditional heteroskedasticity of financial time series was developed by Engle in 1982 for the first time. The model is called Autoregressive Conditional Heteroskedasticity ARCH (Engle, 1982).

$$\delta_t^2 = \alpha_0 + \sum \alpha_1 \varepsilon_{t-1}^2 + u_t$$

The Summation (Σ) runs from $t=1$ to q .

$$(t - q) * R^2 \sim \chi_p^2 \text{ (Chi square)}$$

$$\mathbf{H}_0: \alpha_0, \alpha_1, \text{ and } \alpha_q = 0$$

$$\mathbf{H}_1: \alpha_0 \neq 0, \alpha_1 \neq 0, \text{ or } \alpha_q \neq 0$$

If the value of the test statistics is greater than the critical value from chi square distribution, then the joint null hypothesis will be rejected hence the data displays ARCH effect.

3.4.2. Volatility Analysis

In order to model and forecast volatility in stock market the symmetric GARCH and the asymmetric GJR GARCH, E GARCH and GARCH-M were estimated.

3.4.2.1. GARCH

Following Brooks (2008) the GARCH model which allow the conditional variance to be dependent upon previous own lags, so that the conditional variance equation in the simplest case can be estimated as:

$$\delta_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \delta_{t-1}^2$$

This is a GARCH (1, 1) model. δ_t^2 is known as the conditional variance since it is a one period ahead estimate for the variance calculated based on any past information thought relevant. Using the GARCH model it is possible to interpret the current fitted variance, h_t , as a weighted function of a long-term average value (dependent on α_0), information about volatility during the previous period ($\alpha_1 \varepsilon_{t-1}^2$) and the fitted variance from the model during the previous period ($\beta \delta_{t-1}^2$).

And The GARCH (1,1) model can be extended to a GARCH (p,q) formulation, where the current conditional variance is parameterised to depend upon q lags of the squared error and p lags of the conditional variance as follows.

$$\delta_t^2 = \alpha_0 + \sum \alpha_i \varepsilon_{t-i}^2 + \sum \beta_i \delta_{t-i}^2 + \eta_t$$

The first summation (\sum) runs from $t=1$ to p while the second summation runs from $t=1$ to q .

3.4.2.2. GJR GARCH

Following Brooks (2008) the GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries. The conditional variance is now given by:

$$\delta_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \delta_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

Where $I_{t-1} = 1$ if $\varepsilon_{t-1} < 0$

$= 0$ otherwise

For a leverage effect, we would see $\gamma > 0$. Notice now that the condition for no negativity will be $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + \gamma \geq 0$. That is, the model is still admissible, even if $\gamma < 0$, provided that $\alpha_1 + \gamma \geq 0$.

3.4.2.3. EGARCH

Brook (2008) cited the exponential GARCH model which was proposed by Nelson (1991) and according to Nelson proposition there are various ways to express the conditional variance equation, but one possible specification can be given by:

$$\begin{aligned} \text{Ln}(\delta_t^2) = & \omega + \beta \text{Ln}(\delta_{t-1}^2) + \gamma [(\varepsilon_{t-1}) / (\sqrt{\delta_{t-1}^2})] \\ & + \alpha \{ [|\varepsilon_{t-1}| / \sqrt{\delta_{t-1}^2}] - [\sqrt{2/\pi}] \} \end{aligned}$$

The model has several advantages over the pure GARCH specification. First, since the $\log(\delta_t^2)$ is modeled, then even if the parameters are negative, δ_t^2 will be positive. There is thus no need to artificially impose non negativity constraints on the model parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ , will be negative.

3.4.2.4. GARCH M

Most models used in finance suppose that investors should be rewarded for taking additional risk by obtaining a higher return. One way to operationalize this concept is to let the return of a security be partly determined by its risk. Brook (2008) cited in Engle, Lilien and Robins (1987) suggestion of the ARCH-M specification, where the conditional variance of asset returns enters into the conditional mean equation. Since GARCH models are now considerably more popular than ARCH, it is more common to estimate a GARCH-M model. The GARCH-M model can be in specified as:

$$R_t = \Pi + \beta\delta_{t-1} + \varepsilon_t, \quad \Pi \sim N(0, \delta_t^2)$$

$$\delta_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\delta_{t-1}^2$$

If δ is positive and statistically significant, then increased risk, given by an increase in the conditional variance, leads to a rise in the mean return. Thus δ can be interpreted as a risk premium. In some empirical applications, the conditional variance term, δ_{t-1}^2 , appears directly in the conditional mean equation, rather than in square root form, δ_{t-1} . Also, in some applications the term is contemporaneous, δ_t^2 , rather than lagged.

3.4.3. Forecast Evaluation

For the symmetric loss functions the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil inequality coefficient (TIC) were employed to measure the accuracy of the forecasting models.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSIONS

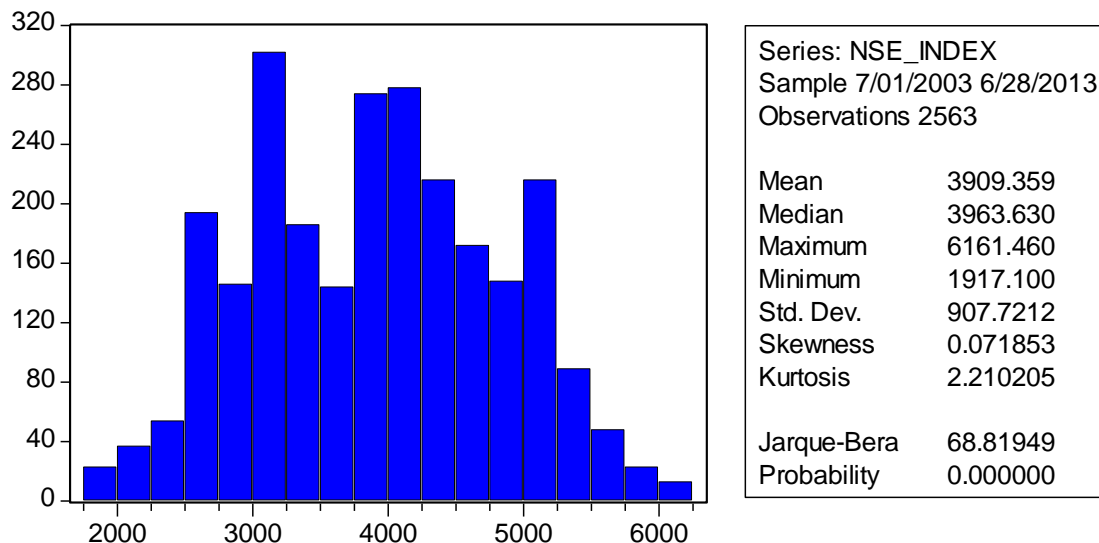
4.1. Introduction

In this study, the sets of data consisting of the daily NSE 20 Share Index were used. The data was obtained from the NSE for the period ranging between 1st July 2003 and June 28th 2013. This chapter presents the results of data analysis and discussion of the findings. The general description of NSE 20 share index is presented in section 4.2 followed by section 4.3 which presented the results of the analysis of stock market efficiency tests and section 4.4 examined the results of volatility.

4.2. Brief Description of NSE 20 Share index

The NSE 20 Share Index is a weighted mean with 1966 as the base year at 100 bases point. It is based on 20 companies calculated on a daily basis. The index is useful in determining the performance of the NSE by measuring the general price movement in the listed shares of the stock exchange.

Figure 4.1. NSE 20 Share Index Histogram covering from July 2003 to June 2013.

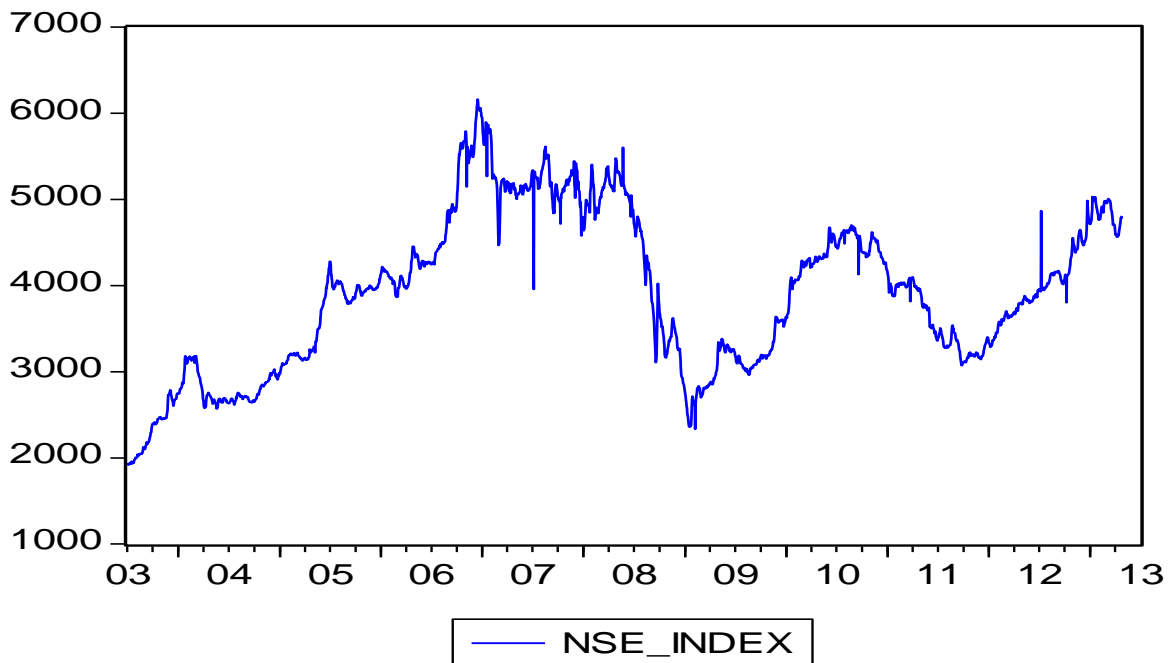


From Figure 4.1, the NSE 20 Share Index achieved all high value in 2007 with 6161.46 bases point while the lowest was 1917.10 bases point which was at the beginning of the

period. The market has rather thin tail and slightly skewed to the right, that show slow rate of growth. Further the market exhibit high standard deviation from its mean value for the period. The standard deviation observed from the data indicates the presence of high volatility in market and risky nature of the stock market.

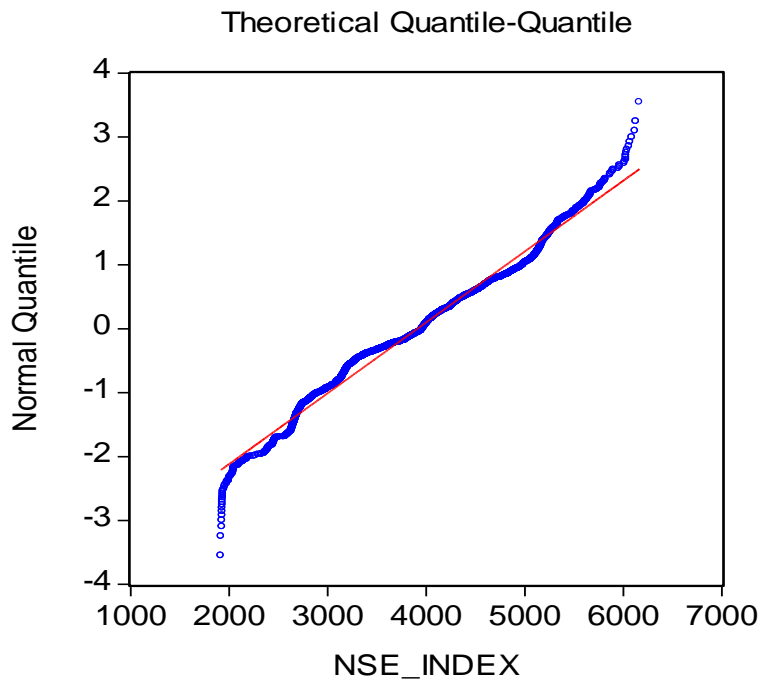
Further by using graphical representation of the market index for the period covered it is possible to identify patterns that exist in the NSE 20 Share Index series. Figure 4.2 shows that persistent increase since 2003 to the mid of 2007 followed by persistent decline until mid of 2008. Since 2009 the market exhibited short term surge in both directions and change in trajectory was common.

Figure 4.2.NSE 20 Share Index Series from July 2003 to June 2013.



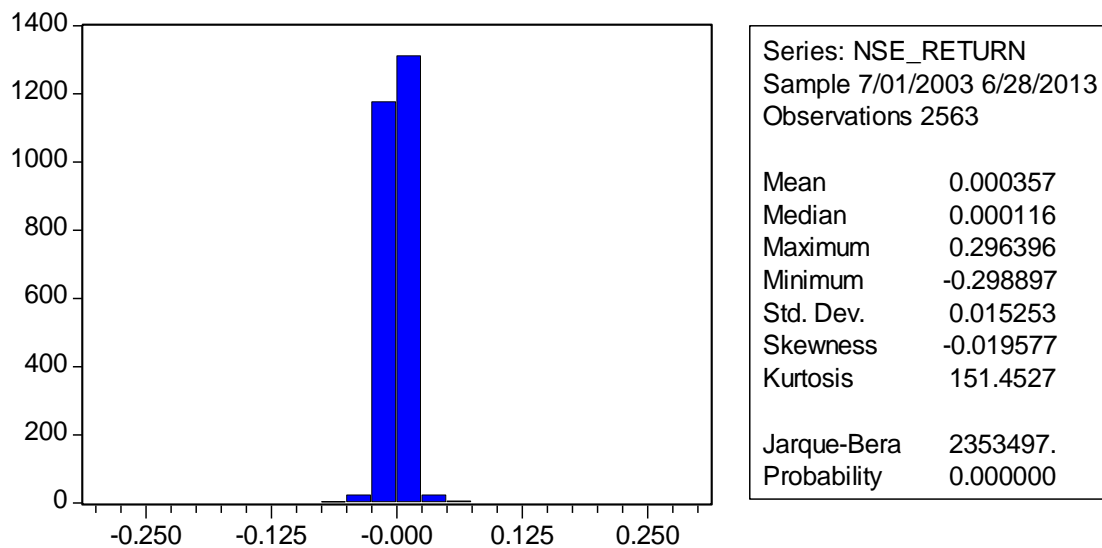
By observing the Quantile-Quantile normal probability distribution pattern it was also possible to assess whether the NSE 20 Share Index distribution are linearly related with standard normal distribution. Figure 4.3 showed that the two lines are close to each other, therefore, the distribution of NSE 20 Share Index is normally distributed.

Figure 4.3.NSE 20 Share Index Quantile-Quantile Distributions.



After generating a series for the daily rate of return of the market by using the daily NSE 20 Share Index it was possible to capture the unique nature and characteristics of the NSE at preliminary state.

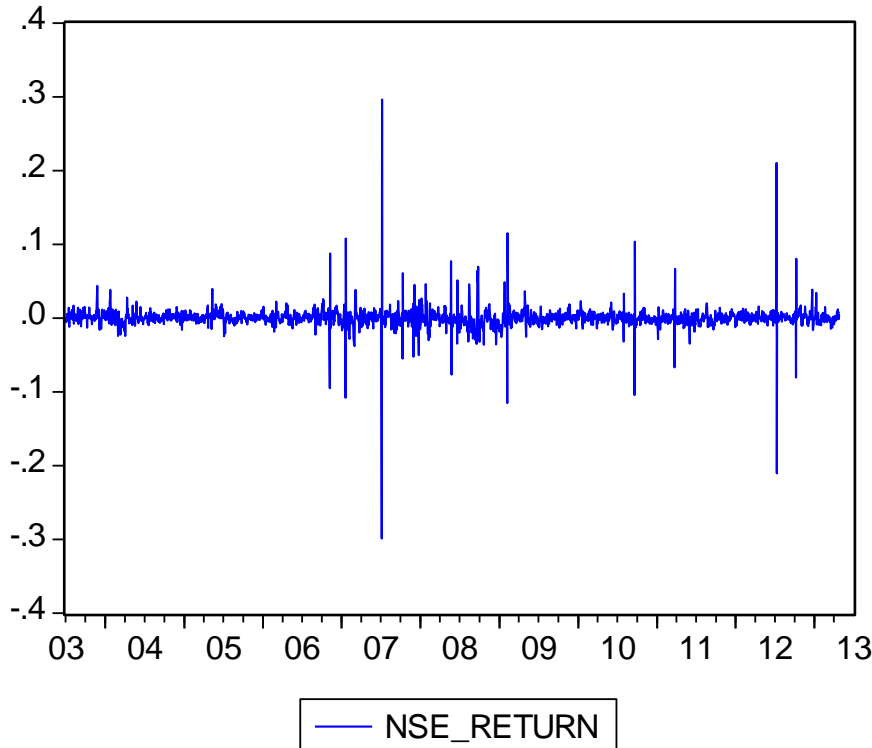
Figure 4.4.Histogram for the Daily Returns of NSE 20 Share Index series.



The market has a mean return of 0.00357 with standard deviation of 0.01525 with the fat tail. Observing Figure 4.4 showed that the rate of return is concentrated around the mean with slight negative skewness. The excess kurtosis and negative skewness observed are consistent with previous studies done on earlier time periods.

Further from the series generated in Figure 4.5 shows that volatility clustering and persistence mainly between 2006 and 2008 and beyond 2012 were current. Along with the highest pick of the NSE 20 Share index in 2007 it was also observed that there was high volatility during this period magnifying the external shock which was exerted in the stock market.

Figure 4.5. Series generated for NSE 20 Share Index rate of return.



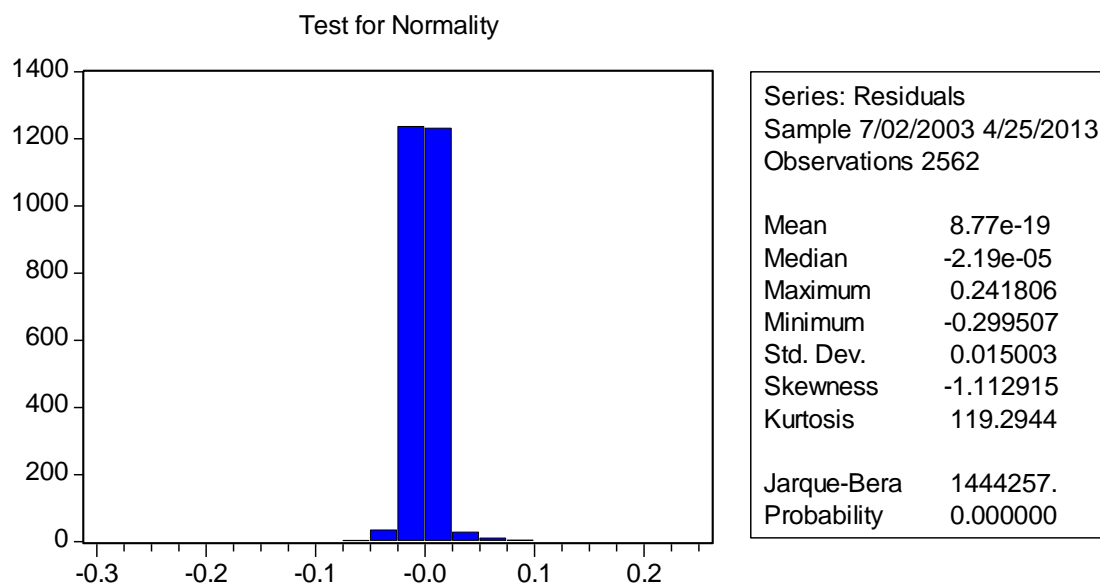
4.3. Results of Stock Market Analysis

This section presents the results of testing the EMH at NSE. The focus of the EMH was on the assumption of normally distributed error term of the returns, absence of serial correlation in the error term and a constant risk premium. The first steps of the analysis were to examine the time series characteristics of the data set and run various tests.

4.3.1. Result of Test for Normality

One reason for the rejection of market efficiency is the presence of non-normally distributed error terms. In this study the JB test of goodness of fit to the normal distribution was implemented. The test was applied to the daily returns of the NSE 20 Share Index. The result is summarized in Figure 4.6. For normal distribution the sample skewness and kurtosis should be close to zero and three respectively while the data set shows fat tails and skewed to the left. The JB test shows that the sample skewness and kurtosis are significantly different from their mean values as measured by chi square distribution. Since the error terms of the daily returns are not normally distributed, a kurtosis of 119.2944 and skewness of -1.1129. Therefore, the assumption that the daily returns are normally distributed is rejected.

Figure 4.6. Test for Normality.



4.3.2. Result of Test for Serial Correlation

The result of the serial correlation test using Breusch-Godfrey Serial Correlation LM Test is presented in Table 4.1 and Appendix A. Another reason for the rejection of the EMH of the stock market is the presence of serial correlation in the error term.

Table 4.1. Breusch-Godfrey Serial Correlation LM Test.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.89E-05	0.000299	0.331349	0.7404
NSE_RETURN(-1)	-0.277153	0.107128	-2.587118	0.0097
RESID(-1)	0.286566	0.108932	2.630679	0.0086

The results indicate that there is statistically significant negative serial correlation in the error terms of the daily returns. Therefore, from this evidence the returns from NSE 20 Share Index are serially correlated and violate the assumption of EMH.

4.3.3. Result of Stationary Test

Rejecting normality and detecting serial correlation in the error terms suggested the presence of trend in the data hence ADF test was conducted to examine the presence trend in data. The stationary test results are summarized in Table 4.2 and Appendix A.

Table 4.2. Unit Root Test.

	t-Statistic	Prob.
Augmented Dickey-Fuller test statistic	-52.57125	0.0000
Test critical values:		
1% level	-3.961630	
5% level	-3.411564	
10% level	-3.127648	

The computed t-statistics in absolute terms was found to be higher than the t-statistics critical level for 1 and 5 percent significance level which are 2.326 and 1.645 respectively. Therefore, the returns are stationary in their first difference form and this implies that returns may deviate from their mean in the short run due to exogenous shocks but in the long run they tend to revert to their mean value in their first difference.

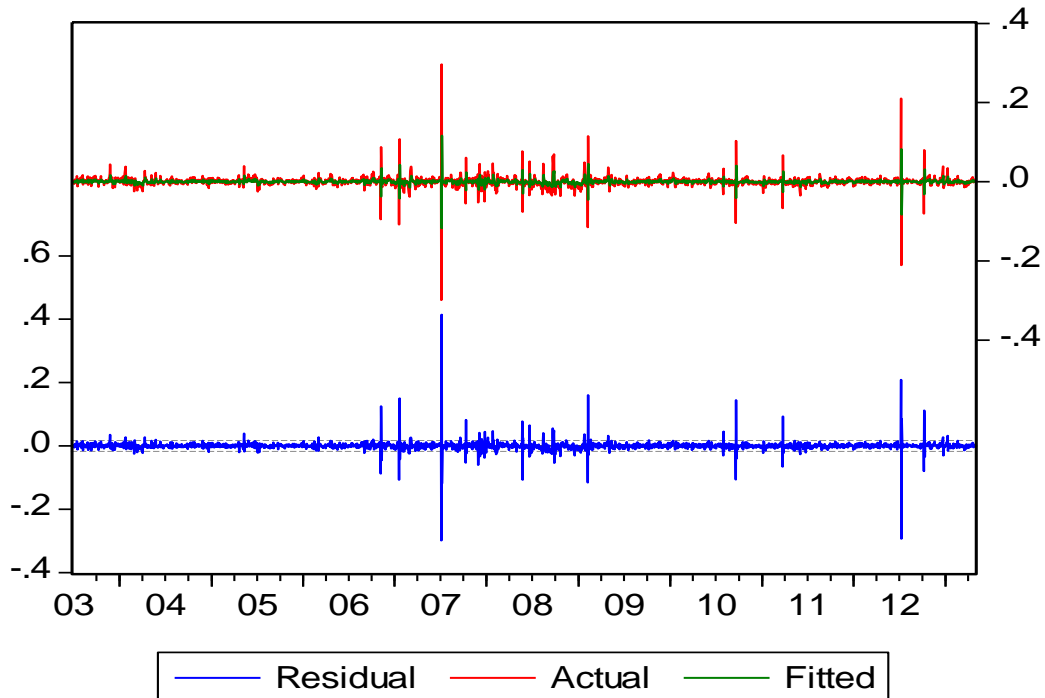
4.3.4. Result of Test for ARCH Effect

The ARCH(1) model was estimated to the daily returns of NSE 20 Share Index and the results are shown in Table 4.3 and Appendix A. The daily returns of the market were on average 0.3937 times dependent on their own lag. Further the error terms of today were also statistically significantly dependent on its own lag.

Table 4.3.ARCH parameter estimation.

	Coefficient	Std. Error	z-Statistic	Prob.
C	-5.08E-05	0.000223	-0.227949	0.8197
NSE_RETURN(-1)	0.393709	0.027257	14.44444	0.0000
Variance Equation				
C	0.000123	3.72E-07	330.7720	0.0000
RESID(-1)^2	0.336162	0.024367	13.79567	0.0000

Figure 4.7.The Residual of the ARCH model with the Actual and Fitted.



Graphically it was clear to observe the autoregressive nature of the residuals with non constant variance. Figure 4.7 shows that the fitted, which are, the estimated errors closely fit the actual observed errors. Both the estimated and the actual returns follow the same patten and this was statistically significant.

From Table 4.4 the ARCH-LM test indicate that the calculated F-statistics is greater than the F-statistics critical level, which rejected the Null Hypothesis, which was, No-ARCH. Therefore, the NSE 20 Share Index daily return exhibit ARCH effect.

Table 4.4.ARCH-LM Test

ARCH Test:

F-statistic	723.2225	Probability	0.000000
Obs*R-squared	564.3045	Probability	0.000000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000119	4.29E-05	2.783688	0.0054
RESID^2(-1)	0.469410	0.017455	26.89280	0.0000

4.4. Result of Volatility Analysis

4.4.1. Result of GARCH Analysis

The GARCH(1,1) model representation was employed to determine the presence of GARCH effect on the daily returns of NSE 20 Share Index. The results shown in Table 4.5 signify that the daily returns exhibit GARCH effect in the data set. The coefficients for the lagged conditional variance in the GARCH estimation show that 0.34 daily returns volatility is carried over the next day. These results indicate the presence of volatility clustering effect in returns of NSE 20 Share Index.

Table 4.5.GARCH parameter estimation.

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000228	0.000553	0.412337	0.6801
NSE_RETURN(-1)	0.337858	0.041803	8.082236	0.0000
Variance Equation				
C	0.000328	9.15E-08	3587.362	0.0000
RESID(-1)^2	0.223344	0.024319	9.183866	0.0000
GARCH(-1)	-0.078552	0.005179	-15.16628	0.0000

The GARCH model can be specified as follows:

$$NSE_RETURN = 0.0002278216325 + 0.3378580761 * NSE_RETURN(-1)$$

$$GARCH = 0.0003281262441 + 0.2233435819 * RESID(-1)^2 - 0.07855207626 * GARCH(-1)$$

4.4.2. Result of GJR GARCH Analysis

The leverage effect, the relationship between stock market volatility and returns, was tested using GJR GARCH model and Table 4.6 summarized the results.

The GJR GARCH model can be represents as follows:

$$NSE_RETURN = -2.019401878e-007 + 0.3574811848 * NSE_RETURN(-1)$$

$$GARCH = 0.0003051586246 + 0.1425137993 * RESID(-1)^2 + 0.1713614897 * RESID(-1)^2 * (RESID(-1) < 0) - 0.04523492343 * GARCH(-1)$$

The presence of leverage effect was detected by analyzing γ , which is 0.171361 which is greater than zero and statistically significant. Therefore, the null hypothesis was accepted, in compliance the existence of leverage effect. This indicate that the higher the volatility rate at NSE the lower the return of the stock market and this concurs with the stylized facts of financial markets.

Table 4.6.GJR GARCH parameter estimation.

	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.02E-07	0.000632	-0.000319	0.9997
NSE_RETURN(-1)	0.357481	0.044080	8.109743	0.0000
Variance Equation				
C	0.000305	1.87E-06	163.0909	0.0000
RESID(-1)^2	0.142514	0.023323	6.110319	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.171361	0.055025	3.114241	0.0018
GARCH(-1)	-0.045235	7.03E-06	-6434.036	0.0000

4.4.3. Result of E GARCH Analysis

To allow for asymmetries and avoid the artificial impositions of negative constraints the E GARCH model was used on the daily returns of the stock market. The summary of the result are shown in Table 4.7.

Table 4.7.EGARCH parameter estimation.

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000227	0.000209	1.089041	0.2761
NSE_RETURN(-1)	0.395548	0.023024	17.17963	0.0000
Variance Equation				
C(3)	-7.058622	0.224303	-31.46916	0.0000
C(4)	0.481970	0.026918	17.90515	0.0000
C(5)	-0.040260	0.021324	-1.888014	0.0590
C(6)	0.227899	0.024553	9.282028	0.0000

And the E GARCH model representation can be captured by:

$$NSE_RETURN = 0.0002273840563 + 0.3955477524 * NSE_RETURN(-1)$$

$$LOG(GARCH) = -7.058622096 + 0.4819701642 * ABS(RESID(-1) / @SQRT(GARCH(-1))) - 0.04026021347 * RESID(-1) / @SQRT(GARCH(-1)) + 0.227899202 * LOG(GARCH(-1))$$

From the study model specification parameter γ , which is C(5), is negative and statistically significant. This entails that, positive shocks to the market contribute to smaller increase in volatility in the stock market than a negative shock equal in magnitude on a daily base. And this is consistent with the previous established stylized facts.

4.4.4. Result of GARCH M Analysis

The GARCH M was estimated for the daily returns. The results are displayed in Table 4.8 shows that the market is likely to respond to volatility asymmetrically.

Table 4.8.GARCH M parameter estimation.

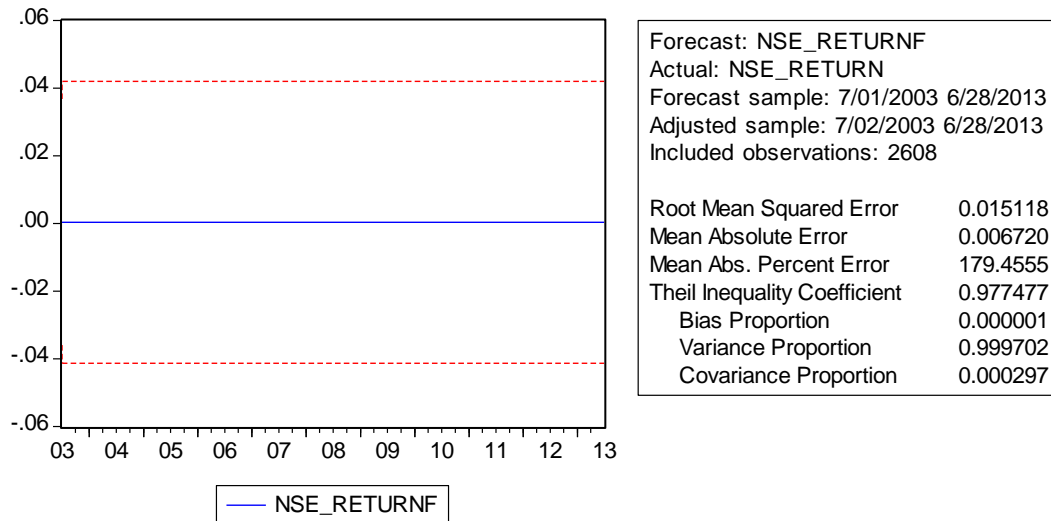
	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	5.239183	1.419228	3.691573	0.0002
C	-0.001689	0.000764	-2.209808	0.0271
NSE_RETURN(-1)	0.336715	0.042713	7.883168	0.0000
Variance Equation				
C	0.000299	1.44E-05	20.70744	0.0000
RESID(-1)^2	0.242780	0.032821	7.397173	0.0000
GARCH(-1)	-0.052156	0.050649	-1.029757	0.3031

The coefficient of the variance term, that is, GARCH parameter is negative and it is not statistically significant. But it is true that the market is likely to increase return as risk increase or vice versa. And in general this model shows that the market does not price risk efficiently.

4.4.5. Result of Forecast Evaluation

The main emphasis of this study was on modeling volatility albeit forecasting is also the prime objective of modeling. Therefore, the volatility forecasts of the series based on the models chosen by the prescribed forecasting performance error functions are generated in Graph 4.8 below. This forecast was generated using Eviews 5 statistical software.

Figure 4.8. Stock Market Volatility Forecast Analysis.



The results of volatility forecasts performance and evaluations are also incorporated in Graph 8. The statistics for accomplishing this are already enumerated in section 3.4.3 of this study. They include Root Mean Squared Error (RMSE) of 0.015118, Mean Absolute Error (MAE) of 0.00672, Mean Absolute Percentage Error (MAPE) of 179.4555 and Theil Inequality Coefficient of 0.977477.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Introduction

This chapter presents the summary of the results of the study and the main conclusion drawn. The organization of this chapter follows that section 5.2 summarize the findings of the study, section 5.3 presents the derived conclusions while recommendation is presented in section 5.4 followed by suggestion for further research in section 5.5 and limitation of the study in section 5.6.

5.2. Summary of the Findings

This study analyzes the nature and degree of volatility at NSE using the NSE 20 Share Index from July 1st 2003 to June 28th 2013. The Index were used to generate the daily returns (R_t) for the stock market by calculating the natural log of (P_t/P_{t-1}) , where P_t captures the daily NSE 20 Share Index at time t . The study used various market efficiency tests whether returns are normally distributed and unit root test. To analyze the volatility persistency, clustering effect, leverage effect and risk return trade off at NSE by using both types of symmetric and asymmetric GARCH family model specifications.

In summary, the empirical evidence about NSE 20 Share Index presented above indicates that the variance of the returns was not constant. It was time varying, which entail that the volatility at NSE can be specified as a process of conditional heteroskedasticity. Further the results violate many of the general assumptions of EMH that the variance of the error terms are constant, are normally distributed and mean reverting. The term structure of the risk prima also contains information that can be used to improve prediction of returns.

There were two main results from the analysis of the data employed in this study. One the stock market is inefficient in its weak form. The NSE 20 Share Index return has a fat tail and it was skewed to the left, hence it was not normally distributed. The daily returns also exhibited serial correlation. The unit root test showed that daily returns are integrated order of one, $I(1)$, which implies that the daily returns are mean reverting in their first difference form.

Second the stock market returns are non linear and they were well described by using GARCH family estimation. The positive and statistically significant ARCH coefficients implied that volatility persistence and clustering effect of the market. The assessment of the predictability to the variance, indicate that stock returns are not random walk rather martingale process, future changes of daily stock returns at NSE are dependent on the past information and therefore significant in explaining expected volatility.

From the parameters estimated using GARCH model the of returns in stock market exhibit volatility clustering effect, which was, higher volatility followed by another higher volatility and vice versa. The leverage effect which higher returns corresponds to lower volatility rates in the market were detected in the GJR GARCH estimation. And the EGARCH model for asymmetric volatility showed that the market responses to the same magnitude of positive and negative external shocks differently. Further the market is not efficient in pricing risk. Therefore, from the empirical evidence of previous section it is possible to deduce that the NSE is not efficient in its weak form and exhibits the stylized facts of financial markets.

5.3. Conclusion

Several conclusions can be drawn from the findings of this study about the nature and characteristics of NSE. First the series of returns generated using NSE 20 Share Index suggested that NSE is not efficient in its weak form. Second the stylized facts of financial time series data, such as negative skewness, leptokurtosis, volatility persistency, and clustering effect were observed. The nonlinear data generating process, serial dependence and leverage effects which are common observations in stock markets were also detected.

5.4. Recommendations

The most significant recommendation to the parties involved with NSE directly or indirectly falls in the realm of the positive relationship between stock market volatility and expected market return, volatility persistence for external shocks and their mean reverting characteristics. To improve the degree of the market efficiency of NSE and reduce volatility thereon the timing and efficiency of information assimilation and dissemination to interested parties is important. Further the introduction of shock

absorbers in the market will reduce the impact of exogenous shocks rather than exploding.

5.5. Limitation of the study

The study was very limited in time and budget but most importantly the availability of data and advanced econometric analysis tools and software's were hard to come by.

5.6. Suggestion for Further Research

It is left to future research to study in more detail the nature and character of the stock market volatility at NSE by using neural network and multi variate GARCH models. The analysis of the causes of the structural break in market time series and how it can be taken into account in the volatility equations could be paramount to the understanding of the stock market. Furthermore, it might be interesting to study the extent of volatility forecasts based on the present models that can be useful in the context of risk management for the stock markets considered.

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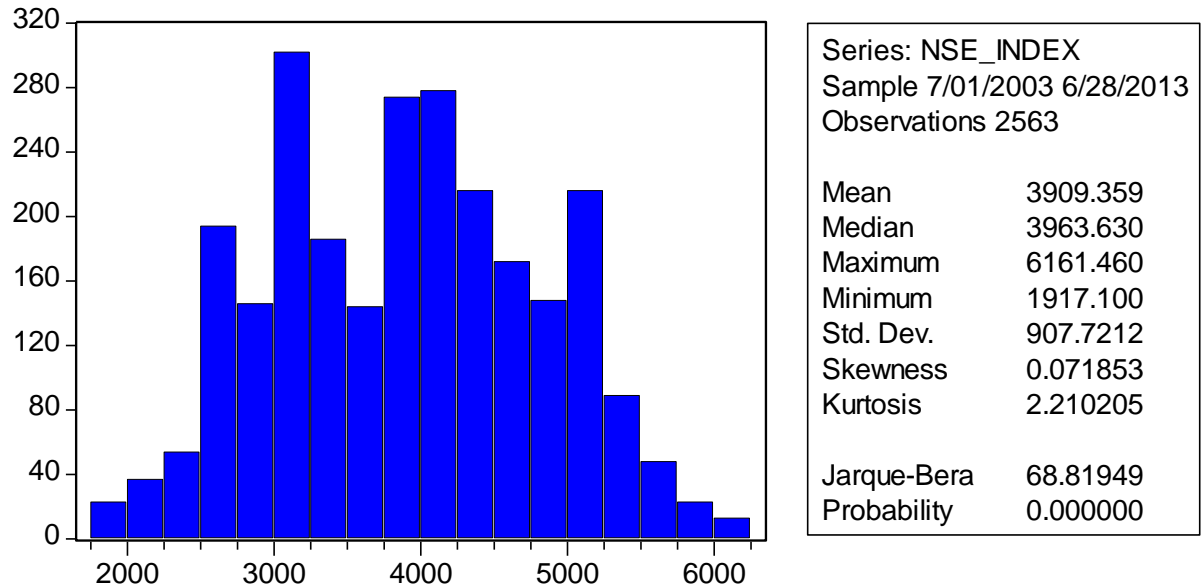
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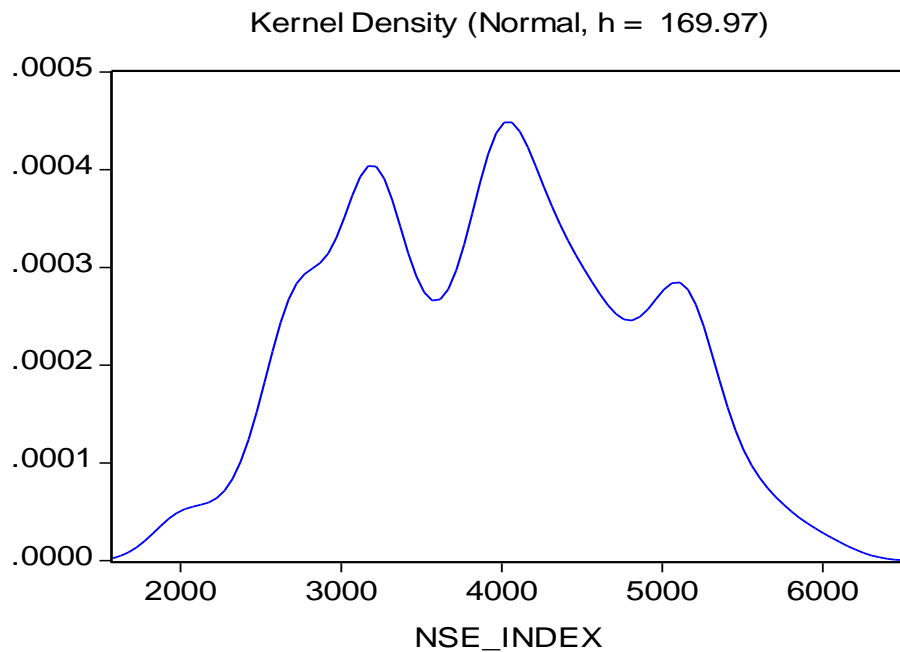
APPENDICES

APPENDEIX A: Market Efficiency Analysis

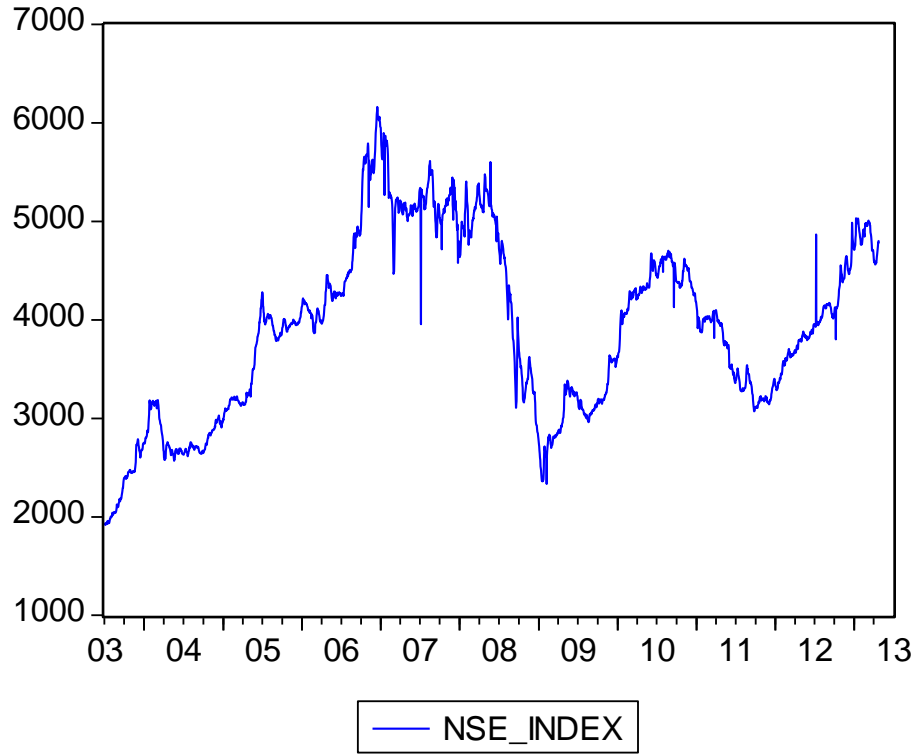
Histogram NSE 20 Share Index



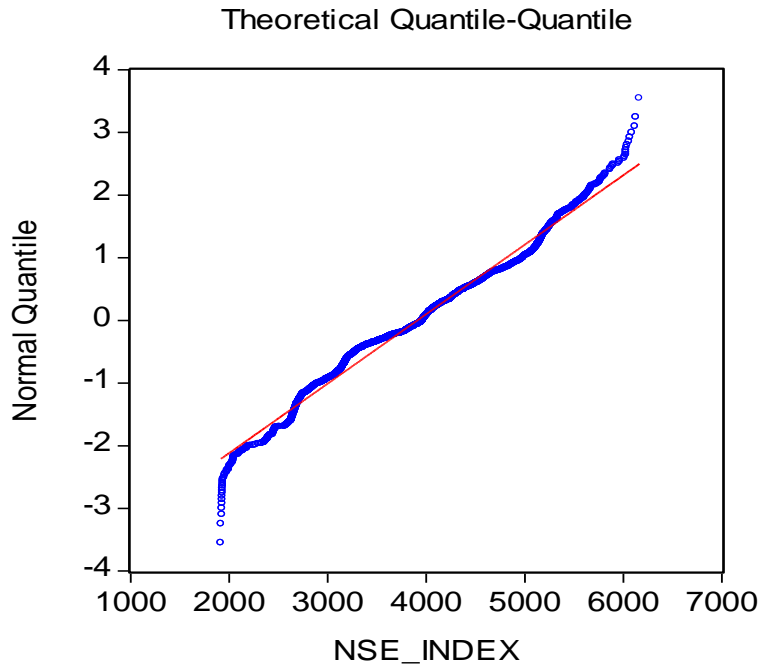
Kernel Distribution NSE 20 Share Index



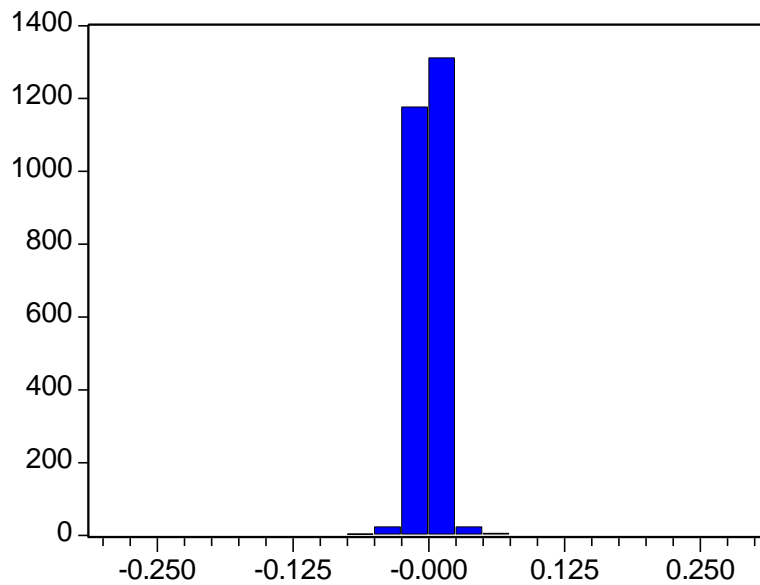
NSE 20 Share Index Series



Quantile

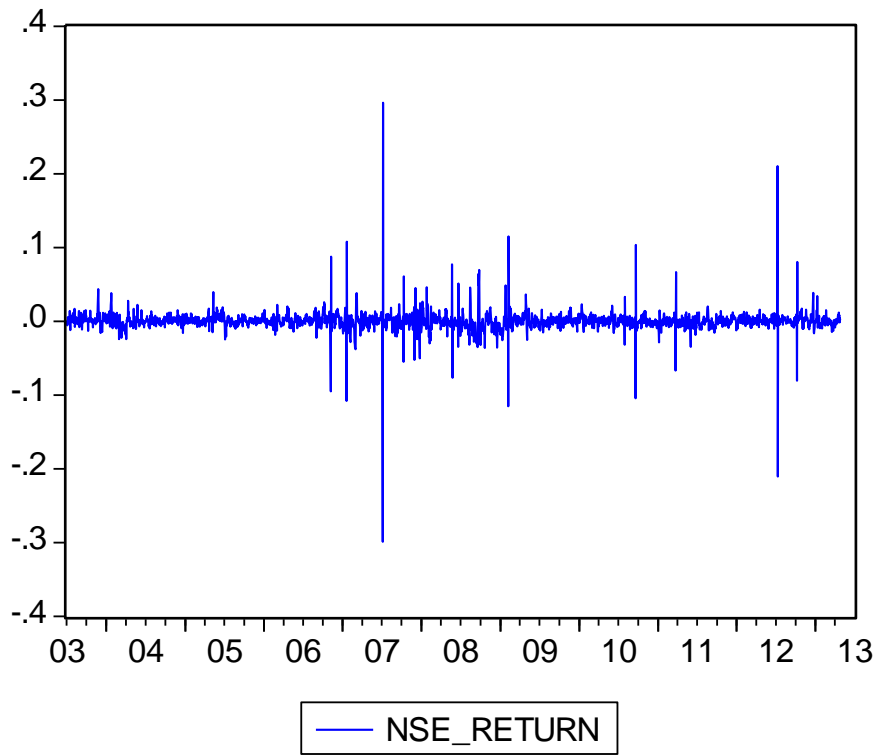
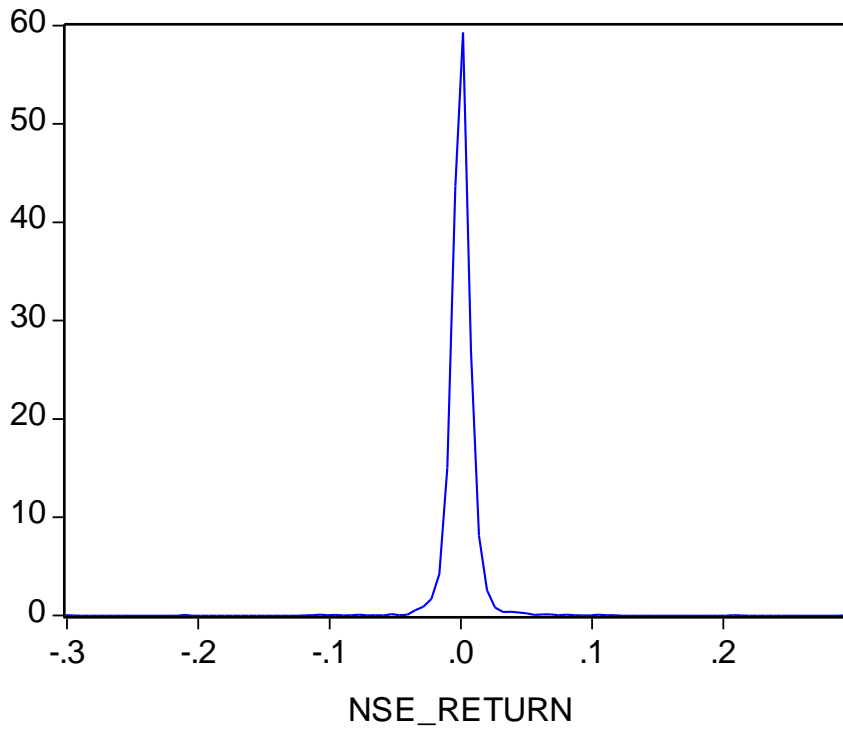


NSE Return

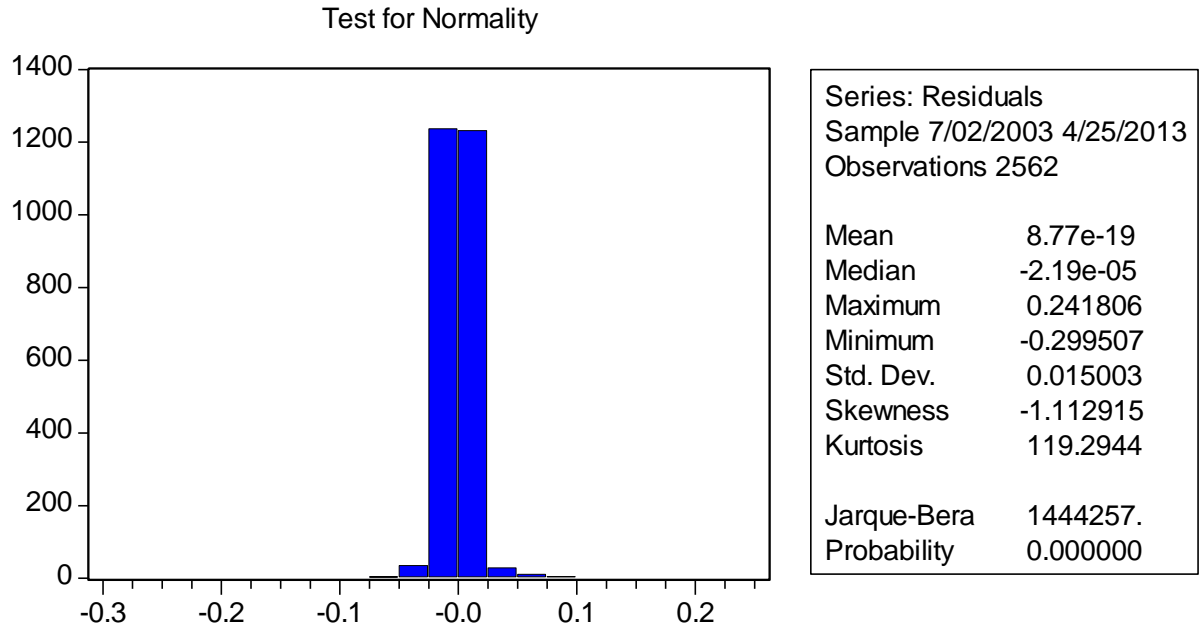


Series: NSE_RETURN	
Sample 7/01/2003 6/28/2013	
Observations 2563	
Mean	0.000357
Median	0.000116
Maximum	0.296396
Minimum	-0.298897
Std. Dev.	0.015253
Skewness	-0.019577
Kurtosis	151.4527
Jarque-Bera	2353497.
Probability	0.000000

Kernel Density (Normal, h = 0.0011)



Test for Normality



Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	6.920470	Probability	0.008573
Obs*R-squared	6.909896	Probability	0.008572

Test Equation:

Dependent Variable: RESID

Method: Least Squares

Date: 10/01/13 Time: 14:56

Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.89E-05	0.000299	0.331349	0.7404
NSE_RETURN(-1)	-0.277153	0.107128	-2.587118	0.0097
RESID(-1)	0.286566	0.108932	2.630679	0.0086
R-squared	0.002697	Mean dependent var	8.77E-19	
Adjusted R-squared	0.001918	S.D. dependent var	0.015003	

S.E. of regression	0.014989	Akaike info criterion	5.561830
Sum squared resid	0.574931	Schwarz criterion	5.554981
Log likelihood	7127.704	F-statistic	3.460235
Durbin-Watson stat	2.004814	Prob(F-statistic)	0.031569

Unit Root Test

Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic based on SIC, MAXLAG=2)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-52.57125	0.0000
Test critical values:		
1% level	-3.961630	
5% level	-3.411564	
10% level	-3.127648	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NSE_RETURN,2)
Method: Least Squares
Date: 10/01/13 Time: 14:17
Sample (adjusted): 7/07/2003 4/25/2013
Included observations: 2559 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
----------	-------------	------------	-------------	-------

D(NSE_RETURN(-1))	-2.789392	0.053059	-52.57125	0.0000
D(NSE_RETURN(-1),2)	0.849693	0.039450	21.53848	0.0000
D(NSE_RETURN(-2),2)	0.256122	0.019128	13.39011	0.0000
C	3.48E-06	0.000659	0.005285	0.9958
@TREND(7/01/2003)	6.78E-10	4.45E-07	0.001524	0.9988
R-squared	0.844540	Mean dependent var	1.21E-06	
Adjusted R-squared	0.844296	S.D. dependent var	0.042127	
S.E. of regression	0.016623	Akaike info criterion	5.354122	-
Sum squared resid	0.705721	Schwarz criterion	5.342697	-
Log likelihood	6855.599	F-statistic	3468.658	
Durbin-Watson stat	2.092782	Prob(F-statistic)	0.000000	

ARCH

Estimation Command:

```
=====
ARCH(1,0,DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1) + C(2)*NSE_RETURN(-1)
```

```
GARCH = C(3) + C(4)*RESID(-1)^2
```

Substituted Coefficients:

```
=====
NSE_RETURN = -5.083645896e-005 + 0.3937089858*NSE_RETURN(-1)
```

```
GARCH = 0.0001231505563 + 0.3361617075*RESID(-1)^2
```

Dependent Variable: NSE_RETURN

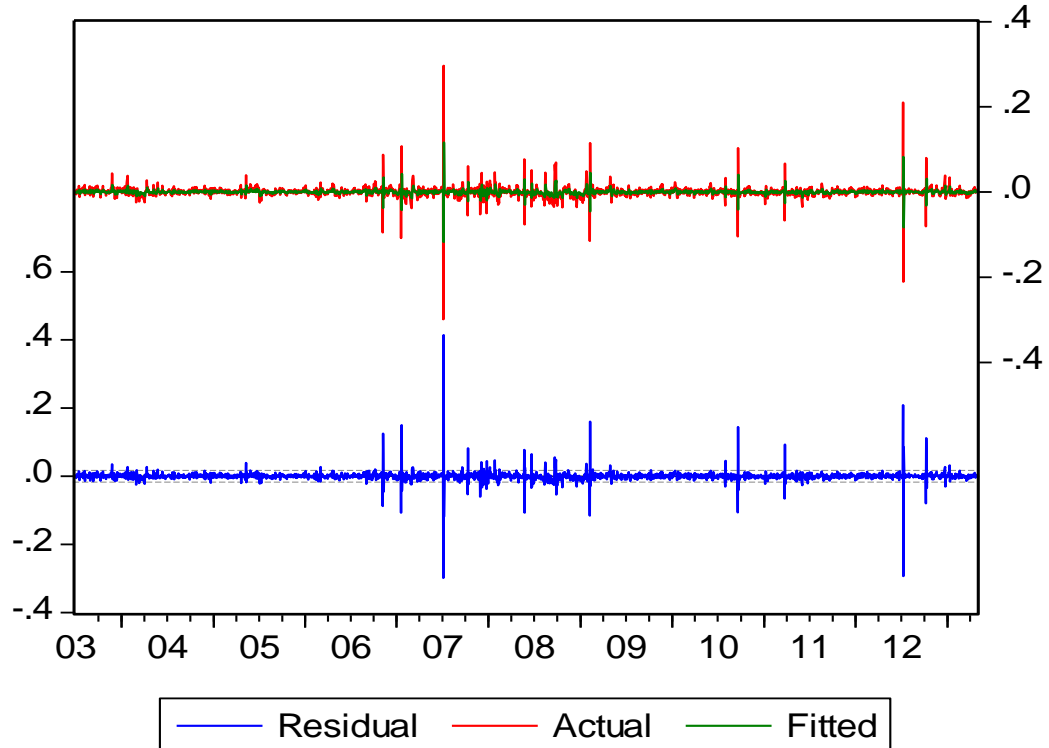
Method: ML - ARCH

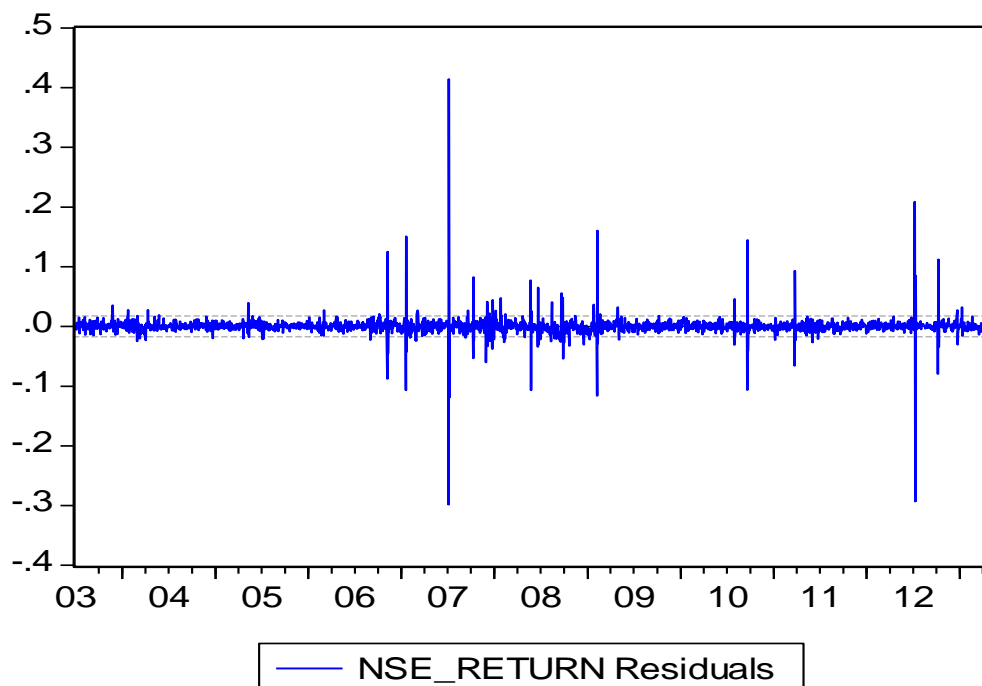
Date: 10/01/13 Time: 15:07

Sample (adjusted): 7/02/2003 4/25/2013

Included observations: 2562 after adjustments
 Convergence achieved after 310 iterations
 Variance backcast: ON
 GARCH = C(3) + C(4)*RESID(-1)^2

	Coefficient	Std. Error	z-Statistic	Prob.
C	-5.08E-05	0.000223	-0.227949	0.8197
NSE_RETURN(-1)	0.393709	0.027257	14.44444	0.0000
Variance Equation				
C	0.000123	3.72E-07	330.7720	0.0000
RESID(-1)^2	0.336162	0.024367	13.79567	0.0000
R-squared	-0.298016	Mean dependent var		0.000357
Adjusted R-squared	-0.299538	S.D. dependent var		0.015256
S.E. of regression	0.017391	Akaike info criterion		-6.004679
Sum squared resid	0.773699	Schwarz criterion		-5.995547
Log likelihood	7695.993	Durbin-Watson stat		2.979078





ARCH Test

F-statistic	723.2225	Probability	0.000000
Obs*R-squared	564.3045	Probability	0.000000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 10/01/13 Time: 14:55

Sample (adjusted): 7/03/2003 4/25/2013

Included observations: 2561 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000119	4.29E-05	2.783688	0.0054
RESID^2(-1)	0.469410	0.017455	26.89280	0.0000
R-squared	0.220345	Mean dependent var		0.000225
Adjusted R-squared	0.220041	S.D. dependent var		0.002448
S.E. of regression	0.002162	Akaike info criterion		-9.434597
Sum squared resid	0.011964	Schwarz criterion		-9.430030
Log likelihood	12083.00	F-statistic		723.2225
Durbin-Watson stat	1.758996	Prob(F-statistic)		0.000000

APPENDEIX B: Volatility Analysis

GARCH

Estimation Command:

```
=====
ARCH(DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1) + C(2)*NSE_RETURN(-1)

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)
```

Substituted Coefficients:

```
=====
NSE_RETURN = 0.0002278216325 + 0.3378580761*NSE_RETURN(-1)

GARCH = 0.0003281262441 + 0.2233435819*RESID(-1)^2 -
0.07855207626*GARCH(-1)
```

Dependent Variable: NSE_RETURN
Method: ML - ARCH
Date: 10/01/13 Time: 15:09
Sample (adjusted): 7/02/2003 4/25/2013
Included observations: 2562 after adjustments

Convergence achieved after 10 iterations

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000228	0.000553	0.412337	0.6801
NSE_RETURN(-1)	0.337858	0.041803	8.082236	0.0000
Variance Equation				
C	0.000328	9.15E-08	3587.362	0.0000
RESID(-1)^2	0.223344	0.024319	9.183866	0.0000
GARCH(-1)	-0.078552	0.005179	-15.16628	0.0000
R-squared	-0.236607	Mean dependent var		0.000357
Adjusted R-squared	-0.238542	S.D. dependent var		0.015256
S.E. of regression	0.016978	Akaike info criterion		-5.737330
Sum squared resid	0.737096	Schwarz criterion		-5.725916
Log likelihood	7354.519	Durbin-Watson stat		2.918385

GJR GARCH

Estimation Command:

```
=====
ARCH(THRSH=1,DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1) + C(2)*NSE_RETURN(-1)

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1)^2*(RESID(-1)<0) +
C(6)*GARCH(-1)
```

Substituted Coefficients:

```
=====
NSE_RETURN = -2.019401878e-007 + 0.3574811848*NSE_RETURN(-1)

GARCH = 0.0003051586246 + 0.1425137993*RESID(-1)^2 + 0.1713614897*RESID(-
1)^2*(RESID(-1)<0) - 0.04523492343*GARCH(-1)
```

Dependent Variable: NSE_RETURN

Method: ML – ARCH

Date: 10/01/13 Time: 15:10

Sample (adjusted): 7/02/2003 4/25/2013

Included observations: 2562 after adjustments

Convergence achieved after 15 iterations

Variance backcast: ON

$$\text{GARCH} = \text{C}(3) + \text{C}(4) * \text{RESID}(-1)^2 + \text{C}(5) * \text{RESID}(-1)^2 * (\text{RESID}(-1) < 0) + \text{C}(6) * \text{GARCH}(-1)$$

	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.02E-07	0.000632	-0.000319	0.9997
NSE_RETURN(-1)	0.357481	0.044080	8.109743	0.0000
Variance Equation				
C	0.000305	1.87E-06	163.0909	0.0000
RESID(-1)^2	0.142514	0.023323	6.110319	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.171361	0.055025	3.114241	0.0018
GARCH(-1)	-0.045235	7.03E-06	-6434.036	0.0000
R-squared	-0.257591	Mean dependent var		0.000357
Adjusted R-squared	-0.260051	S.D. dependent var		0.015256
S.E. of regression	0.017125	Akaike info criterion		-5.758354
Sum squared resid	0.749603	Schwarz criterion		-5.744657
Log likelihood	7382.451	Durbin-Watson stat		2.940434

E GARCH

Estimation Command:

```
=====
ARCH(EGARCH,DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1) + C(2)*NSE_RETURN(-1)
```

```
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))
```

Substituted Coefficients:

```
=====
NSE_RETURN = 0.0002273840563 + 0.3955477524*NSE_RETURN(-1)
```

```
LOG(GARCH) = -7.058622096 + 0.4819701642*ABS(RESID(-1)/@SQRT(GARCH(-1))) - 0.04026021347*RESID(-1)/@SQRT(GARCH(-1)) + 0.227899202*LOG(GARCH(-1))
```

Dependent Variable: NSE_RETURN

Method: ML – ARCH

Date: 10/01/13 Time: 15:17
 Sample (adjusted): 7/02/2003 4/25/2013
 Included observations: 2562 after adjustments
 Convergence achieved after 500 iterations
 Variance backcast: ON
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1)) + \text{C}(6) * \text{LOG}(\text{GARCH}(-1))$

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000227	0.000209	1.089041	0.2761
NSE_RETURN(-1)	0.395548	0.023024	17.17963	0.0000
Variance Equation				
C(3)	-7.058622	0.224303	-31.46916	0.0000
C(4)	0.481970	0.026918	17.90515	0.0000
C(5)	-0.040260	0.021324	-1.888014	0.0590
C(6)	0.227899	0.024553	9.282028	0.0000
R-squared	-0.299828	Mean dependent var		0.000357
Adjusted R-squared	-0.302370	S.D. dependent var		0.015256
S.E. of regression	0.017410	Akaike info criterion		-5.992358
Sum squared resid	0.774779	Schwarz criterion		-5.978661
Log likelihood	7682.211	Durbin-Watson stat		2.981654

GARCH M

Estimation Command:

```
=====
ARCH(ARCHM=VAR,DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1)*GARCH + C(2) + C(3)*NSE_RETURN(-1)
```

```
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)
```

Substituted Coefficients:

```
=====
NSE_RETURN = 5.239183243*GARCH - 0.001688713735 +
0.3367145424*NSE_RETURN(-1)
```

$$\text{GARCH} = 0.0002992198784 + 0.2427798551 * \text{RESID}(-1)^2 - 0.05215645767 * \text{GARCH}(-1)$$

Dependent Variable: NSE_RETURN
 Method: ML - ARCH
 Date: 10/01/13 Time: 15:15
 Sample (adjusted): 7/02/2003 4/25/2013
 Included observations: 2562 after adjustments
 Convergence achieved after 31 iterations
 Variance backcast: OFF

$$\text{GARCH} = \text{C}(4) + \text{C}(5) * \text{RESID}(-1)^2 + \text{C}(6) * \text{GARCH}(-1)$$

	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	5.239183	1.419228	3.691573	0.0002
C	-0.001689	0.000764	-2.209808	0.0271
NSE_RETURN(-1)	0.336715	0.042713	7.883168	0.0000
Variance Equation				
C	0.000299	1.44E-05	20.70744	0.0000
RESID(-1)^2	0.242780	0.032821	7.397173	0.0000
GARCH(-1)	-0.052156	0.050649	-1.029757	0.3031
R-squared	-0.199467	Mean dependent var		0.000357
Adjusted R-squared	-0.201813	S.D. dependent var		0.015256
S.E. of regression	0.016725	Akaike info criterion		-5.770860
Sum squared resid	0.714958	Schwarz criterion		-5.757163
Log likelihood	7398.471	Durbin-Watson stat		2.785667

Forecast

Estimation Command:

```
=====
ARCH(DERIV=AA) NSE_RETURN C NSE_RETURN(-1)
```

Estimation Equation:

```
=====
NSE_RETURN = C(1) + C(2)*NSE_RETURN(-1)
```

```
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)
```

Substituted Coefficients:

```
=====
```


$$\text{NSE_RETURN} = 0.0002278216325 + 0.3378580761 * \text{NSE_RETURN}(-1)$$

$$\text{GARCH} = 0.0003281262441 + 0.2233435819 * \text{RESID}(-1)^2 - 0.07855207626 * \text{GARCH}(-1)$$

Dependent Variable: NSE_RETURN

Method: ML - ARCH

Date: 10/01/13 Time: 15:09

Sample (adjusted): 7/02/2003 4/25/2013

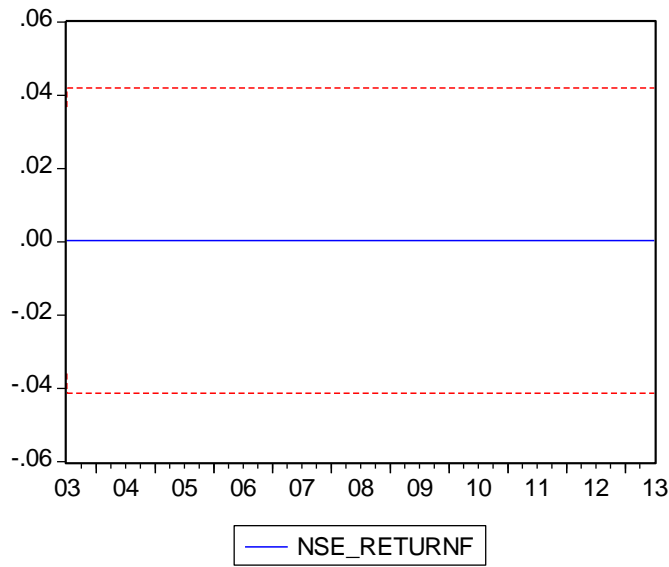
Included observations: 2562 after adjustments

Convergence achieved after 10 iterations

Variance backcast: ON

$$\text{GARCH} = \text{C}(3) + \text{C}(4) * \text{RESID}(-1)^2 + \text{C}(5) * \text{GARCH}(-1)$$

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000228	0.000553	0.412337	0.6801
NSE_RETURN(-1)	0.337858	0.041803	8.082236	0.0000
Variance Equation				
C	0.000328	9.15E-08	3587.362	0.0000
RESID(-1)^2	0.223344	0.024319	9.183866	0.0000
GARCH(-1)	-0.078552	0.005179	-15.16628	0.0000
R-squared	-0.236607	Mean dependent var		0.000357
Adjusted R-squared	-0.238542	S.D. dependent var		0.015256
S.E. of regression	0.016978	Akaike info criterion		-5.737330
Sum squared resid	0.737096	Schwarz criterion		-5.725916
Log likelihood	7354.519	Durbin-Watson stat		2.918385



Forecast: NSE_RETURNF
 Actual: NSE_RETURN
 Forecast sample: 7/01/2003 6/28/2013
 Adjusted sample: 7/02/2003 6/28/2013
 Included observations: 2608

Root Mean Squared Error	0.015118
Mean Absolute Error	0.006720
Mean Abs. Percent Error	179.4555
Theil Inequality Coefficient	0.977477
Bias Proportion	0.000001
Variance Proportion	0.999702
Covariance Proportion	0.000297

