UNIVERSITY OF NAIROBI
DEPARTMENT OF ECONOMICS

"VOLATILITY OF STOCK RETURNS":
AN EMPIRICAL ANALYSIS OF THE NAIROBI STOCK EXCHANGE

BY

MURIU P. WANJIHIA
C/50/7154/2001

SUPERVISORS:

1. **DR. ROSE .W. NGUGI**
2. **PROF. NJUGUNA .S. NDUNG'U**

A THESIS SUBMITTED TO ECONOMICS DEPARTMENT, UNIVERSITY OF NAIROBI AS A FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ARTS IN ECONOMICS.

September 29, 2003

Declaration

This is my original work and has never been presented for any degree in any other university.

NAME: MURIU .P. WANJIHIA

SIGNATURE:____________________

DATE: 26th september 2003

APPROVAL

This research paper has been submitted for examination with our approval as university supervisors.

NAME: DR. ROSE. W. NGUGI

SIGNATURE:____________________

DATE: 29/09/2003

NAME: PROF. NJUGUNA. S. NDUNG'U

SIGNATURE:____________________

DATE: 29/09/03

Dedication

To: My daughter Cynthia Njeri

List of Acronyms

AC	-Autocorrelations.
ADF	-Augmented Dickey – Fuller (Test)
ARCH	-Autoregressive Conditional Heteroscedasticity.
ARMA	-Autoregressive Moving Average.
CDS	-Central Depository System.
CMA	-Capital Markets Authority
DvP	-Delivery versus Payment
E-GARCH	-Exponential Generalized Autoregressive Conditional Heteroscedasticity
GARCH-M	-Generalized Autoregressive Conditional Heteroscedasticity in the mean
IFC	-International Finance Corporation
IID	-Independent and Identically Distributed
LSE	-London Stock Exchange
NSE	-Nairobi Stock Exchange
OLS	-Ordinary Least Squares
R_t	-Stock returns.
T-GARCH	-Threshold Generalized Autoregressive Conditional Heteroscedasticity.
CAPM	-Capital Asset Pricing Models.

List of Tables Page

List of Figures

Acknowledgement

The preparation and completion of this thesis would not have materialized were it not for encouragement and assistance from many persons. I'm therefore indebted to many whom I owe appreciation for their encouragement, guidance and assistance in conducting this study.

I wish to express a lot of gratitude and appreciation to my supervisors, Dr. Rose Ngugi and Professor Njuguna Ndung'u for their tireless guidance, encouragement, through extremely useful suggestions for improving this study, both at the initial and final stages. Without them this study would have proved extremely difficult to initiate. It is their diligent and scholarly guidance that has seen the actualization of this work

This study has relied mainly on primary data collected from NSE. I therefore wish to record my appreciation for the assistance received from the staff at the NSE particularly Susan Wanjeri the Librarian. My colleagues in the M.A. Economics class Messrs. Mbuthia, Kiriga, Masinde, kingángí, Norman-Naaman, Kioo, nyangóro, kajuju warrant a mention here for their encouragement. I am particularly grateful to AERC for granting me an opportunity to specialize in Corporate Finance and Investments at JFE (KCB mgt Centre – karen).

I further register my appreciation to my mentor Professor Germano Mwabu who inspired me into applied research and for his incessant constructive advice. I acknowledge with deep appreciation the moral support and invaluable assistance from my brother James Herman Wanjema and my family.

I wish to state that the views expressed in this study are my own and thus do not represent the views of the University of Nairobi or any other quarters. I am however responsible for any errors and shortcomings of this study.

Abstract

This study analyzes the volatility structure of stock returns in an emerging stock market (NSE) covering the period 2nd January 1992 to 30th June 2003. The study utilizes daily stock returns calculated as log (P_t/P_{t-1}) where P_t represents the value of the NSE -20-share index at time t. The study uses both symmetric and asymmetric ARCH type models in investigating clustering effects, risk-return trade off, and volatility persistency, predictability and leverage effects. The results are as follows. NSE equity returns show negative skewness, excess kurtosis and deviation from normality. Returns are predictable and therefore rejecting the weak form efficiency. Asymmetric test results indicate that conditional volatility is higher with negative shocks implying a leverage effect. Consistent with most previous studies, a positive and significant relationship is indicated between conditional volatility and the stock returns implying that investors are risk averse. The positive and highly significant ARCH coefficient implies 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. The predictability of the second moments is not a random walk but a martingale process. The ARCH-LM test indicates that the returns are generated by a stochastic process and not a chaotic process. The institutional reforms that have taken place in the bourse, such as the entry of foreign investors in 1995 and change of trading system in 2000 are not significant in explaining volatility of the stock returns although the days of the week reflect significant negative returns while volatility is positive and significant on Monday, Tuesday and Thursday.

TABLE OF CONTENTS

Page.

CHAPTER ONE

1.1 Introduction

Financial markets play a key role in the economy by channeling funds from savers to investors, the key indicator being the returns for these savers. Volatility disturbs the patterns of these returns consequently harming the economy. Emerging stock markets have captured the attention of investors and researchers in recent years. The IFC defines emerging markets as those stock markets in countries or territories with income levels that are classified by the World Bank as low or middle income[1]. These markets have remarkably grown in size, demonstrating not only the performance of traded equities but also the broadening of the markets because of the privatization of public enterprises and large number of private floatation. The interest in these emerging markets has arisen from the increased globalization and integration of the world economies in general and that of the financial markets in particular. The globalization and integration of these markets has created enormous opportunities for domestic and international investors to diversify their portfolios across the globe. As a result, rigorous empirical studies examining the nature of volatility of these markets would be of great benefit to investors and policy makers at home and abroad.

A widely held perception about emerging equity markets like Nairobi Stock Exchange (NSE) is that price or return indices in these markets are frequently subject to extended deviations from fundamental values with subsequent reversals as seen in Mexico[2] in 1994-

---

1 Low income countries refer to those whose GDP per capita is $695 or less

2 This was the situation when Mexico was borrowing at an explosive rate of 8% of gross domestic product annually; it simultaneously used up almost $20 billion of international reserves to finance gigantic current-account deficits. At the time, in the middle of an election year, the government both loosened fiscal policy and continued to provide ample liquidity in pesos, even after the public greatly reduced its demand for money. The question of whether stock market anticipated a devaluation of the currency is particularly interesting having been unanticipated event. In the week of devaluation companies with high net exports showed significant positive abnormal returns while low net exporters under-performed relative to the market

1995. In addition, there is a perception that these swings may be due in large part to the growing influence of highly mobile foreign capital, which may have increased volatility (see Richards 1996).

Considerable research has been devoted to the potential benefits from investing in emerging equity markets e.g. Wilcox (1992), Geppert et al (1996). These studies provide valuable information regarding the risk diversification potential from investing in emerging markets. While the relationship between volatility and return, have been examined for some emerging markets, it has not been examined for the NSE using daily index. The questions of stock market volatility, persistence of volatility, and risk premium in the stock market are relevant for Kenya, as the country wants to achieve higher rates of savings, investment and economic growth. Howel (1993) suggests with respect to emerging markets that there is an absence of domestic long-term investors, that foreign investors have become the marginal investors and that the mobility of these investors will result in high volatility. The emerging stock markets offer an opportunity to examine the evolution of stock return distributions and stochastic processes in response to economic and political changes in these economies. Such changes are occurring in a magnitude and direction in these countries, which are not typically observed in the developed stock markets. Equities from these markets have vastly different characteristics than equities from developed capital markets. There are at least four distinguishing features of emerging market stock returns namely;

- Higher sample average returns
- Low correlations with developed market return
- More predictable returns and

- Higher volatility[3].

These market returns are characterized by high unconditional volatility ranging from 18% in Jordan to 104% in Argentina (Harvey 1993). Using the same sample period Harvey in the same year finds that volatility in developed markets ranges from 15% in USA to 33% in Hong Kong.

Since the stock market crash of major market indices around the world[4], of October 19th, 1987, considerable attention has been paid to overall stock market volatility. It has been argued that the 1987 international stock market crash may have had a substantial impact on international stock market behavior. Economists such as Shiller (1991) have argued that stock prices are far too volatile to be explained by fundamentals such as earnings and dividends. The stock market reacts to self-fulfilling expectations and the speed with which information is processed. Romer (1990) argues that increased uncertainty associated with financial distress was one of the driving forces behind the great depression.

If stock market volatility is high today, it tends to be high also during the nearest future.[5] Stock returns data have been characterized by volatility clustering, where large returns are followed by large returns and small returns tend to be followed by small returns leading to contiguous periods of volatility and stability. This exhibits autoregressive conditional heteroscedasticity.

---

3 See Geert et al 1996 for a comprehensive literature

4 An important and often overlooked fact about the Market Crash of October 19,1987 was the fact that it was simultaneous and similar in major stock markets around the world. This event led to a number of studies of commonalities in stock market volatility patterns globally and, more specifically, on their joint dynamics. That is, various studies had uncovered that increases in volatility in some markets, such as the U.S., led to increases in volatility in other markets, such as in Japan, Europe and Latin America, by one day or even up to one month.

5 See Hamelink F and Isakov Dusan 2002

Empirical studies on financial time series have shown that they are characterized by increased conditional variance following negative shocks (bad news). The distribution of the shocks has been also found to exhibit considerable leptokurtosis i.e. it is more peaked than normal (Duffee 1995). The high volatility of emerging markets is marked by frequent, sudden changes in variance. Most models of asset pricing predict that the expected return on any asset is directly related to its covariance with one or more pricing factors. Most portfolio diversification and risk hedging strategies are based on the ability to predict variances and covariance (Theodossiou and Lee 1995).

A cursory look at financial data suggests that some time periods are riskier than others; that is, the expected value of the magnitude of error terms at some times is greater than at others. Moreover, these risky times are not scattered randomly across quarterly or annual data. Instead, there is a degree of autocorrelation in the riskiness of financial returns. The ARCH and GARCH (autoregressive conditional heteroscedasticity and *generalized* autoregressive conditional heteroscedasticity) models are designed to deal with just this set of issues. They have become widespread tools for dealing with time series heteroscedastic variances. The goal of such models is to provide a volatility measure like a standard deviation, which can be used in financial decisions concerning risk analysis, portfolio selection and derivative pricing.[6]

Volatility is a key input for the cost of capital calculation for a segmented market and is critical for effective asset allocation decisions. It makes investors more averse to holding stocks due to uncertainty, who in turn demand a higher risk premium resulting in a higher

6 See Robert Engle 2001 for a comprehensive literature on the use of ARCH/GARCH models in applied econometrics.

cost of capital, which then leads to less private physical investment. In addition, greater volatility may increase the value of the option to wait thereby delaying investments. If the future seems risky, the investor may want to save more in the present thus lowering demand for larger premium. Also weaker regulatory systems in developing markets reduce the efficiency of market signals and the processing of information, which further magnifies the problem of volatility[7].

Since forecasting of volatility is important in designing optimal asset allocation decisions as well as dynamic hedging strategies (Baillie and Myers 1991), the authors believe that tracking a satisfactory volatility specification is a necessity for the valuation of stocks at NSE. This paper provides an empirical study of stock market volatility, persistence, risk premium and volatility clustering thereby broadening our understanding of the behaviour of volatility in an emerging equity market as well as providing further evidence on linear and non-linear volatility using GARCH modeling.

1.2 Kenya Stock Market

Nairobi Stock Exchange was established in 1954, as an extension of the activities at the London stock exchange. There are 53 companies that are publicly quoted at NSE after one company got delisted this year. The NSE attracts special interest for empirical work in the light of the reforms that have taken place over the last 13 years aimed at restructuring and regulating the market. The capital market Authority (CMA) was established in 1989 and became functional in 1990. It regulates the activities of stockbrokers, investment advisers,

7 See Jihyun Lee et al (2000) on long memory in volatility of Korean stock market returns.

insurance companies and listed companies. Trading takes place on Mondays through Fridays between 10:00am and 12:00pm.

Policy changes have also been made which include removal of the role of capital markets committee in regulating shares, elimination of double taxation of dividends by conversion of the withholding tax into a final tax, elimination of the corporate tax on dividend income of the unit trusts, exemption of withholding tax on the dividends of corporate tax exempt bodies, abolition of stamp duties on retail share transactions and deductibility of all costs incurred in the issue of shares, debentures and bonds.

The central depository system (CDS) idea was initiated in 1995 with a view of enhancing liquidity and efficiency in the trading system by reducing the period within which certificates are issued and centralizing registration at the bourse. This would have further facilitated electronic transfer of ownership without the physical movements of certificates thereby minimizing systemic risk. Further, the delivery versus payment (DvP) was introduced in 1st August 2000. The market therefore faced the challenge of settling transactions within 5 days of trading occurring and to provide shareholders with their shares within 7 days of settlement hence creating an environment of a smooth transition to an electronic based settlement and registry. This would further enhance investor confidence and liquidity by making the settlement period shorter and safer.

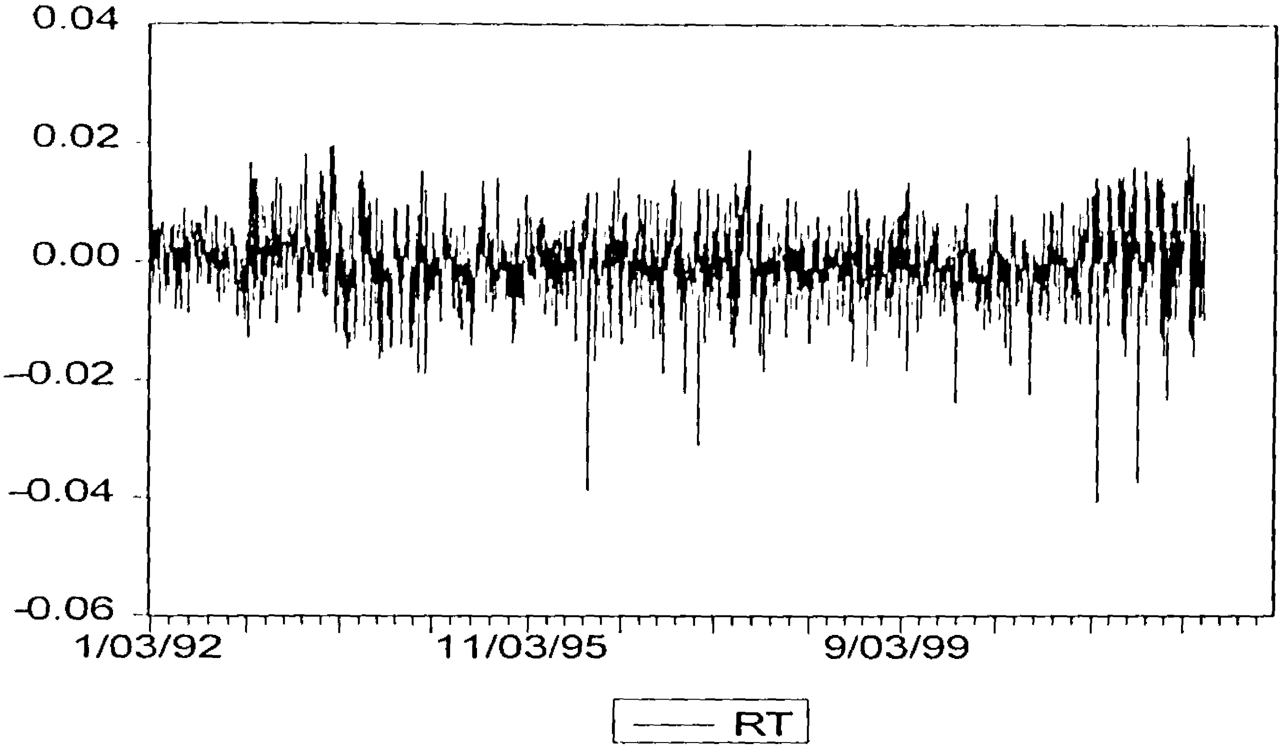
Before, only when bid price was equal to or up to two spreads away from the offer price could a transaction take place. There were daily limits on the movements of quotations whether bid or offer of 15% of opening bid or offer prices. No, bid or offer quotations were more than six spreads from the last quotation appearing on the trading for that security. For less than Ksh 20 the spread was 5 cents, between Ksh 20 and 50 was 25 cents, Ksh 50 to 100 was 50 cents and above Ksh was 100 cents.

In November 1991, share trading moved from coffeehouse to floor-based open outcry system. The open outcry system was adopted to enhance transparency by enabling all brokers to have an equal opportunity to bid for securities and also to enhance handling of the growing trading activity.[a] Foreign investors were allowed to participate in the NSE as from January 1995. However, their participation was limited to 2.5% for individual investors and 20% in aggregate of each stock. This was later revised to 5% and 40% respectively in July 1995. The constituent stocks are classified as agricultural, industrial and allied, financial, commercials and services.

Figure 1 shows a time series plot of daily returns. A visual inspection of the series suggests that the volatility of returns display volatility clustering (the series is oscillating around the mean). In the year 1993/94, an upward surge is evident hitting a record high and an accompanying sharp fall.

[a] see Ngugi (2003) for detailed literature on the development of the Nairobi stock exchange: a historical perspective, Kenya Institute For Public Policy Research And Analysis.

Fig (1) Stock returns for the period 2nd January 1992 to 30th June 2003



Note: The graph excludes all the outlier returns exceeding 0.4

The volatility so far observed, could possibly be due to microstructure changes visa viz. policy changes related to dividends, entry of foreign investors, and improved efficiency of trading system. Policy changes such as taxation may be perceived by investors as a disincentive to investment reducing trading volume and liquidity thus increasing volatility in the market. Improved efficiency in trading system would shorten the registration process, boost liquidity, and increase market activity thereby reducing market risk and volatility. Entry of foreign investors would increase trading volume but withdrawal of investments due to perceived idiosyncratic risk too often, would increase volatility in the market. It is also evident that there has been a downward trend since 1999 to the last elections in 2002. After the elections, the returns trend is similar to 1993/94. By examining the relationship between democratic politics and financial markets, it is conceivable that political expectations regarding the outcome of the 2002 presidential election caused an increase in volatility of the NSE stock market. It is also evident that political information affects volatility by influencing the reservation price of traders. Thus, political uncertainty is solely a function of self-fulfilling and policy expectations—unknown aspects of the next president's policy preferences.

1.3 Statement of the Problem

Stock market helps to increase savings and investment, which are essential for economic development. By allowing diversification across a variety of assets, an equity market helps in reducing the risk the investors must bear. This further reduces the cost of capital, while in turn spurs investment and economic growth. However volatility will ultimately determine the effectiveness of the stock market in development. For example in a stock market, which is informational inefficient, investors face difficulty in choosing the optimal investment as information on corporate performance is slow or less available. The resulting uncertainty may induce investors either to withdraw from the market until this uncertainty is resolved or discourage them to invest funds for long-term. Moreover, if investors are not rewarded for taking on higher risk by investing in the stock market or if excess volatility weakens investors' confidence, they will not invest their savings in the stock market and hence deterring economic growth.

If volatility on returns could be forecasted based on publicly available information this would have important implications for the portfolio choice. Volatility can disrupt the smooth functioning of the financial system and lead to structural or regulatory changes. Volatility reduces the predictability of returns on investment in stocks. In order to boost investment characteristics of volatility at NSE should be studied to inform policy. The examination of the nature of volatility of stock return at the NSE offers:

- Investment managers need to deal with volatility to understand the risk of holding an asset.
- Forecast time intervals may be time varying so that more accurate intervals can be obtained by modeling the variance of the errors.
- More efficient estimators for the market dynamics are potentially available if variance of the errors is handled appropriately.

Volatility is a proxy for investment risk. Persistence in volatility implies that the risk and return trade-off changes in a predictable way over the business cycle, (Schwert 1989). Research conducted in 1980's suggests that prices are more variable than are the changes in future dividends that should be capitalized into prices. Asset prices apparently tend to make long-lived swings away from their fundamental values (see LeRoy and Porter 1981 and Shiller 1981). Further to this, Graham and Dodd (1951) posit in their security analysis that;

> *"...It is fully as important to the stockholders that they be able to obtain a fair price for their shares as it is that dividends, earnings and assets be conserved or increased. It follows that the responsibility of management...includes the obligation to prevent...the establishment of either absurdly high or unduly low prices for their securities."*

Endogenous stock price fluctuations may make the stock price highly volatile, implying that the firm's productivity is stochastic and can be good type or bad type.

Consider the trader who knows that the long-run average daily standard deviation of the NSE index is 1 percent that the forecast he made yesterday was 2 percent and the unexpected return observed today is 3 percent. Obviously, this is a high volatility period, and today is especially volatile, which suggests that the forecast for tomorrow could be even higher. If we also assume that the firm puts up its asset, net worth, as collateral, the informational asymmetry may introduce agency costs that bad firms invest the funds in a negative present value project. In addition, the self-selection mechanism rules out bad firms if and only if the stock price is expected to be high. Consequently, the stock price boom is self-fulfilled when the stock price is expected to be high, while the slump is self-fulfilled when it is expected to be low (Engle 2001). Evidence suggests the volatility of stock prices cannot be accounted for by information about future dividends. Dividends and consumption are constant in the aggregate but that there are good firms and bad firms whose identity may be unknown to the public, as in George Akerlof's (1970) 'lemons' problem. In that case, the collective valuation of the constant dividend stream depends on the degree of informational asymmetry.

With a new political dispensation in Kenya, there is an upward surge of the market returns at the NSE, which can only be compared to the 1993/94 periods hitting and surpassing the 2000 index on 7th may 2003. There is relatively less research about what characterizes volatility at NSE. One of the main problems is that this market is considered highly volatile which may act as a potential barrier to investing. This paper provides further evidence on the linear and non-linear volatility in the NSE using GARCH modeling. GARCH procedure is a robust measure of volatility since these models can incorporate non-linear effects and out performs classical OLS models (See Bollerslev et al 1992).

A well functioning stock market is particularly desirable for a country because it is a potential source of investor confidence in a country's commitment to a market based economy. This would have important implications for the asset allocation process. Investors seeking to avoid risk may choose to reduce their exposure to assets whose volatilities are predicted to increase. Although NSE contributes significantly towards economic growth and still lacks a number of sophisticated financial instruments, characterizing the distribution and dynamics of stock prices is a necessary first step towards its development. From the foregoing, the researchable problem therefore evolves as to what is the nature of volatility of stock returns at the NSE. To reach to a valid conclusion an empirical study should be undertaken with consistent historical data.

1.4 Study Objectives

The main objective of this study is to analyze volatility of stock returns in the NSE.

Specifically the study examines;

- Volatility clustering at NSE.
- Persistence of stock return volatility
- Predictability of volatility changes.
- Risk premia.

Based on the above objectives the study will recommend policies aimed at stabilizing the driving forces of volatility.

1.5 Rationale of the Study

The focus of this study is to examine the return distributions and stochastic processes of such distributions in the NSE following the deregulating and opening up of the market to foreign investors in January 1995 and change in trading system in August 2000. One of the main problems with emerging markets is that they are considered highly volatile which may act as a potential barrier to investing. If the asset return was unexpectedly large in either upward or downward direction then the trader will increase the estimate of variance for the next period.

The degree of stock market volatility can help forecasters predict the path of economic growth. If a high or increasing volatility on the NSE can be attributed to a purely domestic news source this may have different implications both for policy and consumption/ investment decisions than if the volatility comes from a strong sensitivity to world market development. Theory suggests that the price of an asset is a function of volatility or risk of an asset. Understanding of how volatility evolves over time is central to the decision making process. Moreover, optimal inference about the conditional mean of a variable requires that the conditional second moment be correctly specified. Misspecified models of stock volatility may lead to incorrect or invalid conclusions about stock returns dynamics. While time series structure is valuable for forecasting, it does not satisfy our need to explain volatility. An examination of the nature of volatility of stock returns offers theoretical and practical insights. Financial decisions are generally based upon the tradeoff between risk and return; the econometric analysis of risk is therefore an integral part of asset pricing, option pricing and risk management.

This study is useful for a number of reasons. Firstly, to the best of our knowledge, this is the first known study of this kind for the Kenya stock market. Secondly, It utilizes a unique daily data series, dating back to 1992 and which were not utilized in previous studies. Thirdly, it also utilizes the ARCH type models, which are capable of incorporating a number of widely observed behaviour of stock prices such as leptokurtosis, skewness, volatility clustering and persistence. Fourthly, the results of this study will be of great interest to academics, policy makers and investors both at home and abroad. Finally, it may also be useful for international organizations (such as the World Bank) and foreign governments who are interested in the development of capital markets in the emerging countries.

1.6 Organization of the Research Paper

This paper is divided into five sections and references. Following the introduction, in chapter one is a brief overview of the NSE, study problem, objectives and rationale of the study. Chapter two reviews related literature while chapter three discusses methodology and data, which includes the statistical properties of the stock prices and returns in the bourse. Chapter four analyzes the empirical findings of time-varying risk-return behavior of stock prices and returns within the ARCH-type model framework. Chapter five concludes the study and gives some policy recommendations based on the results obtained.

CHAPTER TWO

LITERATURE REVIEW

2.1 Theoretical literature

The issue of stock market volatility has received a lot of attention in the finance literature. The main questions, which have been addressed, include; what are the important causes of stock market volatility? Has it increased over time? Has it been persistent and to what extent? In addition, what role if any, regulators ought to play in the process? Previous researchers have examined these issues. Officer (1973) examined the effects of volatility in business cycle variables. Black (1976) and Christine (1982) relate stock market volatility to financial leverage. Merton (1980), Poterba & Summers (1986) relate stock market volatility to volatility of expected returns. Scott (1991) and Timmerman (1993) examine the extent to which the volatility of stock prices determines the underlying value.

The relationship between the return on an asset and its variance (or volatility) as a proxy for risk has been an important topic in financial research. The theoretical asset pricing models (e.g., Sharpe (1964), Linter (1965), Mossin (1966), Merton (1973, 1980) typically link the return (or the price change) of an asset to its own return variance, or to the covariance between its return and the return on the market portfolio. However, whether such a relationship is positive or negative has been controversial. As summarized in Baillie and DeGennaro (1990), most asset pricing models (e.g., Sharpe (1964), Linter (1965), Mossin (1966), Merton (1973) postulate a positive relationship between a stock portfolio's expected returns and volatility. However, there is also a long tradition in finance that models stock return volatility as negatively correlated with stock returns (Black, 1976; Cox and Ross, 1976; Christie, 1982; Bekaert and Wu, 2000; Whitelaw, 2000) . Furthermore, Glosten, Jagannathan, and Runkle (1993) and Nelson (1991) argue that across time there is no theoretical agreement about the relationship between returns and volatility within a given period of time and that either a positive or a negative relationship between current stock returns and current volatility is possible.

Stock market volatility has undergone an extensive investigation, a large part that focuses on the relationship between stock volatility and stock returns and persistence of shocks to volatility. Mandelbrot (1963) and Fama (1965) found evidence of large changes in stock prices followed by large changes of either signs and small changes followed by small changes of either signs. Research also suggests that changes in stock prices exhibit fatter tails than a normal distribution. The early research therefore confirms unconditional distributions of security price changes to be leptokurtic, skewed and volatility clustered. Considerable research has also been devoted to the potential benefits from investing in emerging equity markets e.g. Bailey et al (1990), Yaari (1994) Erunza (1994). These studies provide valuable information regarding the risk diversification potential from, investing in emerging markets. The ARCH process and its generalization due to Bollerslev (1986) are extensively used in explaining the stochastic characteristic of financial time series and the evidence suggests that conditional heteroscedasticity can well represent time varying stock return volatility and fat tailed distribution parsimoniously while incorporating autocorrelation (see Murinde et al -1999).

Stock market volatility can also be as a response to introduction and or changing of tax laws such as tax transactions, capital gains tax, income tax and related taxes. Studies from the developed stock market have linked the observed autocorrelations in index of stock returns to either non-synchronous trading effects (e.g. Fisher 1966; Scholes and Williams 1977) or to possible time variation in expected returns or risk premia.. Bolster et al. (1989) indicated that change in the tax code in the U.S had a powerful effect on trading behaviour of the stock market and was significant in the 1987 stock market crash. Hu (1998) indicated that changes in stock transaction tax in Hong Kong, Japan, Korea and Taiwan reduced stock market prices. Similar findings are reported in Sweden stock market (Umlauf 1993). The efficiency of related laws for stock trading means more developed, more competitive and more relevant to cope and absorb the stock market volatility and extra ordinary high price volatility. Further to this Levine and Zervos (1998) stated that countries with investor protection laws tend to have better developed stock markets. Schartz (1998) suggested the need for upgrading financial regulatory framework of emerging countries to handle highly volatile capital flow with unanticipated swings.

Stock return volatility could also be asymmetric, rising more following stock price declines ("bad news") than following stock price increases ("good news"). There are hosts of popular explanations for this well-known "asymmetry" in stock return volatility. The "leverage effect" posits that a firm's stock price decline raises the firm's financial leverage, resulting in an increase in the volatility of equity.[9] Others have suggested that this negative relationship between returns and return volatility stems from natural time-variation in the risk premium on stock returns. That is, an unexpected increase in volatility today leads

[9] See F. Black, 1976, Studies of stock price volatility changes, Proceedings of the American Statistical Association Annual Meetings, Business and Economics Section, Washington DC (177-181) and A.Christie, 1982, The stochastic behavior of stock return variances: Value, leverage and interest rate effects, Journal of Financial Economics 10 (407-432).

to upward revisions by market participants of future expected volatility and, therefore, upward revisions of the risk premium, which compensates them for greater risk. But, a higher risk premium lead to a greater discounting of future expected cash flows (holding those cash flows constant) and, therefore, lowers stock prices or negative return today[10]. Black (1976) and Christie (1982) further found that reduction in the equity value of the firm would raise its debt- to- equity ratio, hence raising the riskiness of the firm as manifested by an increase in the future volatility. As a result, the future volatility will be negatively related to the current return on that stock.

In another development Engle, Lilien and Robins (1987), and Bollerslev, Chou and Kroner (1992) in their analysis of risk-return trade-off state that the sign and magnitude of the risk-return parameter depends on the investor's utility function and risk preference, and the supply of securities under consideration. Glosten, Jagannathan and Runkle (1993) discuss special circumstances that would make it possible to observe a negative correlation between current returns and current measures of risk. Investors may not demand high-risk premia if they are better able to bear risk at times of particular volatility. Moreover, if the future seems risky the investors may want to save more in the present thus lowering the need for larger premia. And, if transferring income to future is risky and the opportunity of investment in a risk-free asset is absent, then the price of a risky asset may increase considerably, hence reducing the risk premium. They further claim that across time there is no agreement about the relation between risk and return within a given period of time. Investors may not require

[10] See R. Pindyk, 1984, Risk, inflation and the stock market, American Economic Review 74 (334-351) and French, Schwert and Stambaugh, 1987, ibid.

a high-risk premium if the risky time periods coincide with periods when investors are better able to bear particular types of the risk. Hence both positive and negative relationship between current return and current variance (risk) is possible.

Another explanation based on volatility feedback (Pindyck, 1984; French, Schwert, and Stambaugh, 1987) suggests that if volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline (negative return). More formally, Whitelaw (2000) theoretically shows that a general equilibrium exchange economy characterized by a regime-switching consumption process generates a negative unconditional relationship between expected returns and volatility at the market level. Black (1976), Christie, (1982), Pagan and Schwert (1990), Campbell et al, Engle et al (1993) all report that a negative shock to stock returns will generate more volatility than a positive shock of equal magnitude.

Potterbe and Summers (1986) further argue that a significant impact of volatility on the stock prices can only take place if shocks to volatility persist over a long-time. The market will not adjust to future discount rate if shocks to volatility are not permanent. In other words, stock prices are not affected by the volatility movement if shocks to volatility are transitory.

In another development, Hsieh (1991) in his investigation of chaos and non-linear dynamics in financial markets found strong evidence to reject the hypothesis that stock returns have independent and identical distribution (IID). The cause does not appear to be either regime changes or chaotic dynamics rather the cause appears to be conditional heteroscedasticity (e.g. predictable variance changes). According to Hsieh these findings have several implications;

- If we want to fit conditional density functions on stock returns, we must account for non-linear dependence.
- If we are interested to model the non-linearity in stock returns, we should direct our efforts at conditional heteroscedasticity rather than conditional mean changes.

If the flexible conditional heteroscedasticity model holds up under future analysis, it can provide conditional volatility forecasts.

2.2 Empirical literature

Most of the studies done on volatility of equity returns have mainly been with respect to the developed stock markets and industrial countries. Most of these studies use ARCH models developed by Engle (1982) and later generalized by Bollerslev (1986). French, Schwert and Stambaugh (1987), analyse daily Standard and Poor's 500 Index data for 1928-1984 and report conditional volatility in returns. Several others have investigated inter-temporal relationship between volatility and expected returns in the U.S (see Pindyck 1984). A number of these studies report that variance of returns in time shows strong correlation with prior innovations. (Geyer 1994, Kini et al 1994). Many earlier empirical studies are based on the direct association of variance with risk and the fundamental trade-off between risk and return. According to theories of Sharpe (1964), Litner (1965), Mossion (1966) change in asset price is directly related to its own variance or to the covariance between its return and the return on a market portfolio. Black (1976) and Christie (1982) in contrast point out that stock return tend to be negatively correlated with changes in volatility, accordingly a reduction in the equity value of a firm would raise its debt to equity ratio hence raising the riskiness of a firm as manifested by an increase in future volatility. Consequently, the future volatility will be negatively related to the current return on that stock. (see Chouldhry 1996).

In another study, Theodossiou and Lee (1995) examine stock market volatility and its relation to expected returns for industrialized countries and do not find any relationship between conditional variance and expected returns for any of the markets. However, other empirical applications to data found mixed results regarding the sign and statistical significance of the risk-return parameter. Elyasiani and Mansur (1998) estimates on U.S. data were negative and significant. Chou (1988) and Poterba and Summers (1986) estimates on excess returns on daily S&P index, weekly NYSE returns and U.K stock indices were positive and significant. For emerging markets, Thomas (1995) found positive but insignificant risk-return parameter for Bombay Stock Exchange, and Mecagni and Sourial (1999) found positive and significant risk-return parameter for Egyptian stock markets.

Murinde et al (1999) while investigating the nature of stock market volatility in the emerging East European markets of Hungary and Poland report that volatility can best be specified as a process of conditional heteroscedasticity in both markets. Volatility seemed to be of a persistent nature, while daily returns exhibited non-linearity. They reject the hypothesis that conditional volatility is priced in Hungarian and Polish stock markets. The empirical evidence suggests that the martingale hypothesis that future changes of the daily stock prices in these two markets are orthogonal to the past information can be significantly rejected. Choudhry (1996) in his empirical investigation of stock market volatility and the crash of 1987 give evidence on the changes on the ARCH parameter, the risk premium and volatility persistence before and after the 1987 crash in Argentina, Greece, India, Mexico, Thailand and Zimbabwe. However, these changes are not uniform and vary between the individual markets.

A lot of empirical studies have been done in various stock markets with a view of investigating the role of institutional features in stock market volatility. This includes trading mechanism, cash settlements, type of orders, trading hours, transaction costs and computerization of trading activities. Madhavan (1992) examined the price formation under two trading mechanisms and indicated that a periodic auction trading offers greater price efficiency where a continuous auction trading fails. Theissen (2000) as well found those prices in the call and continuous auction markets are more efficient than prices in the dealer markets. Mendelson (1991) found that the periodic clearing at the beginning of the trading day was noisy and inefficient. In the last decade majority of the world stock exchange switched to electronic trading system. Trading of stock markets using fully computerized and electronic screen systems may reduce the transaction costs and increase transparency but may raise the possibility of destabilizing stock markets through increasing the high price volatility of stock markets during periods of unstable trading e.g. Naudu & Rozeff (1995) found that automation of stock market increases stock price volatility. However Ferril et al (1997) found no evidence to support the contention that automation of trading destabilizes the stock market. Ngugi et al (2002) while investigating the response of the market microstructure to revitalization of Nairobi Stock Exchange (NSE) report that volatility is higher during the reform period (post 1990) reflecting a market in transition which comprised the establishment of a market regulator, shift to a new trading system and a free entry of foreign investors. Through econometric modeling of efficiency, volatility and liquidity, using the firm level data before and after the introduction of reforms they report that;

- The price discovery process shows efficiency gains following the establishment of the market regulator and free entry of foreign investors, but not after a shift to an open out-cry trading system.
- The revitalization period is characterized by a negative relationship between efficiency gains and volatility.

- A free entry of foreign investors leads to a low volatility, efficiency gains and a temporary rise in liquidity.

Richards (1996) in his empirical investigation of volatility and predictability of national stocks asserts that there is little evidence to support the assertion that volatility of returns in emerging markets has increased in recent years. He further argues that there is evidence of positive autocorrelation in emerging market returns at horizons of up to about six months. There is only mixed evidence for subsequent negative autocorrelation as would be implied by models of investor overreaction or bubbles in stock prices.

Duffee[11] (1995) explicitly studies stock returns and volatility of individual firms and finds that the negative relationship between changes in stock return variances and stock returns stems from the fact that the relationship between volatility today and returns today is actually strongly positive, but that between volatility tomorrow and returns today is negative. He finds this regularity for large and small capitalization firms and similar for firms with little and high financial leverage. In addition to de-bunking the leverage and risk premium hypotheses for the asymmetric effect in volatility, he offers another related to the option properties of growth opportunities, rather than assets in place, for a firm. In other words, growth opportunities are "real options" on future cash flows from assets in place and firms with greater volatility would have more valuable growth opportunities and higher equity value.

---

[11] See G. Duffee, 1995, Stock returns and volatility: A firm-level analysis, Journal of Financial Economics37 (399-420) and H. Shin and R. Stulz, 2000, Firm value, risk and growth opportunities, 2001, Dice Center Working Paper, Ohio State University (WP 2000-8).

A newer study by Shin and Stulz (2000) also performs a firm-level analysis but they decompose risk into its market and firm-specific components. They show that changes in market risk are positively correlated with changes in firm value, but changes in firm- specific risk are negatively correlated with changes in firm value, and this new regularity applies mostly to small firms and equally for low- and highly leveraged firms. They suggest that this finding is not consistent with Duffee's "gr owth option" theory and appeal to capital structure and risk management theories that relate to the ease of access to capital markets (especially for large firms) and of economies of scale in setting up risk management programs.

Koutmos (1999) in another development, while investigating asymmetric price and volatility adjustments in emerging Asian stock markets tested the hypothesis that index returns in emerging markets adjust asymmetrically to past information. The empirical evidence supports the hypothesis that both the conditional mean and the conditional variance respond asymmetrically to past information. The study further reports that the cost of failing to adjust prices downward is higher than the cost of failing to adjust prices upward. The faster adjustment of prices to bad news provided an alternative interpretation for the leverage effect, provided that the level of volatility rises with the speed of adjustment of prices.

Henry (1998) while modeling the asymmetry of stock market volatility applied the news impact curve of Engle and Ng (1993) as a metric for the specification of models of the conditional volatility of stock returns. The standard GARCH (1,1) model, which imposes symmetry on the conditional variance of stock returns, is shown to produce biased estimates conditional variance of the US stock market. Glosten, Jagannathan and Runkle (1993) show evidence that such a negative relationship is significant in the US market. Obviously, the empirical findings remain inconclusive.

2.3 Overview of Related Literature

From the foregoing on the above theoretical and empirical studies conducted in various stock markets, different scholars report somewhat similar conclusions. Stock return volatility is predictable and asymmetric in its response to past negative price shocks compared to past positive price shocks. That volatility moves in sympathy with trading activity in the primary market than in the secondary market. It is also evident that as stock prices fall, the weight attached to debt in the capital structure increases. This increase in leverage will lead equity holders who bear the residual risk of the firm to anticipate higher expected future return volatility. It also evident that both positive and negative relationship between current returns and current variances (risk) are possible.

A periodic auction trading offers greater price efficiency where a continuous auction trading fails, while prices in the call and continuous auction markets are more efficient than prices in the dealer markets. A shift to a new trading system and a free entry of foreign investors is seen to reduce volatility. Trading of stock markets using fully computerized and electronic screen systems may reduce the transaction costs and increase transparency thereby increasing stock price volatility. While these explanations are popular, the empirical evidence to support them has been limited in scope and again relatively new studies have suggested that these perspectives may be biased by the fact that they focus on aggregate market returns and not those of individual stocks. However, the above concepts and stated interpretations do not help in predicting future crisis or in suggesting policies for avoiding and reducing the possibility of evolving future stock volatility.

CHAPTER THREE

METHODOLOGY

3.1 Data Description

This study uses daily data from NSE to illustrate the nature of stock market volatility.

The study examines the behavior of an emerging stock market - NSE volatility over the period 2nd January 1992 to 30th June 2003. The data consists of 2810 continuously compounded returns, defined as the first difference of the log of daily stock indices, calculated as $R_t = \log (P_t/P_{t-1})$ where P_t represents the value of the NSE-20 share index at time t.

In order to investigate aggregate stock market volatility, a market index is required. This study utilizes the NSE 20-share index as a proxy for market returns, which is the barometer of the market. A price index is a measure of the relative changes in prices between various points in time given no change in volume. The 20-share index comprise of the 'blue chip' companies seen to be representing the general market performance and form the bulk of market capitalization. Companies that account for 20-share index account for 83% of the market turnover, 56% volume and 79% of market capitalization.

3.2 Variables definition

R_t is the continually compounded rate of return on a stock or a portfolio of stocks. R_{t-1} is the first lag of the daily returns. DMON through DFRI are dummy variables capturing day of the week effect. D1995 is a dummy variable capturing entry of foreign investors in the bourse as from 1st January 1995. It is zero before entry of foreign investors and unity thereafter. D2000 is a dummy variable capturing change in trading system. This involves the reduction of the number of days it takes between the actual sale and its confirmation. That is, settling transactions within five days of trading occurring and providing shareholders with their shares within seven days of settlement. It is zero before the change in July 2000 and unity after the change. DASYM is a dummy variable capturing asymmetry which take the value of one if the ex-post returns are less than zero or otherwise.

3.3 Conceptual Framework

3.3.1 Understanding Heteroscedasticity

Under standard assumptions, the conditional mean is non-constant, conditional variance is constant and the conditional distribution is normal. However, in some situations, the basic assumption of constant conditional variance may not be true. A time series is said to be heteroscedastic, if its variance changes over time otherwise it is homoscedastic. When the variance is not constant, we can expect more outliers than expected from normal distribution i.e. when a process is heteroscedastic, it will follow heavy-tailed or outlier-prone probability distributions. For example, suppose we have noticed that the recent stock returns have been usually volatile, we expect that tomorrow's return is also highly volatile. If we model this stock return data using ARMA model, we cannot capture this type of behaviour of the process (changing conditional variance over time). Processes like this, where additional information from past were allowed to affect the variance, calls for modeling the conditional heteroscedasticity.

Various conditional volatility models are compared with regard to their ability to explain certain characteristics of the unconditional distribution of stock returns such as skewness and volatility clustering. The autoregressive conditional Heteroscedasticity (ARCH) models were introduced by Engel (1982) and make the conditional variance of the time t prediction error a function of time, system parameters, exogenous and lagged endogenous variables and past prediction errors. The inherent uncertainty or randomness associated with different forecast periods seems to vary over time and large and small errors tend to cluster together. This certainly suggests application of ARCH type models. In finance, portfolios of financial assets are held as functions of the expected mean and variance of the rate of return. Since any shift in asset demand must be associated with changes in expected mean and variance of rate of return, ARCH models are the best suitable models. To have any hope of selecting an appropriate time series model, we must have a good understanding of what empirical regularities the model should capture.

Fat tails: When the distribution of financial time series such as stock returns is compared with the normal distribution, fatter tails are observed. Asset returns tend to be Leptokurtic. The documentation of this empirical regularity by Mandelbrot (1963), Fama (1965) and others led to a large literature on modeling stock returns.

Volatility clustering: This refers to the observation of large movements being followed by large movements. This is an indication of persistence in shocks. Correlograms and corresponding Box-ljung statistics show significant correlations, which exist at extended, lag lengths. The volatility-clustering phenomenon is immediately apparent when asset returns are plotted through time. As Mandelbrot (1963) wrote, "Larg e changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes..."

Leverage effects: The so-called "leverage effect," first noted by Black (1976), refers to the tendency for changes in stock prices to be negatively correlated with changes in stock volatility. A firm with debt and equity outstanding typically becomes more highly leveraged when the value of the firm falls. This raises equity returns volatility if the returns on the firm as a whole are constant. Leverage terms allow a more realistic modeling of the observed asymmetric behavior of returns according to which a "good-news" price increase yields lower subsequent volatility, while a "bad-news" decrease in price yields a subsequent increase in volatility. Black (1976), however, argued that the response of stock volatility to the direction of returns is too large to be explained by leverage alone. This conclusion is also supported by the empirical work of Christie (1982) and Schwert (1989). However, it is unclear that leverage will have any impact on the non-market or idiosyncratic component of volatility.

Long memory: Especially for high-frequency data volatility is highly persistent and there exists evidence of near unit root behaviour of the conditional variance process. This observation led to two propositions for modeling persistence: unit root or long memory process.

In trying to understand volatility at the NSE we are confronted with the following challenges:

Given the evidence of non-normality in the market returns (see Harvey 1995a) it is unlikely that the standard implementation of Autoregressive conditional heteroscedasticity (ARCH) models is fruitful. We thus study models that explicitly account for leptokurtosis and skewness. Given the existing evidence on return predictability (see Bekaert and Harvey (1995) our variance specification allows for time varying conditional means.

The GARCH model is one way of capturing the persistence of volatility observed in time series. The model can be modified to incorporate sudden changes in the variance also. It is conceivable that a given time series would have both kinds of structure. According to the GARCH (p, q) model the conditional variance of a time series depends upon the squared residuals of the process, (Bollerslev 1986). The GARCH model has the advantage of incorporating heteroscedasticity into the estimation procedure. All GARCH models are martingale difference implying that all expectations are unbiased. Lamourex and Lastrapes (1990) have shown that when ARCH/ GARCH models are applied to data that include certain changes in variance, then the conditional variance may be found to strongly persist over time. For all the series under study, descriptive statistics are obtained including a test for autocorrelation using the Ljung-Box statistic and a version of this statistic that accounts for the possibility of ARCH (Diebold 1988).

With regard to previous research (e.g. Hsieh 1991), we filter out linear dependencies in the conditional mean due to the day- of- the- week effect and the serial correlation expected to result from infrequent trading. In examining the random walk hypothesis, presence of linear and non-linear dependencies needs to be established by developing models capable of providing reasonable predictions of the future volatility at the bourse. We as well test for the sensitivity of expected volatility to information held in past returns where sign on returns influences future volatility. Volatility is negatively correlated with the direction of actual price changes. (See Ngugi et al 2002).

We use a lagged dummy variable (Asymmetry) in the conditional variance equations, which take the value of one if the ex post returns are less than zero or zero otherwise. A positive significant result indicates marked-up shifts variance when previous periods returns are negative. To estimate the GARCH model we control for factors that contribute to serial correlation. Since the study uses daily data we estimate the model using institutional dummies and also control for thin trading. Thin trading tends to increase autocorrelation in stock returns. The participation of foreign investors in the market is expected to reduce thin trading; we capture this using the dummy, D1995 (Jan). A shift in trading system form seven days in delivery and settlement to five days is expected to reduce transaction costs and influence the incentive to trade thus impacting on volatility. We therefore capture this by constructing a dummy, D2000 (August), when the clearance system shifted from t+7 to t+5).[12] To adjust for the day-of-the-week effect we construct equivalent dummies, which correspond to particular days. We further carry out diagnostic tests based on the hypothesis that the standard ARCH may under- predict or over-predict volatility.

3.4 Model specification

In the following sub-section, we discuss several models that we use to describe the dynamics of NSE index returns. Speculative prices are characterized by volatility clustering, thus model conditional second moments using variations of the GARCH process.

[12] it takes a total of five days for delivery and settlement but before 1st August it used to take seven days. This minimizes transaction costs, improves efficiency in trading system, hence increasing the incentive to trade.

Let R_t be the continually compounded rate of return on a stock or a portfolio of stocks, over a single period from time t_{-1} to t. The expected return and volatility of returns to such a decision are the conditional mean and variance of R_t denoted as,

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

$$R_t = \alpha + R_{t-1} + \mu_t \text{...}(1)$$

and $h_t =$ var(R_t/R_{t-1}) respectively.

We estimate the Engel (1982) ARCH model to confirm the presence of ARCH effects.

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \text{...}(2)$$

$$where\ \omega > 0, \alpha_i \text{........} \alpha_p \geq 0$$

are constant parameters. The conditional variance h_t under the ARCH (p) model reflects only information from time t_{-p} to t_{-1} with more importance being placed on the most recent innovations implying

$\alpha_i < \alpha_j$ for i > j.

The model however has only one memory period. The study therefore goes further to employ the linear generalized ARCH (GARCH) model introduced by Bollerslev (1986) and subsequent variants. The GARCH model corresponds to an infinite order ARCH model. This particular specification makes σ_t^2 liner in lagged values of h_{t-j}. In this model, the volatility today depends upon the volatility for the previous q days and upon the squared returns for the previous q days. As in the ARCH (p) model, the returns, conditioned on past returns may have a non-Gaussian distribution, and the model coefficients are estimated by a maximum-likelihood method.

We estimate the mean and a variance equation specified as;

$$R_t = R_{t-1} + \eta_1 DMON + \eta_2 DTUE + \eta_3 DWED + \eta_4 DTHU + \eta_5 DFRI + \eta_6 D1995 + \eta_7 D2000 + \mu_t \text{..........}(3)$$

$$h_t = \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \beta\Pi \text{..........}(4)$$

Where q >o and p >o define the orders of the processes while ω, β_j and α_i are nonnegative parameters to be estimated. If p=0 the process reduces to ARCH (q) and for p=q=0, ε_t is a white noise process. h_t is the conditional variance of daily stock returns. Day of the week dummy variables, the change in trading system and entry of foreign investors to discern eventual deterministic seasonal effects will be included in the Π vector. When the restriction $\Sigma\alpha_i + \Sigma\beta_j = 1$ then the shocks to the current volatility of stock returns may remain persistent for a long time in the future. This process is known as the "integrat ed GARCH (IGARCH)" (Nelson 1990). If the estimated coefficients sum close to unity, then strong persistence of shocks is present.

Given the IGARCH process Chou et al (1992) suggest that as in the martingale model for conditional mean of stock returns, current information remains important for forecast of the conditional variance for all horizons.

GARCH-M Model

The relationship between the conditional volatility and expected returns is examined using GARCH in mean model. Engel et al (1987) provides an extension to the GARCH model where the conditional mean is an explicit function of the conditional variance. The GARCH-

M model provides a more flexible framework to capture various dynamic structures of conditional variance and it allows simultaneous estimation of parameters of interest and hypothesis. GARCH-M model is very sensitive to model misspecification. Consistent estimation in the GARCH-M model requires that the full model be correctly specified (Bollerslev, Chou and Kroner, 1992, p. 14)

The estimation equation is expressed as;

$$R_t = \Phi_t + \delta_1 h_t + \delta_2 DMON + \delta_3 DTUE + \delta_4 DWED + \delta_5 DTHU + \delta_6 DFRI + \delta_7 D1995 + \delta_8 D2000 + \mu_t \quad (5)$$

$$\varepsilon_t / \psi_{t-1} \cap N(0, h_t) \quad (6)$$

$$h_t = \omega + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{j=1}^{q} \alpha_j (\varepsilon_{t-j})^2 + \beta \Pi \quad (7)$$

Equation 5 is the mean equation while equation 7 is the variance equation

Where;

δ_1 – This measures risk aversion or the time varying risk premium.

α_j -Existence of the ARCH effect (volatility clustering)

R_t – Stock return

Φ_t- the mean R_t conditional on past information ψ_{t-1}

$\omega > 0$, $\alpha_{j\geq 0}$, $\beta_{j\geq 0}$ are inequality restrictions imposed to ensure that the conditional variance h_t is positive. The presence of h_t in (1) provides a way to directly study the explicit trade-off between risk and expected returns. According to Eagle & Bollerslev (1986), If $\alpha + \beta = 1$ this implies persistence of a forecast of the conditional variance over all finite horizons and an infinite variance for the unconditional distribution of ε_t. Since the sum of $\alpha + \beta$ represents change in the response function of shocks to volatility per period, a value greater than unity implies that the response function of volatility increases with time and a value less than unity implies that shocks decay with time. (Chou 1998)

Asymmetric GARCH Models

The ARCH (p) and GARCH (p,q) models impose symmetry on the conditional variance of stock returns and produce biased estimates when stock prices movements are large and negative and therefore may not be appropriate for modeling and forecasting stock return volatility. In particular they fail to model leverage effect. The study thus proceeds to estimate asymmetric models with a view of establishing the validity of the symmetric distribution null hypothesis.

(a) E- GARCH model

We employ the Nelson (1991) model to allow the conditional volatility to be an asymmetric function of the past data, specified as;

$$\log(h_t) = \omega + \alpha_1 z_{t-1} + \gamma_1(|z_{t-1}| - \mathrm{E}[|z_{t-1}|]) + \beta_1 \log(h_{t-1}) + \beta_2 \Pi \qquad (8)$$

Where $z_t = \varepsilon_t / h_t$ and is the standardized residual. γ is the asymmetric component.

Where h_t is the conditional variance, ω, α, β are constant parameters. The term in parenthesis represents a magnitude effect. The model is capable of capturing any asymmetric impact of shocks on volatility. For an emerging market like NSE, asymmetry is defined through the idiosyncratic shock. E-GARCH allows good news and bad news to affect volatility in a different manner. Logarithmic construction ensures that estimated conditional variance is strictly positive.

(b) The T-GARCH (1,1) (Threshold GARCH)

An alternative model capturing asymmetries in financial data is the threshold GARCH. It is often observed in true returns that bad news has a greater impact on volatility than good news. The (TGARCH) specification tests whether downward movements in the market are followed by higher volatility than upward movements of the same magnitude. The estimation equation is specified as;

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 \kappa_{t-1} + \beta_1 h_{t-1} + \beta_2 \Pi \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

$$where \quad \kappa_t = 1 \quad if \quad \varepsilon_t \angle 0 \quad and \quad 0 \quad otherwise$$

If bad news has a greater impact on volatility than good news, a leverage effect exists, and we expect $\alpha_2 < 0$ and vice versa. The β parameter measures the degree of persistence in the conditional variance. The sum of the parameter values of alpha and beta measure the persistence in volatility shocks. If the sum of these parameters for the model is less than one, the shock dies out over time; a value close to one means that the shock will affect the conditional variance and the forecast of it for quite some time. If the sum of the parameters is equal to one the shock will affect volatility into the indefinite future. Π in the equation are vectors of parameters and other variables, respectively. The Day of the week dummy variables, the change in trading system and entry of foreign investors to discern eventual deterministic seasonal effects will be included in the Π vector.

4.1 EMPIRICAL RESULTS AND DISCUSSIONS

Table 1: Summary statistics for stock returns

Panel A						
	Part 1			Part 2		Part 3
	Period before entry of foreign investors (02/01/92-31/12/94)	Period after entry of foreign investors but before t+5 trading system (02/01/95-31/07/00)	Period after entry of foreign investors with a change in trading system to t+5 (01/08/95-30/06/03)	Period before change in trading system from t+7 to t+5 (02/01/92-31/07/00)	Period after change in trading system from t+7 to t+5 (01/08/00-30/06/03)	Entire sample period (from 02/01/92-30/06/03)
Mean	0.0009	-0.0005	0.0002	0.00001	0.0002	0.0001
Median	0.0008	-0.0006	-0.0003	0.0001	-0.0003	-0.0001
Maximum	0.0199	0.0193	0.0261	0.0199	0.0262	0.0261
Minimum	-0.0367	-0.0495	-0.0410	-0.0494	-0.0410	-0.0494
Std. Dev.	0.0060	0.0058	0.0073	0.0059	0.0073	0.0063
Skewness	-0.1322	-0.7897	-0.1933	-0.5143	-0.1936	-0.3868
Kurtosis	5.9486	9.7052	5.9323	8.2402	5.9323	7.5068
Jarque.B	272.7973	2655.474	261.3634	2483.509	261.3634	2446.5
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	747	1343	717	2090	717	2808

Panel B			
Paired samples test of Mean differences and variance			
Period	Mean	t- statistic	F-statistics
Before and after entry of foreign investors with t+7 trading system	0.0014	4.6247(0.0000)	28.7580(0.0000)
Before and after entry of foreign investors with t+5 change in trading system	0.0008	2.3380(0.0196)	4.7416(0.02959)
Before and after change in trading system, from t+7 to t+5	0.0008	2.3909(0.0170)	0.3634(0.5466)

Note: The table is divided into two panels A and B. Panel A is further divided into 3 parts; part one includes the period before the entry of foreign investors, the period after the entry of foreign investors but with no change in trading system and the period after the foreign investors and with a change in trading system. Part two is the period before change in trading system from seven days of delivery and settlement to five days independent of any other reforms that might have taken place. Part three include the entire period under study. Panel B shows the mean and dispersion comparison between different periods under study.

From Table 1 panel A, it is clear that average stock returns decline after the entry of foreign investors from 0.0009 to -0.0005. However this improves to 0.0001 in the period characterized by entry of foreign investors and change in trading system. The period characterized by a change in trading system from t+7 to t+5, before and after shows similar results with average returns declining from 0.0002 to 0.0001. The entire sample period has a positive mean return of 0.0001. The returns also exhibit negative skewness (the left tail is extreme) an evidence of fat tails as shown by high kurtosis, which exceeds the normal value. The left tail becomes thicker after the entrance of foreign investors. This implies that the returns were higher prior to the entry of foreign investors. On the contrary the left tail become less thick to the left after change in trading system. Jarque-Bera value rejects significantly the null hypothesis of normality in the distribution of returns.

From the daily standard deviation it is evident that the daily returns are less volatile after the entry of foreign investors (i.e. after Jan 1995) declining from 0.0060 to 0.0057 but increases with entry of foreign investors and change in trading system to 0.0073. Volatility become more pronounced with a change in trading system, after August 2000 increasing from 0.0059 to 0.0073.Therefore the period characterized with a change in trading system has a higher volatility than the entry of foreign investors. Turning to panel B, the t-test for the mean difference shows significant difference of returns at 5 % with the entry of foreign investors, even before change in trading system. It also shows a significant difference in returns after the change in trading system, while dispersion is significant, with the exception of change in trading system.

Table 2: Summary statistics for weekdays

Panel A					
	MON	TUE	WED	THU	FRI
Mean	0.0005	0.0001	-0.00003	0.0002	-0.0001
Median	0.0001	0.0002	-0.0002	-0.0001	-0.0003
Maximum	0.0313	0.0196	0.0211	0.0213	0.0215
Minimum	-0.0367	-0.0494	-0.0389	-0.0265	-0.0410
Std. Dev.	0.0072	0.0062	0.0063	0.0059	0.0064
Skewness	0.4207	-0.7111	-0.3496	0.1455	-0.7106
Kurtosis	6.5577	11.0010	6.7352	4.8727	9.1776
Jarque-Bera	309.6272	1529.91	334.5495	83.2123	930.912
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	556	556	556	556	556

Panel B		
Mean difference		
Between weekdays	t- statistics for the mean difference between the weekdays	F- statistics of the variance between the weekdays
mon-tue	0.893 (0.372)	0.7513(0.386)
tue-wed	0.441 (0.659)	0.1902(0.662)
wed-thu	0.631 (0.528)	0.3674(0.544)
thu-fri	0.649 (0.516)	0.4150(0.519)
fri-mon	1.398 (0.163)	1.6779(0.195)

From the descriptive statistics in table 2, Monday has a higher mean return of 0.00048 followed by Thursday of 0.00018. Wednesday and Friday however show negative average returns. Monday has higher volatility compared to the other days as shown by the standard deviation of 0.0075. This implies that the higher the returns the higher the risk premium required by the investors for non-diversifiable risk. The t-test for the mean difference shows no significant returns between the weekdays while the F-statistics shows insignificant volatility between the days.

Table 3: Autocorrelations of stock returns

Time Period	Part1			Part2		Part3
	Before entry of foreign investors (02/01/92-31/12/94)	After entry of foreign investors but with no change in trading system (02/01/95-31/07/00	After entry of foreign investors with change in trading system (t+5) 02/01//95-30/06/03	Before change in trading system from t+7 to t+5 (02/01/92-31/07/00	After change in trading system from t+7 to t+5 (01/08/00-30/06/03)	Entire period
AC1	0.255(0.0000)	0.113(0.0000)	0.291(0.0000)	0.177(0.0000)	0.291(0.0000)	0.217(0.0000)
AC12	0.076(0.0000)	0.050(0.0000)	0.017 (0.0000)	0.069(0.0000)	0.017 (0.0000)	0.051(0.0000)
AC24	0.089(0.0000)	-0.019(0.0000)	0.042(0.0000)	0.036(0.0000)	0.042(0.0000)	0.036(0.0000)
AC36	-0.025(0.0000)	-0.041(0.0000)	0.002(0.0000)	-0.016(0.0000)	0.002(0.0000)	-0.016(0.000)
Autocorrelations of squared returns						
AC1	0.106(0.0040)	0.072(0.008)	0.146(0.0000)	0.081(0.0000)	0.146(0.0000)	0.110(0.0000)
AC12	0.081(0.0000)	-0.012(0.017)	0.068(0.0000	0.016(0.0000)	0.068(0.0000	0.041(0.0000)
AC24	0.012(0.0110)	-0.007(0.214)	0.001(0.0000)	-0.002(0.0000)	0.001(0.0000)	0.005(0.0000)
AC36	0.052(0.0000)	0.009(0.608)	0.004(0.0000)	0.022(0.0000)	0.004(0.0000)	0.021(0.0000)

Table 3 provides results for serial correlation tests after correcting for it using the lagged return variable. Daily returns and squared returns are tested for the presence of autocorrelation and stationarity. The returns show autocorrelation with significant coefficients (as shown by the *p*-values) with various lags before and after the entry of foreign investors (1995) as well as with a change in trading system (2000) leading to the rejection of the null hypothesis of no serial correlation and homoscedastic daily returns. The returns shows evidence of ARCH effects as judged by the autocorrelations of both the returns and squared returns.

Table 4: Unit Root Test (ADF)

ADF test statistic	With Intercept		With Intercept And Trend	
	Calculated values	Critical values	Calculated values	Critical values
Rt	-19.36	-3.435(at1%) -2.8631(at 5%)	-19.39	-3.96 (at 1%) -3.41 (at 5%)
AR 1	-16.93	-3.4357(at1%) -2.8631(at 5%)	-16.96	-3.96(at 1%) -3.41(at5%)
	ARIMA (1, 0) Estimates			
C	0.000039(0.7338)			
AR 1	0.217(0.0000)			
Adjusted R-squared	0.99			
ARCH LM STATISTIC	0.108(0.0000)			

Significant first order autocorrelation is a common feature in return series suggesting that ARMA (1, 0) can be estimated to characterize daily returns. Following Box and Jenkins (1976), the series should be stationary before ARMA models are used and therefore this calls for testing stationarity of the return series using the unit root test of Dickey and Fuller (1979). The results show that the series is not integrated and therefore stationary. ADF statistic is significant at all levels. The coefficient for the first order auto regression is significant, although the model fails to capture non-linear dependencies. By incorporating other factors such as entry of foreign investors and change in trading system and estimating ARMA model to deal with serial correlation shows that these variables are not significant. However applying ARCH-LM[13] test to the residuals indicates presence of heteroscedasticity suggesting that ARMA (1, 0) does not remove heteroscedasticity. This implies that we can only explain the Return-Generating Process by an ARCH-type model.

[13] ARCH-LM test provides a hypothesis that the coefficient of the lagged squared residuals are all zero and therefore no ARCH

Table 5: GARCH (1, 1) Results

	Mean equation				
	1	2	3	4	5
C	0.1995(0.0000)				
Return (t-1)	0.0002(0.0066)	0.2006(0.0000)	0.2177(0.0000)	0.1831(0.0000)	0.2107(0.0000)
DMON		-0.0003(0.1354)	-0.0003(0.2063)	0.0006(0.018)	-0.0006(0.0311)
DTUE		-0.00015(0.468)	-0.0003(0.2564)	0.0008(0.0028)	-0.0007(0.0121)
DWED		-0.00031(0.1499)	-0.0003(0.1939)	0.0007(0.0136)	-0.0006(0.025)
DTHU		-0.00004(0.8507)	0.0001(0.7682)	0.0010(0.0005)	-0.00092(0.0014)
DFRI		-0.00051(0.0309)	-0.0005(0.0197)	0.0005(0.0734)	-0.0004(0.1202)
D1995				-0.0013(0.0000)	-0.0013(0.0000)
D2000				0.00001(0.9770)	0.0002(0.3118)
	Conditional volatility equation				
C	0.000002(0.003)	0.000002(0.0000)	0.00002(0.0127)	0.000002(0.0022)	0.00003(0.0198)
ARCH (1)	0.09973(0.0000)	0.0987(0.0000)	0.15011(0.0000)	0.09958(0.0000)	0.15006(0.0000)
GARCH (1)	0.8620(0.0000)	0.8643(0.0000)	0.60011(0.0000)	0.8647(0.0000)	0.60005(0.0000)
DMON			-0.00002(0.1327)		-0.000015(0.1494)
DTUE			-0.00001(0.6025)		-0.00001(0.6496)
DWED			-0.00002(0.029)		-0.00002(0.0379)
DTHU			-0.00002(0.0324)		-0.00002(0.047)
DFRI			-0.00001(0.2325)		-0.000015(0.1807)
D1995					0.0000001(0.9507)
D2000					0.0000015(0.3167)
R-squared	0.0444	0.0451	0.0451	0.0484	0.05038
Adjusted R^2	0.0430	0.0423	0.0407	0.0450	0.0446
Log likelihood	10448.28	10453.97	10417.2	10469.26	10430.99
Durbin-Watson	2.0208	2.0239	2.0630	1.9920	2.0578
F-statistic	32.557(0.0000)	16.51514(0.0000)	10.15768(0.0000)	8.70623(0.0000)	8.70623(0.0000)
	ARCH-LM test				
C	0.9961(0.0000)	0.9966(0.0000)	1.0236(0.0000)	0.9965(0.0000)	1.0402(0.0000)
Residual-squared(t-1)	0.0188(0.7864)	0.0045(0.7291)	0.0098(0.2991)	0.0047(0.7207)	0.010129(0.2917)
R-squared	0.00002	0.00002	0.0001	0.0001	0.0001
F-statistic	0.07345(0.7864)	0.0570(0.8114)	0.2720(0.6023)	0.0627(0.80235)	0.2878(0.5916)

From the estimated GARCH (1, 1) the lagged value of daily returns is positive and significant. All days exhibit negative returns in all the five models. However only model 5 shows significant coefficients for the mean returns. The entry of foreign investors shows significant negative returns while change in trading system from t+7 to t+5 has a positive but insignificant impact on the mean returns. In terms of conditional volatility equation the sum of coefficients turn out to be 0.75, when we include the days of the week and 0.96

otherwise, which is less than 1 suggesting that the process is stationary (mean reverting) while innovations have persistent impacts on the changes of returns. Since the sum of α and β is very close to 1 shocks to variance have substantial persistence implying significant ARCH and GARCH effects. The results show negative but insignificant impact of volatility in the days of the week with the exception of Wednesday and Thursday, which are significant. The impacts of structural changes on volatility are positive but not significant. The ARCH-LM test indicates presence of heteroscedasticity. The results show presence of significant autoregressive conditional heteroscedasticity implying that daily returns do not conform to random walk model in the NSE.

The relationship between the conditional volatility and expected returns (risk-return trade-off) is examined using GARCH in the mean model.

Table 6: GARCH-M Results

	Mean equation				
	1	2	3	4	5
C	-0.001319(0.0106)				
Return (t-1)	0.1973(0.0000)	0.1987(0.0000)	0.2236(0.0000)	0.1794(0.0000)	0.2166(0.0000)
DMON		-0.0012(0.0133)	-0.0040(0.0001)	-0.0005(0.4242)	-0.0030(0.0025)
DTUE		-0.0010(0.352)	-0.0045(0.0002)	-0.0003(0.6051)	-0.0036(0.0027)
DWED		-0.0012(0.0157)	-0.0040(0.0002)	-0.0005(0.4041)	-0.00306(0.0034)
DTHU		-0.0010(0.0671)	-0.0035(0.0001)	-0.0002(0.7478)	-0.0026(0.0051)
DFRI		-0.0014(0.0071)	-0.0043(0.0000)	-0.0001(0.213)	-0.0033(0.0008)
D1995				-0.0013(0.0000)	-0.0013(0.004)
D2000				-0.0001(0.7397)	-0.0001(0.8401)
Garch	0.1859(0.0551)	0.1566(0.0549)	0.6770(0.0001)	0.2066(0.0248)	0.6762(0.0001)
	Conditional volatility equation				
C	0.0000016(0.0028)	0.0028(0.0000)	0.0000103(0.02009)	0.000002(0.0026)	0.000014(0.1066)
ARCH (1)	0.1004(0.0000)	0.10123(0.0000)	0.15024(0.0000)	0.10872(0000)	0.15013(0.0000)
GARCH (1)	0.8605(0.0000)	0.8595(0.0000)	0.6002(0.0000)	0.846596(0.0000)	0.600132(0.000)
DMON			0.00000193(0.0824)		0.000006(0.5221)
DTUE			0.00000809(0.4531)		-0.000005(0.681)
DWED			-0.0000081(0.4158)		-0.00001(0.2458)
DTHU			-0.0000062(0.4721)		-0.00001(0.2571)
DFRI			0.00000092(0.9216)		-0.000003(0.7338)
D1995					0.00000019(0.877)
D2000					0.0000011(0.4696)
R-squared	0.0502	0.05021	0.0544	0.0546	0.0592
Adjusted R^2	0.0485	0.0471	0.0497	0.0508	0.053212
Log likelihood	10455.28	10455.97	10420.59	10471.12	10434.01
Durbin-Watson	2.0207	2.0240	2.0563	1.9869	2.0491
F-statistic	29.6679(0.0000)	16.4377(0.0000)	11.4981(0.0000)	14.6823(0.0000)	9.7645(0.0000)
	ARCH-LM test				
C	1.00106(0.0000)	1.00143(0.0000)	1.07937(0.000)	1.00796(0.000)	1.06015(0.0000)
Res-squared(t-1)	0.000435(0.9719)	0.00021(0.9907)	-0.01997(0.0264)	-0.00398(0.729)	0.01831(0.0469)
R-squared	0.00007	0.0002	0.000399	0.000016	0.000335
F-statistic	0.981601(0.0005)	0.990746(0.0001)	1.119496(0.2912)	0.833023(0.0445)	0.94129(0.3320)

A GARCH-M (1, 1) model was estimated in which the conditional variance (*h*) was linearly introduced into the mean equation. This means that the model does connect time varying volatility to the mean of daily stock returns. The influence of volatility on stock returns δ_1 is found to be positive and significant at 0.676, thus we find evidence of a significant time varying risk premium (as advocated by the theories of CAPM), implying stock returns are affected by volatility trends. The conditional volatility is therefore priced at NSE. The mean return is negative in all days of the week. The entry of foreign investors and change in trading system also shows negative returns. The results show significant ARCH and GARCH effects of 0.96, when we exclude models 3 and 5 on the basis of ARCH-LM test, implying clustering and persistence. The coefficients indicate shocks are not explosive and are therefore covariance stationary. The results indicate that the response function of the volatility of the shock decays at the rate of 0.96 per day thus after a month the proportion of shock remains at 0.10(0.86^{20}), which is negligible. The ARCH-LM test indicates presence of heteroscedasticity.

ARCH/GARCH models ignore information on the direction of returns, only the magnitude matters. The study now turns attention to models that can explain asymmetry in the bourse.

Table 7: E-GARCH Results

	Mean equation				
	1	2	3	4	5
C	-0.00019(0.0637)				
Return (t-1)	0.18773(0.0000)	0.18929(0.0000)	0.18907(0.0000)	0.17287(0.0000)	0.17225(0.0000)
DMON		-0.0003(0.1830)	-0.00028(0.2438)	0.0006(0.0417)	0.00064(0.0244)
DTUE		0.00006(0.8032)	0.00006(0.8149)	0.00085(0.002)	0.0009(0.0011)
DWED		-0.00037(0.1276)	-0.00038(0.1182)	0.00053(0.0579)	0.00053(0.0548)
DTHU		0.00017(0.4578)	0.00019(0.3996)	0.00109(0.0003)	0.00109(0.0001)
DFRI		-0.00044(0.0594)	-0.00042(0.0693)	0.00051(0.0566)	0.00053(0.0451)
D1995				0.00119(0.0000)	-0.00122(0.000)
D2000				0.00016(0.585)	-0.00003(0.906)
	Conditional volatility equation				
C	-0.73586(0.0037)	-0.73975(0.0025)	1.16421(0.0006)	0.69052(0.0013)	-1.1703(0.0006)
ARCH(α_1)	0.18987(0.0000)	0.19253(0.0000)	0.18878(0.0000)	0.19156(0.0000)	0.18288(0.0000)
γ (Asym)	0.04638(0.0025)	0.04730(0.002)	0.04684(0.0015)	0.04533(0.0029)	0.04545(0.0018)
(β)E-GARCH(1)	0.94214(0.0000)	0.94198(0.0000)	0.94718(0.0000)	0.94675(0.0000)	0.95056(0.0000)
DMON			0.58813(0.0135)		0.63328(0.0113)
DTUE			0.53756(0.0528)		0.57014(0.0526)
DWED			0.35539(0.1795)		0.42205(0.1264)
DTHU			0.54442(0.0438)		0.59650(0.0337)
DFRI			0.38833(0.1285)		0.41296(0.1301)
D1995					-0.0032(0.7847)
D2000					0.01232(0.3767)
R-squared	0.04498	0.04537	0.04555	0.04767	0.04889
Adjusted R^2	0.04328	0.04230	0.04076	0.04392	0.04275
Log likelihood	10465.86	10468.39	10474.83	10483	10490.61
Durbin-Watson	1.99672	1.99958	1.99939	1.96801	1.96926
F-statistic	26.39588(0.0000)	14.77614(0.0000)	9.5199(0.0000)	12.7230(0.0000)	7.96445(0.0000)
	ARCH-LM test				
C	0.98591(0.0000)	0.98749(0.0000)	0.98292(0.0000)	0.98728(0.0000)	0.98270(0.0000)
Residual-squared(t-1)	0.014662(0.3430)	0.01293(0.3826)	0.01708(0.2871)	0.01318(0.3833)	0.01743(0.2758)
R-squared	0.00022	0.00017	0.00029	0.00017	0.00030
F-statistic	0.6031(0.437439)	0.46898(0.49351)	0.8183(0.365743)	0.48748(0.4851)	0.85242(0.3559)

Unlike the earlier symmetrical models, some days report positive mean returns. From the estimation results, the entry of foreign investors is seen to significantly have a negative impact on returns, while change in trading system impacts positively on the returns though quite insignificant. Monday, Tuesday and Thursday show positive and significant volatility.

The persistence measure on conditional volatility as measured by β is highly significant and close to one (0.95056) implying that once volatility increases, it is likely to remain high over several future periods. The positive and statistically significant ARCH coefficient α_1 (0.18288) confirms the presence of volatility clustering, while the positive and statistically significant asymmetry coefficient γ (0.04545) implies the presence of asymmetry. This suggests that there is an asymmetric response of conditional variance to negative and positive stock return innovations in this market. Volatility is higher during market declines than market booms. Since β is <1 the model is not integrated. This finding is in contrast to the results reached for the U.S market (Pagan and Schwert 1990), but in agreement with those of Koutmos *et al* (1993). Investors in the NSE seem to believe that the market booms are not supported by economic fundamentals and market returns behave as speculative bubbles.

Threshold GARCH

The study further estimated the threshold GARCH to ascertain the presence or absence of leverage effect. To capture the asymmetry effects we incorporate a dummy variable DASYM, in the conditional variance equation, which takes the value of one when returns are negative and zero otherwise.

Table 8: T-GARCH Results

	Mean equation				
	1	2	3	4	5
	-0.0002(0.0637)				
urn (t-1)	0.1877(0.0000)	0.1923(0.0000)	0.2177(0.0000)	0.1748 (0.0000)	0.2106(0.0000)
MON		-0.0003(0.1459)	-.00044(0.0785)	0.0007(0.0233)	-0.0006(0.0374)
TUE		-0.0001(0.7026)	-0.0004(0.1207)	0.0001(0.0010)	-0.0007(0.0141)
WED		-0.0003(0.1992)	-0.0006(0.0254)	0.0007(0.0111)	-0.0005(0.0764)
THU		0.0001(0.7975)	-0.0002(0.3844)	0.0011(0.003)	-0.00081(0.0058)
FRI		-0.0004(0.0704)	-0.0008(0.0022)	0.0006(0.0339)	-0.0003(0.3315)
1995				-0.0011(0.0000)	0.0014(0.0000)
2000				0.00002(9394)	0.0003(0.2744)
	Conditional volatility equation				
	0.000002(0.0025)	0.000002(0.0000)	0.00002(0.0407)	0.00001(0.19900)	0.00002(0.0667)
RCH (1) (α_1)	0.13144(0.0000)	0.13341(0.0000)	0.15005(0.0001)	0.146520(0.0000)	0.15021(0.0001)
SID<0)*ARCH (α_2)	0.0828(0.0002)	0.0850(0.0000)	0.0500(0.3681)	-0.11001(0.0000)	0.04976(0.03711)
RCH (1) (β)	0.85863(0.0000)	0.85736(0.0000)	0.60011(0.0000)	0.86624(0.0000)	0.60030(0.0000)
MON			-0.00001(0.5359)		-0.00001(0.4577)
TUE			-0.000001(0.993)		-0.000001(0.906)
WED			-0.00001(0.2324)		-0.00001(0.1952)
THU			-0.00001(0.2164)		-0.00001(0.2112)
FRI			-0.000004(0.5993)		-0.00001(0.3930)
1995					0.000001(0.3395)
2000					0.000001(0.5091)
ASYM			-0.000002(0.0312)	0.000002(0.018)	-0.000002(0.014)
squared	0.04495	0.04548	0.04127	0.050255	0.04808
justed R^2	0.04325	0.04241	0.03612	0.046177	0.04159
g likelihood	10468.62	10470.15	10421.21	10486.9	10433.91
rbin-Watson	2.00546	2.00625	2.05479	1.977330	2.05263
statistic	26.3802(0.0000)	14.81504(0.0000)	8.01351(0.0000)	12.3245(0.0000)	7.41170(0.0000)
	ARCH-LM test				
	0.9879(0.0000)	0.9890(0.0000)	1.0040(0.0000)	0.9832(0.0000)	0.9902(0.0000)
esidual-squared(t-1)	-0.0137(0.3824)	-0.0127(0.5016)	0.01576(0.0689)	0.0180(0.2922)	-0.0150(0.0923)
-squared	0.0002	0.0002	0.0002	-0.0003	0.00024
-statistic	0.52865(0.4672)	0.45166(0.5016)	0.69721(0.4037)	0.9068(0.3410)	0.6349(0.4256)

When the conditional variance equation is specified as T-GARCH almost similar results as with the E-GARCH specification is found. β is a measure of degree of persistence. The sum of the estimated α_1(0.146520), α_2(-0.110061) and β(0.86624) parameters in the conditional variance equation is 0.902706, which indicate a high degree of persistence. Since this value is close to one, shocks will affect the conditional variance and the forecast of it for quite some time. α_2 is less than zero and highly significant and therefore bad news has a greater impact on volatility than goods news, suggesting that leverage effect does exist. Volatility is higher during market declines than market booms. By testing for asymmetric responses and on the basis of ARCH-LM test, we find that volatility is positive and significant in model 4 and therefore responds asymmetrically to shocks. The results suggest marked-up shifts in variance when previous period returns are negative. This corroborates results achieved earlier from the E-GARCH model.

Table 9: Summary statistics from the estimated models

Panel A				
	GARCH 1,1	GARCH-M	E-GARCH	T-GARCH
AC 1	-0.012(0.514)	-0.018(0.332)	0.017(0.355)	-0.015(0.425)
AC 12	0.01(0.927	0.008(0.662)	-0.004(0.600)	0.007(0.802)
AC 24	-0.008(0.872)	-0.009(0.608)	-0.023(0.681)	-0.006(0.763)
AC 36	0.872(0.477)	-0.011(0.271)	-0.013(0.55)	-0.007(0.421)
Mean	0.0002	0.00012	0.0002	0.0004
Std. Deviation.	0.0061	0.00611	0.0061	0.0061
Skewness	-0.5033	-0.6766	-0.4803	-0.5038
Kurtosis	7.83297	7.94953	7.7976	7.8173
Jarque-Bera	2851.39	3080.5	2800.9	2833.95
Probability	0.0000	0.0000	0.0000	0.0000
Panel B				
Unit root for conditional volatility				
ADF	-10.0538(-3.4357)	-12.4814(-3.4357)	-8.7086(-3.4357)	-10.3135(-3.4357)
PP- statistic	-10.24747(-2.5676)	-13.4420(-2.5676)	-8.3510(-2.5676)	-10.3113(-2.5676)

Note: Table 9 panel A reports the prob. Values of the Ljung-box test statistics for standardized squared residuals for the presence of serial correlation while panel B report the stationarity test on the models variance residuals

The ARCH procedure does not normalize residuals as indicated by the presence of skewness, kurtosis and Jarque-Bera statistic. The standardized residuals are examined for autocorrelation. This has dramatically reduced from that observed in the portfolio returns. The p-values are now over 0.5 on average indicating that we can accept the hypothesis of no residual ARCH. All residuals are seen to be free from serial correlation at the five- percent level in any of the residual tests. The value of skewness statistics indicate rejection of the symmetric distribution null hypothesis while the values of kurtosis statistics suggest that there is significant leptokurtosis in the distribution of residuals from the return series. The Jarque-Bera statistics indicates rejection of normality hypothesis in all cases under study. The presence of persistence in volatility clustering implies the inefficiency of NSE. The above evidence shows that the estimated asymmetric conditional variance processes are appropriate for explaining the evolution of the variance for the NSE stock returns. The unit root for conditional volatility shows that the variance residuals are significant at all levels and therefore stationary.

CHAPTER FIVE

5.1 Summary and Conclusion

This study analyzes the volatility structure of stock returns in an emerging stock market (NSE) covering the period 2nd January 1992 to 30th June 2003. The study utilizes daily stock returns calculated as log (P_t/P_{t-1}) where P_t represents the value of the NSE20-share index at time t. The study uses ARCH type models both symmetric and asymmetric in investigating clustering effects, risk-return trade off and leverage effects. In estimating the GARCH models the study controls for thin trading using the lagged Rt-1 and other sources of statistical serial correlation such as the day-of-the-week-effect.

The results are as follows. Volatility can be specified as a process of conditional heteroscedasticity. The significant and positive lagged R_{t-1} shows predictability of stock returns and therefore not efficient in the weak form (returns are predictable on the basis of past returns). Asymmetric test results indicate that conditional volatility is higher with negative shocks, implying a leverage effect. By comparing various conditional volatility models with regard to their ability to explain certain characteristics of the stock returns such as leptokurtosis, skewness and volatility clustering, the asymmetric E-GARCH (1,1) and T-GARCH (1,1) are found to provide a satisfactory description of the returns. The ARCH-LM test shows that, to some extent, a stochastic process rather than a chaotic process generates stock returns.

The positive and highly significant ARCH coefficient implies persistence in volatility clustering an indication of inefficiency of the NSE market. An assessment of predictability of the variance, shows that the stock returns is not random walk but a martingale process, future changes of daily stock prices in the NSE are dependant on the past information and therefore significant in explaining expected volatility.

The persistence of conditional volatility as measured by $\alpha + \beta$ is 0.96 which is less but close to unity, an indication that it is stationary (mean reverting), while innovations have persistent impacts on the changes of returns. Shocks are not explosive but since the sum of $\alpha + \beta$ approaches unity, the persistence of shocks to volatility is quite high and there is a tendency for volatility response to shocks to display a long memory. However, since it is less than unity, there is a tendency for volatility response to decay over time. These findings confirm the time varying risk in the stock returns in NSE. The conditional variance changes over time. This is an indication that periods of relatively high (or low) volatility are found to be time-dependent.

There is significant positive relationship between conditional volatility and the stock returns as measured by the GARCH-M model. The hypothesis that volatility is a significant determinant of stock returns is therefore confirmed. This is in conformity with Chou (1988) and Poterba and Summers (1986) estimates on excess returns on daily S&P index, weekly NYSE returns and U.K stock indices which were positive and significant. This is also consistent with the portfolio theory implying that the investors may demand a higher risk premium in anticipation of higher returns. The risk is therefore priced at the NSE, implying that investors trading stocks are compensated with higher returns for bearing higher levels of risk. When volatility is priced, an anticipated increase in volatility raises the required return on equity.

NSE has experienced dramatic transformations during the 1990s and the year 2000. The institutional reforms that have taken place in the bourse, such as the entry of foreign investors in 1995 and change of trading system in 2000 are not significant in explaining volatility of the stock returns. The opening up of the stock market and change in trading system did neither reduce time-varying risk nor reduce volatility persistence over time. We however cannot reject the calendar effects. Days of the week reflect significant negative returns while volatility is positive and significant on Monday, Tuesday and Thursday. These results are expected to provide further insight about the true driving forces of volatility in the NSE stock returns.

5.2 Policy Recommendations

The findings of this study have some important policy implications. For example, the positive relationship between market volatility and expected market return immediately implies that the time-varying risk premium theory is valid in explaining the stock market behavior. To improve the market efficiency and hence reduce volatility the timely disclosure and dissemination of information to the shareholders and investors on the performance of listed companies should be emphasized.

5.3 Areas for Further Research

Future research attempt could investigate the applicability of the models examined in this study to individual firm stock prices. In addition, the same models could be tested as to whether they can explain intra-day volatility behaviour. Better volatility-improved forecasts can be obtained if high frequency (intra-day) returns data are taken into account. Future research could also employ the non-parametric specification of conditional variance of Pagan and Ullah (1988) to study volatility at the NSE.

SELECTED BIBLIOGRAPHY

Aggarwal R. et al (1999), "V olatility in emerging stock markets" *Journal of Financial & Quantitative Analysis* 34, 33 – 56

Ajayi R. A. & Mehdian S. M. (1994), "Test of inventors, reactions to major surprises: the case of emerging markets." *Journal Of International Financial Markets, Instructions And Money*, 4 115 – 128.

Alonso, A & Rubio G (1990), "Overreaction in the Spanish equity market." *Journal of Banking & Finance* 14, 469 – 448.

Anthony Richards, (1996), "Volatil ity and predictability in national stock markets. How do emerging and mature markets differ? IMF Staff Papers Vol. 43 No. 3

Baillie, R. T., and R. P Degennaro, (1990), "Stock Returns and volatility." *Journal of Financial And Quantitative Analysis.*

Bekaert G, and C. R. Harvey, (1999), "Emerging equity market volatility." *Journal of Financial Economics* 43: 29-77.

Bekaert, Geert and Gugus Wu (2000), "Asymmetric volatility and Risk in equity markets." *Review Of Financial Studies* Vol.13, No 1, 1-42.

Black, F (1976),"Studies of stock price volatility changes." *American Statistical Association.* PP 177 – 81.

Blume, M. E. (1971) "On the Assessm ent of Risk", *Journal of Finance*, 26, 1-10.

Bolsfer et al (1989), "Tax induced trading the effect of the 1986 tax reform act on stock market activity." *Journal of finance* 44: 327 – 344.

Bollerslev, T. (1986), "Generalized Autoregressive conditional Heteroscedaticity." *Journal of Econometrics* 31:307 – 327.

Bollerslev, T., Chou, R.Y. and Kroner, K.E (1992), ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence, *Journal of Econometrics , 52, 5-59.*

Brailsford, T. J. and Faff R. W. (1993), "Modeling Australian stock market volatility; *Australian Journal of Management, 18, 109 – 32.*

Brooks et al (1997), "An examination of the effects of major political change on stock market volatility, the South African experience." *Journal of International Financial Markets, Institutions and Money, 7, 255 – 275.*

han, Y & Wei K. C. (1996), " Political risk & stock price volatility: The case of Hong Kong". Asia Pacific basin, *Journal of Finance 4, 259 – 275.*

Chou, R. Y. (1988),"V olatility persistence and stock valuations. Some empirical evidence Using GARCH." *Journal of Applied Econometrics 3: 279 – 294.*

Choudhry, T (1996), "Stock market volatility and the crash of 1987. Evidence from six emerging markets." *Journal Of International Money And Finance 15: 969 – 981.*

Christinesen B. J. and N. R., Prabhala (1998), "The relation between implied and realized volatility." *Journal Of Financial Economics, 50:125 – 150*

Christie, A. A. (1982),"The stochastic behaviour of common stock variance: value, leverage and interest rate effects." *Journal Of Financial Economics, 10: 407-32.*

David Hsieh, (1991), "Cha os and non-linear dynamics. Application to financial markets" *Journal of Finance VOL.XLVI No.5.*

Delong et al (1989), "The size and incidence of the losses from noise trading." *Journal of finance 44, 681 – 696.*

Drost, F. C. and Nijman, T. (1993), "Temporal aggregation of GARCH processes. *Econometrica, 61, 909 – 927.*

Engle R. F. (1982), "Autoregressive conditional Heteroscedasticity with estimates of the Variance of U.K inflation." *Journal of Econometrics, 50, 987 – 1008.*

Fama, E. F. (1965), The behaviour of stock – market prices." *Journal of Business. 38: 34-105.*

French, K., Scwert, W. and Stambaugh, R., (1987) Expected Stock Returns and Volatility, *Journal of Financial Economics, 19, 3-29.*

Geert Bekaert et al, (1997), "Emerging equity market volatility" *Journal of Financial Economics Vol. 43:29-77*

Georgio de Santis, (1997), "Stock returns and volatility in emerging markets" *Journal of International Money And Finance. Vol. 16 Pp261-579*

Glosten, L. R., et al (1993), "On the relation between the expected value and the volatility of the nominal excess return on stocks." *Journal Of Finance. 48"1779 – 1801.*

Goya, Amit, (2000), "Predictabilit y of stock return volatility, from GARCH models, working paper. University of California.

ory Koutmos, (1999), "Asymmetric price and volatility adjustment in emerging Asia stock markets" *Journal Of Business Finance And Accounting Vol. 26(1)*

ıelink. F. (2002), "Determination of stock market dynamics." University of Luasanne.

S. Y. (1998), "The effects of stock transaction tax on the stock market, experience from Asian markets." *Pacific-Basin Finance Journal 6, 347-364.*

K. Sengupta and Yijuan Zheng (1995), "Empirical tests of chaotic dynamics in market volatility". *Applied financial economics. 5: 291-300*

ıyun lee et al, (2000), "Long memory in volatility of Korean stock market returns." Korean advanced institute of science and technology.

ɔhnston and DiNardo (1997), "Econometrics methods". University o f California

ɔmo, K. S. (1998), "Fi nancial liberalization, crises and Malaysia policy responses." *World Dev. 26: 1564 – 1574.*

Kearney, C. (2000), " The determination and international transmission of stock market volatility." *Global Finance Journal. 11, 31-52.*

Kim, K. A. (2001), "Price lim its and stock market volatility." *Economic letters 71:141-146.*

Levine & Zervos (1998), "Ca pital control liberalization and stock market development." *World Dev, 26: 1169 – 1183.*

Merton, R. C. (1980), "On estimating the expected return on the market an explanatory investigation." *Journal Of Financial Economics.*

Murinde et al, (1999), "Volatility in East European emerging stock markets, evidence on Hungary and Poland" University of Birmigham.

Nelson D. B. (1990), "Stationarity and persistence in the GARCH (1,1) model." *Econometric Theory 6: 318 – 334.*

Nelson, Daniel B. (1991), "Con ditional heteroscedasticity in asset returns: A new approach." *Economet rica 59: 347 – 370.*

Ngugi et al (2002), "Does the revitalization process really enhance stock market microstructure?" Evidence from the Nairobi Stock Exchange.' *African Finance Journal, Vol. 4, Part 1.*

n Henry, (1998),"Modeling the asymmetry of stock market volatility" *Applied financial economics.*

rba, JM & Summers, L. H. (1986), "T he persistence of volatility and stock market fluctuations." *American economic review, 76: 1142-51.*

eep Yadar et al (1999),"N on-linear dependence in stock returns. Does trading frequency matter?" *Journal of business finance and accounting vol.26 (5)*

vert, G. W. (1989a), "Why does stock market volatility change over time?" *Journal of Finance 44: 1115-1153.*

ana, E. (1995), "Quadratic ARCH models." *Review of economic studies. 62: 639-661.*

tt, L. O. (1991), "Financial market volatility: a survey." *International Monetary Fund Staff Papers 38:582-625*

iq Choudhry (1996), "Stock market volatility and the crash of 1987: Evidence from six emerging markets" *Journal of international money and finance, vol. 15 no.6 pp969-981*

mermann, A. G. (1993), "H ow learning in financial markets generates excess volatility and predictability in stock prices." *Quarterly Journal of Economics. 108: 1135 – 45.*