FORECASTING VOLATILITY OF THE INDIAN STOCK MARKET

By

KHADILKAR GURUPRASAD HARI

THESIS

Submitted in partial fulfillment of the requirement for the degree of

Master of Science in Co-operation & Banking

(Rural Banking & Finance Management)

Faculty of Agriculture

Kerala Agricultural University, Thrissur

Department of Rural Banking & Finance Management
COLLEGE OF CO-OPERATION, BANKING & MANAGEMENT
VELLANIKKARA, THRISSUR-680 656
KERALA, INDIA

2009

Declaration

DECLERATION

I, hereby declare that the thesis entitled ***"Forecasting volatility of the Indian stock market"*** *is a bonafide record of research work done by me during the course of research and that the thesis has not previously formed the basis for the award to me of any degree, diploma, fellowship or other similar title, of any other university or society.*

Vellanikkara
29-10-09

Khadilkar Guruprasad Hari

Certificates

CERTIFICATE

*Certified that this thesis entitled **"FORECASTING VOLATALITY OF THE INDIAN STOCK MARKET"** is a record of research work done independently by **Khadilkar Guruprasad Hari** under my guidance and supervision and that it has not previously formed the basis for the award of any degree, fellowship or associateship to him.*

29/10/09

Vellanikkara

Dr. Molly Joseph
Professor & Head
Dept. of Rural Banking and Finance Mgt.
College of Co-operation, Banking and Mgt.
Vellanikkara, Thrissur
(Chairperson)

CERTIFICATE

We, the undersigned members of the Advisory Committee of ***Mr. Khadilkar Guruprasad Hari*** *(2007-15-104) a candidate for the degree of Master of Science in Co-operation & Banking with major field in Rural Banking and Finance Management, agree that the thesis entitled* ***"Forecasting volatility of the Indian stock market"*** *may be submitted by,* ***Mr. Khadilkar Guruprasad Hari*** *in partial fulfillment of the requirement for the degree.*

29/10/09
Dr. Molly Joseph
Professor & Head
Dept. of Rural Banking & Finance Mgt.
College of Co-operation, Banking and Mgt.
Vellanikkara, Thrissur
(Chairperson)

29/10/09
Dr.E.V.K. Padmini
Professor
Dept.of rural Banking & Finance Mgt.
College of Co-operation, Banking and Mgt.
Vellanikkara, Thrissur
(Member)

Dr. K.A. Suresh 29/10/09
Professor
Dept.of Development Economics
College of Co-operation, Banking and Mgt.
Vellanikkara, Thrissur
(Member)

29/10/09
Smt. T.K.Ajitha
Assistant Professor (Sel.Gr.)
Dept.of Agricultural Statistics
College of Horticulture
Vellanikkara, Thrissur
(Member)

External Examiner

Acknowledgement

ACKNOWLEDGEMENT

Well to say this is my research work is totally untrue. Actually this was my fathers dream. My mother's blessings and her constant support brought this dream in reality. Without Shree Siddhivinayaka who always directed me toward right path and gave me energy to come over all the obstacles, it was impossible to achieve. There are so many wonderful people in the world that made their contribution. I would like to thank all of them and in particular, my major advisor, Dr. Molly Joseph. Who instilled a perfection in my life. Smt. Ajitha. T.K., Assistant Professor (Sel.Gr.), Department of Agricultural Statistics, College of Horticulture. Who have guided me in all the way, without loosing a temper at single moment. Dr. K.A.Suresh, Professor, Department of Development Economics, College of Co-operation, Banking and Management. Looking towards him, I understood how the real politeness and simplicity is incarnates itself with knowledge. Dr. E.V.K. Padmini, Professor, Department of Rural Banking and Finance Management, College of Co-operation, Banking and Management. Who was always helpful and caring too much for her students. Shree. Boniface,P.J, Assistant Professor(Sel. Gr.) He allowed me to work for long hours in computer lab. My batch mate Anajaly, K.N., helped me a lot in completing all course work on time. I will always remember her punctuality & sincerity. To 'Maximum city'- Mumbai which gave me a much needed enthusiasm, every time I went there.

While doing post graduation I realized that, graduation is a journey of passion and post graduation is a progress of patience. Whenever I became restless, impatient, my best friends Abhishek, Rahul,

handled me perfectly, without caring for STD tariff!! My friend, philosopher and guide, Gauri Joshi, who read my mind, handled my out-of control emotions and gave honest comments whenever required. She's respected me, supported me, injected me with enthusiasm each time I lost it, helped me get up when I fell. Seniors Ajay, Atul, Vijitha, Onnikrishnan, and my orkut friend Tanaya Pandit did their job perfectly. My school mates Vikrant, Ratnadeep, Dhanajay, Ameya, Rushikesh, Advait, Aniket, who have cared me same as they were in school. Mahesh Damale of Angram Capital who gave me more insights about the capital market. My brothers Sameer Joglekar, Anil Bhave, Abhay Gogate, Dhananjay Khadilkar, sisters Medha Bhide, Dr.Vinaya Kamat. Joshi family and Bhide family from Ratnagiri, with irrational and unbreakable belief in me, always supported by all means.

To general bogie of Indian railway, where I learnt real banking, cooperation with the people and experienced unthinkable, which took me closer to the reality of life. To management & staff of Ramdev Bhojanalaya and Delhi Cafe, Thrissur. With their kind service, who kept me alive and happy, by providing delicious food at reasonable rates.

There are also the people who I did not meet at all, but who's work I read during the course of this research work. V.P.Kale, Veer Savarkar, Paulo Coelho, Suketu Mehata, Chetan Bhagat, Nandan Nilekani, Sudha Murthy, Rhonda Byrne, Khaled Hosseini, Kishore Biyani, Muhammad Yunus, Asha Miro, Karan Bajaj, Juan Arias, Rashmi Bansal, Lance Armstrong, Amitav Ghosh, V.D.Bhat, Arvind Adiga, kept me awake late in to the night with their illuminating, and varied style of depiction. I owe a grate deal to English daily 'The Economic Times' who attracted me towards economics with its unique style of interpretation. Weekly magazine 'The Week' for its diversified coverage. Online dailies like Maharashtra Times, Loksatta, Lokmat, Times of India, Sakaal, who kept me intact with my home town.

Friend Raj Bhosale, Navanath and my hostel mates, Midhun, Vishakh, Naval-Kishore, Reni, Anand, Sachu, Shrijesh, Sagar, Dennis, and Nataraj for bearing me in my stay.

And lastly all the bitter experiences, who taught me a lot, and shaped my character all the way. Jai ho !!

Khadilkar Guruprasad Hari

Dedicated to,

The victims of 26/11

Mumbai terrorist attack.

Contents

CONTENTS

List of Tables

LIST OF TABLES

List of Figures

LIST OF FIGURES

Introduction

CHAPTER 1

INTRODUCTION

The growth of the equity market in India has been phenomenal in the present decade. Liberalisation of the Indian economy has attracted individual investors and institutional investors from all over the world. As such, Indian stock market scenario is very bright, because of large population, availability of skilled young labour and increasing middle class income. Moreover, Indian economy is in a booming stage. All these demographic dividends and its future prospects are reflected in the Indian stock markets as well. As a result, Indian stock market is one of the most volatile markets in the world.

In financial markets volatility presents a strange paradox to the market participants, academicians and policy makers. Without volatility, superior returns could not be earned, since a risk free security offers meager returns. On the other hand, if it is 'high' it will lead to losses for the market participants and represent costs to the overall economy. Extent of volatility in the stock, bond and foreign exchange markets raises important public policy issues about the stability of financial markets and the impact of volatility on the economy. As an investment strategy, investor needs to identify the prevailing or actual volatility in the stock market. The present study is an attempt in this direction, in as much to enquire into the volatility behaviour of the Indian stock market and to identify a suitable model for forecasting its volatility.

1.1 Significance of the study

Price fluctuations are a daily occurrence in the stock markets, as investors react to economic, business and political events. If a stock is highly volatile, i.e., if there are large fluctuations in its prices, risk averse investors might avoid participating in the market. As the Indian financial market gets integrated with the world economy, the Indian stock markets react to the global events in accordance with the trends in international markets. As a result any good news from the Federal Reserve will be reflected in the soaring market indices in India, whereas any overseas financial crisis creates turmoil in the Indian markets by huge market crashes. Due to increased integration of global financial markets, its effect on sentiments of Indian investors cannot be ruled out. These sentiments will increase the volatility in the market.

Sometimes volatility may be more prominent in some sectors, and least in certain other sectors. If investors wish to invest in a particular volatile sector they may earn more income without going for the entire market index. So inorder to maximise income and reduce risk, investors should focus sector-wise, which warrants analysis of sector-wise volatility. If an investor is able to forecast market volatility successfully he/she can use it as a powerful tool and earn more profit on his/her investments. Finally, volatility could be assessed based on different models. Investor has to identify which model suits to his/her priorities, the different investment strategies and products available in the market, as one model might not be suitable for different products and strategies of investments, such as short term or long term, equities, futures, options etc. A study on the forecasting of volatility of Indian stock market would facilitate the introspection of past trends and its impact on income generation, which in turn enables the participants to make more promising decisions. As such forecasting sector-wise volatility of the Indian stock market and identifying a suitable model for forecasting its volatility would be of great significance not only to the participants of the market but to the economy as a whole.

1.2 Statement of the problem

Volatility is the tendency of the underlying security's market price to fluctuate either up or down. Volatility reflects the magnitude of price change; it does not imply any bias in the movement of the price, whether in one direction or other. Broadly the factors, which result in volatility, can be classified into two categories - endogenous and exogenous. Endogenous factors are those, which emerge from different fields like corporate, economy, and politics within the country. These factors are of two types - micro and macro. Micro factors are specific, like dividend decisions, major expansion plans, and receiving of big contracts which have significant impact upon the value of the stock of that company. Macro level factors affect the whole economic structure of the economy, and thereby, the behaviour of the stock market. The impact of these factors clearly gets reflected in the stock market in terms of volatility. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security's value does not fluctuate dramatically, but changes in value at a steady pace over a period of time.

The steady rise in the Indian stock market indices since the year 2003 drew in many new investors from different walks of life into the market. Many of them are ignorant of the relation between risk and reward associated with their investments. Moreover they rely on the advice of their brokers and are unable to take decisions on their own in highly volatile market conditions. As a result, they miss the opportunity of making money and often end in loss. Hence to be successful in a stock market, one needs to understand past trends of volatility in the market. The analysis of past volatility will help investor to forecast what lies in future and make more accurate decisions. Hence the present study is focused on forecasting volatility of the Indian stock market as a whole, by analysing the price movements in the biggest stock exchange of India, viz., National Stock exchange, (NSE). The sector – wise volatility of NSE is also forecasted with respect to five top companies listed in the Nifty. The study also aims at identifying an appropriate model for forecasting volatility of the Indian stock market.

1.3 Objectives of the study

The objectives of the study are:

i) to examine the volatility behaviour of the Indian stock market

ii) to forecast the sector- wise volatility of the Indian stock market and

iii) to identify the most efficient volatility forecasting model among the five models used.

1.4 Utility, scope and limitations of the study

Volatility forecasting has now become an important area of research in financial markets. It will help in better pricing of options and better risk management for the investors. Volatility of stock markets, if compared with the periodic movements in commodity exchanges like bullion market, crude oil prices, and foreign exchange market i.e. exchange rates of dollar, euro etc. would reveal about their interconnectivity and inter balance. The study also helps to investigate the relative efficiency of the various volatility forecasting models which would be beneficial to the investors.

The methods used in this research and the conclusion of this research work would provide additional insights about the volatile nature of the market. With regular observations and analysis one would be able to discover the profitable use of the forecasting methods and their indications.

For examining the volatility behaviour of the Indian stock market, only S&P CNX Nifty index of the National Stock Exchange is selected. The scope of the sector – wise volatility of the Indian stock market is limited to five companies representing five sectors, based on the criterion of market capitalization. Due to lack of continuous data, one company among the top five ranks, based on market capitalisation was replaced by the sixth company. One of the two companies in the top five, representing same sector have also been avoided. Analysis was done using daily close price of the selected stocks for the period 1994 to 2008. Although ample number of models for forecasting is available, as revealed by the review of literature, only five models have been selected for forecasting volatility and comparing their efficiency.

1.5 Organization of the report

The report is organized in five chapters. The first chapter deals with the significance of the study, statement of the problem, objectives, utility, scope and limitations of the study and organization of the thesis. The second chapter discusses the review of literature relevant to the topic of study. The third chapter gives a description about the methodology adopted for the study. The fourth chapter is earmarked for results and discussions. The last-chapter highlights the summary of findings and conclusion of the study, followed by references and abstract of the thesis.

Review of Literature

CHAPTER 2

REVIEW OF LITERATURE

A review is an evaluation of a publication, where author studies former research work related to the current subject of study and which gives a broader base for studying the relevance of the present situation with respect to past observations and past findings. The aim of the review is to find out the most logical and already proved part of analysis, which is most specific with the topic of study. It is the analysis of present situation, based on past experiences or references, for future prospects.

Sometimes due to technological advancement and other scientific development, old findings may become irrelevant in the present curcumstances. So review procedure is necessury to keep pace with this ever changing state of science. Review of available literature gives a thorough understanding of the topic to the researcher. It sharpens the skills and knowledge of the researcher by making the person upto date with regard to progression of the field of study. In short, review brings the reader upto date with current literature on a topic and forms the basis for another goal, such as the justification for future research in the area. Hence here, a brief review of the available literature, on various topics related to the present study is attempted and presented under three sub headings:

2.1. Volatility of developed stock markets

2.2. Volatility of developing stock markets

2.3 Volatility of the Indian stock market.

The history of stock trading dates back to the 17th century. The Amsterdam Stock Exchange (or Amsterdam Beurs) is said to have been the first stock exchange to introduce continuous trade in the early 17th century. The Dutch pioneered short selling, option trading, debt-equity swaps, merchant banking, unit trusts and other speculative instruments. Over the years, stock markets have developed in terms of technology, turnover and trading practices. With the process of globalisation some new stock markets have also come into the picture.

2.1 Volatility of developed stock markets

The stock markets of United States, United Kingdom, France, Germany, Hong Kong, Japan, Australia and New Zealand are considered as developed stock markets. The abstract of various studies related to volatility in developed stock markets is discussed in this section.

Bradfort and Becht (1992) in their study on excess volatility and the German stock market for the period 1876 to1990, examined the volatility of prices relative to dividends in order to avoid most of the biases in estimated volatility ratios generated by Shiller's (1981) original tests. Study was divided into pre World War I and post World War II period, using German data. They found some evidence of excess volatility in the post World War II German stock market, although no sign of excess volatility at all in the pre World War I German stock market. Actually it had market behaviour different from that of the American market. Study proved that the absence of excess volatility in the German stock market before World War I strengthens Shiller's conclusions for the United States.

De Long and Grossman (1993) examined the excess volatility in the London stock market based on the long run British stock prices over the period from 1870 to 1990. They found that the British stock market did exhibit 'excess volatility' if the pre World War I period is included in the sample. British price/dividend ratios before World War I were low compared to those of other nations or to post World War I Britain. Study further concluded that the British market had exhibited signs of excess volatility over the past century.

Franses and Dijk (1996) studied forecasting stock market volatility using non-linear Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models. Study analysed the performance of the GARCH model and two of its non-linear modifications to forecast weekly stock market volatility. Analysis was aimed at the forecasting of volatility and not the mean of the time series. Results proved that the Quadratic Generalised Autoregressive Conditional Heteroscedasticity (QGARCH) model is the best when the estimation sample does not contain extreme observations and that the Glosten, Jagannathan and Runkle (GJR) model could not be recommended for forecasting.

Andersena *et al.* (1999) analysed the modelling and forecasting of realised volatility. Study was based on formal links between realized volatility and the conditional covariance matrix. Analysis focused on the spot exchange rates for the U.S. dollar, the Deutsche Mark and the Japanese Yen, covering a period of more than a decade. Study found that forecasts from a simple long-memory Gaussian vector auto regression for the logarithmic daily realized volatilities performed admirably compared to a variety of popular daily ARCH and more complicated high-frequency models. Results hold promise for practical modeling and forecasting of the large covariance matrices relevant in asset pricing, asset allocation and financial risk management applications.

Hol and Koopman (2000) forecasted the variability of stock index returns with stochastic volatility models and implied volatility. Study compared the predictive ability of Stochastic Volatility (SV) models to that of volatility forecasts implied by option prices. Study used the SVX model, which is developed by combining SV model with implied volatility as an exogenous variable in the variance equation which facilitates the use of statistical tests for nested models. This model when extended to volatility model with persistence adjustment term it is called as SVX+ model. The out-of-sample volatility forecasts were evaluated against daily squared returns and intraday squared returns for forecasting horizons ranging from one to ten days. Using intraday squared returns as a measure of realised volatility, the study revealed that the SVX+ model produces the most accurate out-of-sample volatility forecast.

Laws and Gidman (2000) studied forecasting stock market volatility and the application of volatility trading models. Study examined the ability of GARCH and GARCH plus Implied Volatility models to forecast stock market volatility on the FTSE100 index (Financial Times Stock Exchange Index). Study also investigated whether successful volatility trading models could be developed. An at-the-money index call was bought/sold if the volatility forecast was above/below the implied volatility by a certain threshold. It was found that forecasting techniques that include both market - based information and times - series information produced better forecasts. These combined models also produced more profitable signals.

Bluhma and Yub (2001) forecasted volatility taking evidence from the German stock market. Study compared two basic approaches to forecast volatility. The first approach used various univariate time series techniques while the second approach made use of volatility implied in option prices. Study showed that the model rankings were sensitive to the error measurements as well as to the forecast horizons. The results indicated that it was difficult to state which method was the clear winner. However, when option pricing is the primary interest, the SV model and implied volatility should be used. When Value at Risk (VaR) is the objective, the ARCH-type models are useful. Furthermore, the trading strategy suggested that the time series models are not better than the implied volatility in predicting volatility.

Hwang and Satchell (2001) studied GARCH model with cross-sectional volatility. Study introduced GARCH models with cross-sectional market volatility, which is called as GARCHX model. The cross-sectional market volatility is equivalent to common heteroskedasticity in asset specific returns, and an important component in individual asset volatility. Study aimed at finding daily return volatility using UK and US data. Empirical results showed that the return volatility (squared returns) is better specified with GARCHX models. To investigate the forecasting performance of the GARCHX model, data used included four daily return volatility series of three stocks, i.e., Abbey National, Unilever, British Airways, and one index, i.e., the FTSE100 index. Study found that daily return volatility could be better specified with GARCHX models, but GARCHX models did not necessarily perform better than conventional GARCH models in forecasting.

Claessen and Mittnik (2002) reported that 'implied volatility' is a biased but highly informative predictor for future volatility. Moreover, implied volatilities are informationally efficient relative to other historic volatility information sources. In their study on forecasting stock market volatility and the informational efficiency of the DAX index (Deutscher Aktien IndeX) options market, alternative strategies for predicting stock market volatility were examined. The in–sample fitting and out–of–sample forecasting results showed that historic returns contained no information beyond the market's volatility expectation that is reflected in DAX–index option prices.

Herath and Kumar (2002) examined the Jackknife estimator for estimating volatility of a stock. Study demonstrated the application of a statistical technique to estimate the volatility of a stock, based on re-sampling method. Although jackknife method is computationally intensive in case of small sample data it is easy to implement as it does not place a heavy burden on data requirements. To demonstrate its practical use, the pricing bias was analysed using the stochastic volatility estimate as input in Hull and White (1987) model. Results indicated that the proposed technique is ideal for small data sets when implementing stochastic option pricing models. In addition, it could easily be implemented on a spreadsheet and does not need special statistical packages or computer programs as required for the bootstrap method.

Martens *et al.* (2002) studied about a comparison of seasonal adjustment methods when forecasting intraday volatility. Study compared volatility forecasts over a thirty-minute horizon for the spot exchange rates of the Deutsche Mark and the Japanese Yen against the US dollar. Database for the study included two major exchange rates - the DEM/USD and the YEN/USD. Explicitly modelling the intraday seasonal pattern improves the out-of-sample forecasting performance. Study found that a seasonal estimated from the log of squared returns improves with the use of simple squared returns, and that the flexible Fourier form (FFF) is an efficient way of determining the seasonal. The Periodic GARCH (P-GARCH) model provided the best forecasts of out-of sample for both the currencies.

Yu (2002) evaluated the performance of nine alternative models for predicting stock price volatility using daily New Zealand Stock Exchange (NZSE) data, i.e. NZSE 40 index. Four different measures were used to evaluate the forecasting accuracy. After comparing the forecasting performance of all nine models, he found that the SV model is superior according to the (Root Mean Square Error) RMSE, Theil's-U (TU) and three asymmetric loss functions. Other findings of the study were that the ARCH – type models could perform well or badly depending on the form chosen. the performance of the GARCH (3, 2) model, the best model within the

ARCH family, was sensitive to the choice of assessment measures and the regression and the exponential weighted moving average models did not perform well according to any assessment measure, in contrast to the results found in various markets. Study also revealed that the added information could not improve the out-of sample forecasting performance.

After studying about modelling and forecasting of realised volatility, Anderson *et al.* (2003) reported that practical modelling and forecasting of large covariance's matrices is relevant in asset pricing, asset allocation and financial risk management. Analysis provided a framework for integration of intraday data into the measurement, modelling and forecasting of daily and lower frequency volatilities and return distribution. Study developed formal link between realised volatilities and the conditional covariance matrix. Using continuously recorded observations for the Deutsche mark/ Dollar and Yen/ Dollar spot exchange rates, study found admirable performance of a forecasts from simple long memory Gaussian vector auto regression for the logarithmic realised daily volatilities. Moreover the autoregressive forecasts coupled with the lognormal-normal distribution produced well calibrated density forecasts of future returns and correspondingly accurate quantile predictions.

Athanassakos and Kalimipalli (2003) examined the relationship between analysts' forecast dispersion and future stock return volatility using monthly data for a cross section of 160 U.S. firms from 1981 to 1996. Analysts forecast dispersion refers to the disagreement among analysts with regard to the expected earnings per share (EPS) of a given firm. Using future return volatility as the dependent variable and future market volatility and analysts' forecast dispersion, as the independent variables, time series-cross sectional estimations were carried out. Study revealed that there is a strong and positive relationship between analysts' forecast dispersion and future return volatility. Even after accounting for market volatility, the dispersion measure had incremental information content. These results were robust across subsamp/e periods and subsamples based on the number of analysts following a firm, forecast dispersion, and market capitalization. A strong seasonal relationship between the dispersion measure and future volatility was found. The importance of dispersion on future return volatility was high in January and the first few months of the year and declined thereafter. Such information content of analysts' earnings forecast dispersion was of great importance for active portfolio management, option pricing, and arbitrage trading strategies.

Guo and Savickas (2003) studied idiosyncratic volatility, stock market volatility and expected stock returns by using daily Center for Research on Security Prices (CRSP) stock files, which span from July 1962 to December 2002. It was reported that the value-weighted idiosyncratic stock volatility and aggregate stock market volatility jointly exhibited strong predictive power for excess stock market returns. The stock market risk-return relation was found to be positive, as stipulated by the Capital Asset Pricing Model (CAPM). Also, idiosyncratic volatility appeared to be a pervasive macro variable.

Jiang and Tian (2003) studied model-free implied volatility and its information content. Study was based on an estimator of the model-free implied volatility and it investigated its information content in the S&P 500 index options. Like Black-Scholes implied volatility, the model-free implied volatility was not based on any specific option pricing model .Study compared and contrasted the efficiency of the model free implied volatility as a volatility forecast against two other commonly used volatility forecasts - the Black-Scholes implied volatility and past realized volatility. Results suggested that the model-free implied volatility is an efficient forecast for future realized volatility and subsumes all information contained in the Black-Scholes implied volatility and past realized volatility. Study also found that under the log specification, the model-free implied volatility is an unbiased forecast for future realized volatility after a constant adjustment.

Balaban *et al.* (2004) studied about forecasting stock market volatility further international evidence. Volatility was defined as within- month standard deviation of continuously compounded daily returns on the stock market index of each country for the ten – year period 1988 to 1997. Daily observations of stock market indices of fifteen countries covering the period December 1987 to December 1997 were used for analysis. Study evaluated the out-of-sample forecasting accuracy of eleven models for monthly volatility in fifteen stock markets. The first half of the sample was retained for the estimation of parameters while the second half was for the forecast period. Eleven models, viz., a random walk model, a historical mean model, moving average models, weighted moving average models, exponentially weighted moving average models, an exponential smoothing model, a regression model, an ARCH model, a GARCH model, a GJR-GARCH model and an EGARCH model were used. First, standard (symmetric) loss functions were used to evaluate the performance of the competing models: mean absolute error, root mean squared error, and mean absolute percentage error. According to all of these standard loss functions, the exponential smoothing model provided superior forecasts of volatility. On the other hand, ARCH-based models generally proved to be the worst forecasting models. Asymmetric loss functions were employed to penalize under-/over-prediction. When under-predictions were penalized more heavily, ARCH-type models provided the best forecasts while the random walk was the worst. However, when over-predictions of volatility were penalized more heavily, the exponential smoothing model performed the best implying that buyers of options are best served by using this model, while the ARCH-type models were universally found to be inferior forecasters.

Figlewski (2004) focused on the empirical performance of different historical variance estimators and of the GARCH model for forecasting volatility in important financial markets over horizons upto five years. The brief investigation of data periodicity suggested that there is a difference between the behaviour of volatility estimated over the same time period with daily and with monthly observations. Results revealed that historical volatility computed over many past periods provides the most accurate forecasts for both long and short horizons. Substantially lower errors of root mean squared forecast were observed for long term volatility forecasts than short term forecasts. The GARCH model requires quite a large data sample for easy estimation of its coefficients, which makes monthly data hard to use.

Lux and Kaizoji (2004) examined the forecasting volatility and volume in the Tokyo stock market. They investigated the predictability of both volatility and volume for a large sample of Japanese stocks. The particular emphasis was on assessing the performance of long memory time series models in comparison to their short-memory counterparts. They proved that, for FIGARCH (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity model) and ARFIMA (The model, known as Autoregressive Fractionally Integrated Moving Average allows for increased flexibility in modeling low-frequency dynamics.) models, pooled estimates i.e., averages of parameter estimates from a sample of time series, give much better results than individually estimated models. And selection of long-memory models performed better in most cases than the naive sample variance and GARCH forecasts. Time series methods, thus, seemed to be better suited for forecasting large realizations of volatility rather than small or medium ones.

Busch *et al.* (2005) forecasted exchange rate volatility in the presence of jumps using data of options on Deutsche Mark (DM) futures traded on the Chicago Mercantile Exchange (CME). Analysis included implied volatility from option prices. Study measured the foreign exchange rate volatility based on high-frequency (5-minute) $/DM exchange rate returns using nonparametric statistical techniques to compute realized return volatility and its separate continuous sample path and jump components, and measures based on prices of exchange rate futures options, allowing calculation of option implied volatility. Study found that implied volatility is an informationally efficient but biased forecast of future realized exchange rate volatility. Furthermore it showed that, log-normality is an even better distributional approximation for implied volatility than for realized volatility in this market. Study also revealed that the jump component of future realized exchange rate volatility is to some extent predictable, and that option implied volatility is the dominant forecast of the future jump component. Results suggested that option market participants in part base their trading strategies on information about future jumps.

Campbell (2005) examined stock market volatility and the Great Moderation. Using data on corporate profits forecasts from the Survey of Professional Forecasters, he decomposed real stock returns into a fundamental news component and a return news component and analysed the effects of the great moderation on each. The empirical results showed that the Great Moderation has had very different influences on the two fundamental components of stock returns. The volatility of news about stock fundamentals, such as dividends, earnings or cash flow, has abated since the onset of the Great Moderation. And study revealed no significant link between macroeconomic volatility and the volatility of return news.

In the study, financial asset returns, direction-of-change forecasting and volatility dynamics, Christoffersen *et al.* (2005) considered three sets of phenomena that feature prominently and separately in the financial economics literature - conditional mean dependence (or lack thereof) in asset returns, dependence (and hence forecastability) in asset return signs, and dependence (and hence forecastability) in asset return volatilities. Study focused on the sign dependence and the relationship of sign dependence to conditional mean independence and volatility dependence. The authors showed that they are very much interrelated, and hence explored the relationships in detail. Volatility dependence produces sign dependence, so long as expected returns are nonzero. It is statistically possible to have sign dependence without conditional mean dependence Sign dependence is not likely to be found in very high-frequency (e.g., daily) or very low-frequency (e.g., annual) returns. The link between volatility dependence and sign dependence remains intact in conditionally non-Gaussian environments, as with time – varying conditional skewness and/or kurtosis.

A study by Maheu and Liu (2005) aimed at investigating the benefits of volatility instruments called realized power variation and realized bipower variation in modelling and forecasting volatility. High frequency foreign exchange data on the JPY-USD and DEM-USD spot rates were used for the analysis. Bayesian methods were used to evaluate the importance of additional volatility instruments in modelling and forecasting realized volatility. Study found robust improvements in both foreign exchange and equity markets when power variation terms were included for models of one period ahead volatility. Results also showed power variation to be useful for longer horizon forecasts. Bayesian model average was the best performer over others which were included in the study.

Marcucci (2005) compared the different GARCH models in terms of their ability to describe and forecast their financial time series from one day to one month horizon. Excessive persistence which generally finds into the GARCH models that implies too high and too smooth volatility forecasts was also taken into account. Markov regime switching GARCH models were also analysed. While forecasting volatility on shorter horizons, Markov regime switching GARCH models outperformed all other GARCH models. At longer horizons standard GARCH models fared the best. Study also found that no model clearly outperformed others at all horizons under the risk evaluation criterion.

Shan (2005) demonstrated that financial markets significantly affect short term stock prices, by examining how non-accounting information particularly contained in analyst's forecasts contributed to the fluctuation of future stock returns from the perspective of EMH. Data for the study was taken from the compustat, CRSP and I/B/E/S database of NYSE firms. Results indicated that variance of future stock returns negatively associated with unfavourable non-accounting information and positively associated with the volatility of the non accounting information variable. These results are valid for measures of both the systematic and idiosyncratic volatilities. Study has set the new theoretical link between non accounting information in analysts' forecasts and stock return volatility.

The objective of a study by Ahoniemi (2006) was to produce useful forecasts for option traders. The prices for call and put options on the S&P 500 index were considered for the study. Numerous time series models of the VIX index were estimated and daily out of sample forecasts were calculated from all relevant models. Study modelled the implied volatility of the S&P 500 index. The results showed that an ARIMA model enhanced with exogenous regressors has predictive power regarding the directional change in the VIX index. GARCH terms are statistically significant, but do not improve forecasts. The use of a filter to leave out the signals for a very small change in the VIX improved the results in most cases. Results proved a certain degree of predictability in the direction of change of the VIX index that could be exploited profitably by option traders.

Dopke *et al.* (2006) compared forecasts of stock market volatility based on monthly real-time and revised macroeconomic data based on a new dataset on monthly real time macroeconomic variables for Germany. The data set covered the period from 1994 to 2005. A statistical, a utility-based, and an options-based criterion were used to evaluate volatility forecasts. They reported that the statistical and economic value of forecasts of stock market volatility based on real-time data was comparable to the value of forecasts based on revised macroeconomic data. Result implied that real-time macroeconomic data could be utilised to forecast stock market volatility by the investors. And researchers could employ revised macroeconomic data to study the equilibrium relations between macroeconomic variables and stock market volatility.

Kalev (2006) developed a global volatility estimator and forecasted market uncertainty. The study utilised tick-by-tick data of equity indices, globally traded stocks and commodity futures from different time zones. The aim of the study was to produce an efficient and robust risk estimator to sudden changes of the price movements and price discontinuities. The data sample consisted of intraday transactions, quote data (tick-by-tick transaction data) and midpoint of the best bid-ask quotes. Study evaluated the performance of the out-of-sample forecasted volatility comparing the Root Mean Squared Error (RMSE), which was estimated in a consistent heteroskedasticity manner. The results of the study projected global and local one-day ahead, one-week ahead and up to one-month ahead volatilities, which are crucial for making optimal investment allocations and informed decisions.

Using 40 years of US excess stock return and macroeconomic data, Flad (2006) studied whether macroeconomic factors help forecast stock market volatility. Study was based on Arbitrage Pricing Theory (APT) models that incorporate macroeconomic information in forecasting stock market volatility. He reported empirical evidence that suitably extracted factors of both data sets are good proxies for systematic driving forces of excess returns. And pooling of information allowed for the incorporation of additional risk factors that govern the influence of subtle economic variables and interrelationships, which would otherwise have been omitted from consideration. Study revealed that suitably selected diffusion indices are good proxies for the forces that drive US excess returns.

Sucarrat (2006) analysed the factors that determine the volatility of weekly Norwegian exchange rates. Study aimed at implementing and evaluating general-to-specific modelling of exchange rate volatility. He studied the weekly Norwegian exchange rate volatility in the krone against the euro (against the German Mark in euro equivalents before 1999) by means of statistical methods. Results revealed that increased global market activity, measured by increased quoting in the Norwegian krone against the euro in the global inter bank market from one week to the next, increased volatility from one week to another. The general shift upwards in weekly

Norwegian exchange rate volatility around the beginning of 1997 was not due to a general increase in market activity. The results suggested that increase in both Norwegian and US stock market volatility increased weekly Norwegian exchange rate volatility, and that their impact was equal.

Chou, and Wang (2007) examined the empirical performance of the conditional autoregressive range (CARR) model. Analysing data on the UK stock market over the period 1999 to 2000, the authors found that CARR model produces sharper volatility forecasts than the commonly adopted model, the GARCH. Furthermore, they found that the inclusion of the lagged return and trading volume could significantly improve the forecasting ability of the CARR model. Their empirical results also suggested the existence of a leverage effect in the U.K. stock market. The CARR model provided a simple, yet effective framework for forecasting the volatility dynamics. The empirical results provided strong support for the application of the CARR model in the U.K. stock market.

The study of Eriksson *et al.* (2007) introduced a parsimonious and yet flexible nonnegative semi parametric model to forecast volatility. The new model was an extension of the linear nonnegative autoregressive model by way of a Box-Cox transformation. The model is semi parametric as only the support and not the functional form of the error distribution is assumed to be known. Its out-of-sample performance was evaluated against a number of standard methods, using data on S&P 500 monthly realized volatilities. Results showed that forecasts from the new model performed exceptionally well under the mean absolute error and the mean absolute percentage error measures.

Chen *et al.* (2008) studied about the application of Support Vector Regression (SVR) based on GARCH model in forecasting volatility of financial returns. Real time data on British Pound-US Dollar (GBP) daily exchange rates and New York Stock Exchange (NYSE) daily composite index were used. The analysis showed that, under both varying and fixed forecasting schemes, the SVR-based GARCH outperformed the Moving Average (MA), the recurrent Neural Network (NN) and the parametric GARCH based on the criteria of mean absolute error (MAE) and directional accuracy (DA). Study concluded that the problem of good estimation and poor forecasts could be resolved using their recurrent SVR method. The real data results, together with the simulation evidence, consistently supported the use of the three recurrent SVR-based GARCH models in forecasting one- and multi-period-ahead volatility error magnitude and direction.

Chen *et al.* (2008) used realised volatilities based on the high frequency information during the after-hours period to predict daily volatility. The authors extended the GARCH and long – memory forecasting models to include additional information: the whole night, the pre open, the post close realized variance, and the overnight squared return. Study investigated individual stocks instead of market indices. For four NASDAQ stocks viz., Microsoft (MSFT), Amgen (AMGN), Cisco systems (CSCO), and Yahoo (YHOO), it was found that the inclusion of the preopen variance could improve the out-of-sample forecastability of the next day conditional day volatility. The post close variance and the overnight squared return, did not exhibit any predictive power for the next day conditional volatility. Their findings supported the results revealed of prior studies that traders trade for non-information reasons in the post close period, while they do for information reasons in the pre open period.

Perron and Qu (2008) analysed the properties of the autocorrelation function, the periodogram and the log periodogram estimate of the memory parameter when the level shift component is specified by a simple mixture model. Study used log-squared returns as a proxy for the volatility of some assets returns, including daily S&P 500 returns. Their results explained many findings reported and uncovered new features. Results revealed that a short-memory process with level shifts should be viewed as a serious contender to model volatility. All estimates considered clearly followed a pattern that would obtain if the true underlying process was one of short-memory contaminated by level shifts. The simple random level shifts model clearly outperformed a standard GARCH model and, in many cases, it also provided better forecasts than a fractionally integrated GARCH model.

In his study on global financial crisis-and the volatility spillovers across stock markets, Yılmaz (2008) identified five major rounds of the global financial turmoil. The upward jumps in the volatility spillover index were clearly associated with increased stock market tensions around the globe. Analysis showed that the time interval from one round of the crisis to the next got shorter and shorter as the financial crisis advanced to further stages. And, as the crisis unfolds, the impact of each round of the crisis on balance sheets of the financial corporations could be expected to intensify.

Anon. (n.d) analysed the forecasting ability of the CARR model as an alternative to the GARCH model by using different symmetric and asymmetric error statistics. It sheds some light on the behaviour of the S&P500 index. Both statistics showed that the CARR model performed generally better than the GARCH model in a context of high volatilities and a downward trend. However, when the volatilities were lower and the market was rising, the GARCH model performed better than CARR, considering both symmetric and asymmetric error statistics, and for most of the forecast horizons. Based on their findings, it was concluded that in downward trend contexts, the volatility was clearly high and the CARR model was preferred. However in upward trend context, it is important to use all daily information (open, high, low and close) in order to obtain an efficient volatility measure. It was pointed out that by only looking at opening and closing prices, or high and low prices, it might be wrongly concluded that volatility on a given day is small, if both prices are similar, despite large intraday price fluctuations.

Choi *et al.* (2008) explored the possibility of structural breaks in the daily realized volatility of the Deutschemark/Dollar, Yen/Dollar and Yen/ Deutschemark spot exchange rates with observed long-memory behaviour. Analysis was based on the data of spot exchange rates for the U.S. dollar, the Deutschemark, and the Japanese yen. Study proposed a VAR-RV-Break model that provides a superior predictive ability when the timing of future breaks was known. Results showed that structural breaks in the mean could partly explain the persistence of realized volatility. With unknown break dates and sizes, the authors found that a VAR – RV- I (d) long memory model provided a robust forecasting method even when the true financial volatility series were generated by structural breaks.

Most of the studies in developed stock markets used GARCH and EGARCH models for forecasting long term stock market volatility. Markov regime switching GARCH models have outperformed all other GARCH models, in one study for forecasting volatility on shorter horizons. Real-time macroeconomic data can be utilised to forecast stock market volatility by the investors. Though most of the studies are about forecasting of stock market volatility, some studies which forecasted volatility in exchange rates also form part of the review. Certain other studies tried to find the linkage between stock market volatility and exchange rates of currencies.

2.2 Volatility of developing stock markets

With the process of globalisation, stock markets in the developing countries have gained importance.Though these markets are not developed totally, these markets offer lucrative returns to the investors. The developing stock markets include those of Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand, Argentina, Brazil, Chile, Mexico, Jamaica and Turkey. The abstract of various studies related to volatility in developing stock markets are discussed in this section.

The study by Levine (1996) was based on both industrial and developing countries. Some developing countries have more liquid stock exchanges than countries with higher per capita GDP. Study suggested that stock market liquidity helps forecast economic growth even after accounting for a variety of non financial factors that influence economic growth. After controlling for inflation, fiscal policy, political stability, education, the efficiency of the legal system, exchange rate policy, and openness to international trade, stock market liquidity is still a reliable indicator of future long term growth. Results indicated that stock market volatility rose in most of the countries following liberalization. Volatility did not fall significantly in any of these countries following liberalization.

Duarte and Fonseca (2002) compared implicit and deterministic volatility in the Portuguese stock market index (PSI). Study resorted to the bisectional method to extract implicit volatility and to ARCH and GARCH family models to extract deterministic volatility. The results led to the conclusion that GARCH volatility (within the sample) was the series that provided better forecast of the PSI-20 series volatility. And Black and Scholes formula was not the most adequate to evaluate options on the PSI-20 futures, which was clearly proved by the difficulties in the attempt of modelling implied volatility. Modelling volatility with ARCH models was one among several alternatives to the Black and Scholes model. Within the ARCH family, results revealed that the GARCH model was the most adequate for the series under analysis. This result was also in accordance with similar results obtained in other markets, such as the S&P 500 options.

Kasman and Kasman (2002) examined the volatility of Turkish stock market at the industry level over the period 1992 to 1999. Study was based on the firm- level return data set to estimate the volatility components. Since the nature and composition of the industries were not the same, they studied the volatility of each industry separately. Individual firms were aggregated into 15 industries according to the industry classification of ISE. The volatility series at the level of each industry were constructed. The results indicated that large industries, such as, chemical, banking, metal products and machinery, tend to have high-level volatility. The results also indicated that two of the large industries in their sample, viz., chemicals and banking, had an industry-beta higher than 1.0. Other industries, however, had a substantially low industry beta. The time series behaviour of volatility series was also analyzed. Food, investment trusts, ferrous metals and insurance industries exhibited significant positive trend and metal products, machinery exhibited significant negative trend. The cyclical behaviour of volatility series in industries belonging to manufacture sector was also checked. The results indicated that the volatility series had no forecasting power for future output growth in that industry.

Tang and Chen (2002) analysed the volatility feature in the Chinese stock market. The feature of volatility in China's stock market showed that the market mechanism is still not complete. GARCH (1,1) and EGARCH (1,1) models were applied to stock return series in China over the period from 4th January 1993 to 7th April 2000. They found that normal GARCH (1,1) and EGARCH (1,1) models simulation effect was not as good as Student-*t* GARCH (1,1) and Student-*t* EGARCH(1,1) models. Empirical results also supported the volatility clustering effect. Although the two values of ϕ in Student-*t* EGARCH (1,1) that are so-called "leverage effect" were negative, they were not statistically significant. The implication was that Student-*t* GARCH (1,1) model could explain volatility of Chinese stock market than Student-*t* EGARCH(1,1) model. The values of parameter that measures the persistence of volatility in Student-*t* GARCH (1,1) and EGARCH(1,1) models were high, but the null hypothesis that the process is IGARCH process was rejected. Thus, the impact of shock on the conditional variance was not permanent. The impact of volatility on Chinese stock market lasted relatively shorter. There were sudden arrival and disappearance phenomena in the volatility. Study revealed that excessive speculation exist in current Chinese stock market. In the light of the existing problems in China's stock market, the article put forward suggestions on accelerating the development of stock market in China.

Bautista (2004) reported the estimates of the magnitude of volatility during abnormal times relative to normal periods for seven East Asian economies using a rudimentary univariate Markov - switching ARCH method. The main interest of this study was to determine the extent of volatility of these markets relative to their tranquil periods. Volatility was assumed to evolve according to a three-state Markov regime switching process. The results showed that global and regional events such as the 1990 Gulf War and the 1997 Asian currency crisis led to high volatility episodes whose magnitude relative to normal times differed from country to country. Country-specific events such as the opening up of country borders in the mid-1990s were also observed to lead to high volatility periods.

Longmore and Robinson (2004) compared the performance of linear GARCH models in forecasting the volatility of returns in the foreign exchange market with that of asymmetric models. The authors studied the information content of macroeconomic and market microstructure variables for forecasting over a 30-day horizon. The paper also examined the relevance of the volatility spill-overs using multivariate GARCH model. A long memory process was found for the exchange rate, with the effects of shocks being asymmetric. The non-linear GARCH model gave better results than the linear models in terms of the explanatory power. These models also performed well in the out – of – sample forecasts, although the model that accounted for excessive kurtosis provided better forecasts in some cases. The main influence on market volatility were the expected liquidity conditions, level of trade and spill – over effects from other financial markets.

An extensive comparison between stochastic volatility models and GARCH models was conducted by Al-Deehani (2005). The author investigated volatility spillover among the stock markets of the six member countries of the Gulf Cooperation Council (GCC) by applying the concept of stochastic volatility and structural time series modelling. Using daily observations of exchange rates, the study compared on likelihood ratios and Bayes factors. Likelihood ratios and Bayes factors tests gave strong evidence against the use of Gaussian GARCH models as compared with stochastic volatility models.The results provided strong evidence for bidirectional and unidirectional contemporaneous volatility spillover but revealed weak evidence for lagged volatility spillover. Volatility in the Qatar stock market did not seem to affect or be affected by volatility of any of the other five markets. Moreover, volatility in one market cannot be explained totally by volatility in the other five markets.

Using five of the most actively traded stocks in the Brazilian financial market, Carvalho *et al.* (2005) showed that the normality assumption commonly used in the risk management area to describe the distributions of returns standardized by volatilities is not compatible with volatilities estimated by EWMA or GARCH models. In sharp contrast, when the information contained in high frequency data was used to construct the realized volatility measures, the authors attained the normality of the standardized returns, giving promise of improvements in Value-at-Risk statistics. They also described the distributions of volatilities of the Brazilian stocks, showing that they were nearly lognormal. They also estimated a simple model to the log of realized volatilities that differed from the ones in other studies. The main difference was that no evidence of long memory in the log of the realized variance was observed. The estimated model was compared with commonly used alternatives in an out-of-sample forecasting experiment. On average the EWMA intervals were less precise (larger) than those yielded by the linear model developed by the authors. On the other hand, combining the realized variance approach with GARCH-type models improved the coverage of the forecast intervals to as close to the nominal coverage as the EWMA intervals.

Chen and Lian (2005) in their paper compared six models for forecasting the performance of the ASEAN equity markets of Malaysia, Singapore, Thailand, Indonesia and the Philippines before, during and after the Asian financial crisis. In the pre crisis period, the OLS, ARCH-M (ARCH in mean) and TARCH models had better forecasting performance than the other models. In the crisis period, the ARCH-M model had the best forecast performance for three markets, while the remaining two markets were the best forecast with the random walk model. . However, in the post-crisis period, the TARCH and EGARCH models were found to be the most suitable models. The forecasts were the most reliable in the pre-crisis period and the poorest in the crisis period. Study testified that the best forecasting model was related to the market conditions, and also possibly to the different stages of development of the markets. The different variants of the GARCH model adequately captured the time-varying returns volatility. But the asymmetry of the market returns was not significant in all the markets modelled by the TARCH and EGARCH models.Ordinary Least Square (OLS) models are often used for time series data. ARCH-M model provides an explicit link between the risk (conditional volatility) and the best forecast of a time series.

The aim of Patev and Kanaryan (2005) was to give the investment community a model for assessment and forecasting of the Bulgarian stock market risk. The study examined the risk of the Bulgarian stock market, measured by Value-at-Risk. Data regarding daily returns of the SOFIX index - the first official index of the Bulgarian stock market - over the period 24th October 2000 to 19th November 2004 were considered for the study. The results of the research showed that the SOFIX index has basic characteristics of most of the emerging stock markets, namely, high risk, significant autocorrelation, non-normality and volatility clustering. Three models had been applied – Risk Metrics, EWMA with't' distributed innovations and EWMA with GED (Generalized Error Distribution) distributed innovations. The EWMA with't' distributed innovations and EWMA with GED distributed innovations adequately evaluated the risk of the Bulgarian stock market. Results proved that EWMA models allow modelling and forecasting both time-varying volatility and kurtosis in returns. The model could be applied in thin stock markets with insufficient number of observations. Student –t distribution and Generalised error distribution are the most appropriate tools to reflect the fat tailed behaviour of stock market returns.

Selcuk (2005) investigated daily stock market volatility in a sample of emerging market economies utilizing an asymmetric stochastic volatility (ASV) model which was estimated with Markov Chain Monte Carlo (MCMC) method. The results indicated that the ASV model captured the volatility dynamics in those stock markets successfully. Particularly, it was shown that volatility had a significant persistency and the variability of volatility was higher as compared to advanced economies. Analysis provided evidence for significant negative correlation between shocks to the stock market index and shocks to volatility, the so-called "leverage effect". Furthermore, the results showed that the higher variability of volatility implied lower persistency in volatility series and vice versa. In addition, persistency in volatility and the magnitude of leverage effect are negatively correlated; high persistency is associated with relatively lower leverage effect.

Chowdhury *et al.* (2006) studied how the macroeconomic risk associated with industrial production, inflation, and exchange rate was related to the stock market return in the context of Bangladesh capital market. Monthly data for the period 1990 to 2004 were considered for the study. Since many macroeconomic variables and stock returns are believed to follow GARCH process, this technique was used to find the predicted volatility series for the variables considered in the study. Finally, Vector Autoregression (VAR) was employed to investigate the relation between the variables. Results showed that there was significant unidirectional causality going from industrial production volatility to market return volatility and from market return volatility to inflation volatility. Study concluded that there is relation between stock market volatility and macroeconomic volatility. Considering all the findings, it was concluded that there is relation between stock market volatility and macroeconomic volatility, but it is not that strong as suggested by standard finance theory which warrants further study reconfirming the result in other emerging markets.

The research of Hoffmann *et al.* (2006) identified critical micro level factors that drive investors' behaviour and explained complex macro level phenomena that result from the aggregation and interaction of micro level investor behaviour. The influence of changing levels of trend - following versus fundamental investors on the stock market dynamics was investigated. It was found that with lower proportions of trend - following investors, the standard deviation of returns was much smaller than with larger proportions of trend - following investors. This result revealed that social interaction amongst investors might lead to an increasing level of stock market volatility, as measured by the standard deviation of the returns.

Magnus and Fosu (2006) modelled and forecasted volatility (conditional variance) on the Ghana Stock Exchange using a random walk (RW), GARCH (1,1), E-GARCH (1,1) and T-GARCH (1,1) models. The unique 'three days a week' Databank Stock Index (DSI) was used to study the dynamics of the Ghana stock market volatility over a ten – year period. The competing volatility models were estimated and their specification and forecast performance compared with each other, using Akaike information criteria (AIC), Log-likelihood (LL) information criteria and Brock, Dechert, and Scheinkman (BDS) nonlinearity diagnostic checks. The DSI exhibited the stylized characteristics such as volatility clustering, leptokurtosis and asymmetry effects associated with stock market returns on more advanced stock markets. The random walk hypothesis was rejected for the DSI. Overall, the GARCH (1, 1) model outperformed the other models under the assumption that the innovations followed a normal distribution.

Pan and Zhang (2006) explored a number of linear and GARCH – type models for predicting the daily volatility of two equity indices in the Chinese stock market, viz., the Shanghai and Shenzhen indices. The data set used was the daily Shanghai stock exchange composite index (shzh) and Shenzhen stock exchange component index (szzh). Under the framework of three distributional assumptions, the forecasts were evaluated using traditional metrics and also how they performed in a modern risk management setting -Value at Risk. They found that the relative accuracies of various methods were sensitive to the measure used to evaluate them. Results indicated that for the Shenzhen stock market, the traditional method was superior, and the moving average model was favoured for the forecasting of daily volatility. In the Shenzhen stock market, the asymmetry model, i.e. the GJR and EGARCH model performed better than other GARCH-type models, but with little gain. The models with skewed student $-t$ distribution ranked better than models with other distributions, but again the difference was small. Although the authors could not find one model that performed best under all the criteria, it appeared that the worst performing method for forecasting the one-day-ahead volatility in the Shanghai and Shenzhen indices was the random walk model.

In their paper, Qayyum and Kemal (2006) examined the volatility spillover between the stock market and the foreign exchange market in Pakistan. For long run relationship they used Engle Granger two step procedures and the volatility spillover was modelled through bivariate EGARCH method. The estimated results from cointegration analysis showed that there was no long - run relationship between the two markets. The results from the volatility modelling showed that the behaviour of both the stock exchange and the foreign exchange markets were interlinked. The returns of one market were affected by the volatility of the other market. Particularly the returns of the stock market were sensitive to the returns as well as the volatility of foreign exchange market. On the other hand returns in the foreign exchange market were mean reverting and they were affected by the volatility of stock market returns. Study revealed that there is strong relationship between the volatility of foreign exchange market and the volatility of returns in stock market.

Diebold and Yilmaz (2007) studied the relationship between real fundamental volatility and real stock market volatility world wide using a broad international cross section of stock markets covering approximately forty countries. Fundamental volatility was calculated on the basis of data collected on real GDP and real personal consumption expenditure of the countries. Stock market volatility was measured using the major stock index series from the IMF's International Financial Statistics (IFS). The study was based on financial economic theory, which suggested that the volatility of real activity should be related to stock market volatility. Study clearly focused on international cross sections obtained by averaging over time. The authors found a clear link between macroeconomic fundamentals and stock market volatilities, with volatile fundamentals translating into volatile stock markets. The study also proved that volatility in the GDP of countries resulted in the volatility of their respective stock markets.

Engle and Range (2008) proposed modelling equity volatilities as a combination of macroeconomic effects and time series dynamics. High frequency return volatility was specified to be the product of a slow-moving component, represented by an exponential spline, and a unit GARCH. This slow-moving component was the low-frequency volatility, which in this model coincided with the unconditional volatility. This component was estimated for nearly 50 countries over various sample periods of daily data. Low-frequency volatility was then modelled as a function of macroeconomic and financial variables in an unbalanced panel with a variety of dependence structures. It was found to vary over time and across countries. The low-frequency component of volatility was greater when the macroeconomic factors of GDP, inflation, and short-term interest rates were more volatile or when inflation was high and output growth was low. Volatility was higher not only for emerging markets and markets with small numbers of listed companies and market capitalization relative to GDP, but also for large economies. The model allowed long horizon forecasts of volatility to depend on macroeconomic developments, and delivered estimates of the volatility to be anticipated in a newly opened market.

In his study, Karadag (2008) examined both uni-regime GARCH and Markov Regime Switching GARCH (SW-GARCH) models to analyze Turkish Stock Market volatility. The data set used in this study was the daily closing prices of value-weighted ISE-100 index. The author investigated various models to find out whether SW-GARCH models are an improvement on the uni-regime GARCH models in terms of modelling and forecasting Turkish stock market volatility. Using seven statistical loss functions, he also applied Superior Predictive Ability (SPA) test and Reality Check test (RC) to compare forecast performance of various models. For short horizons of one day and one week, overall, uni-regime GARCH models were highly outperformed by SW-GARCH models. Also, among all models, the most accurate forecasts were obtained with SW-GARCH model under GED. In the case of two weeks of forecast horizon, it was noticed that standard GARCH and GJR- 75 GARCH models were significantly outperformed by SW-GARCH and EGARCH models. No superior models were identified between EGARCH and SW-GARCH models. Lastly, when forecasting performance of models at one month horizon were considered, EGARCH and SW-GARCH models performed better than other models. Moreover, there was evidence that EGARCH models are better than SW-GARCH models in forecasting at one month horizon.

Kovacic (2008) investigated the behaviour of stock returns in an emerging stock market, namely, the Macedonian Stock Exchange, focusing on the relationship between returns and conditional volatility. The conditional mean follows a GARCH-M model, while for the conditional variance one symmetric (GARCH) and four asymmetric GARCH types of models (EGARCH, GJR, TARCH and PGARCH) were tested. The author also examined how accurately these GARCH models forecasted volatility under various error distributions. Three distributions were assumed, i.e. Gaussian, Student $-t$ and Generalized Error Distribution. The empirical results were that (i) the Macedonian stock returns time series displayed stylized facts such as volatility clustering, high kurtosis, and low starting and slow decaying autocorrelation function of squared returns; (ii) the asymmetric models showed a little evidence on the existence of leverage effect; (iii) the estimated mean equation provided only a weak evidence on the existence of risk premium; (iv) the results were quite robust across different error distributions; and (v) GARCH models with non-Gaussian error distributions were superior to their counterparts estimated under normality in terms of their in-sample and out-of-sample forecasting accuracy. For estimated GARCH-type models based on the returns data, the sum of the ARCH and GARCH coefficients was close to unity. Increase in volatility would decrease returns, which is an unexpected result, but could be theoretically justified. The results related to the relationship between returns and conditional volatility could be regarded as quite robust across the models and alternative error distributions. The "true volatility" could be better estimated by selecting shorter time intervals, i.e. by using intra-day trading data or minimal and maximal values of returns.

Khedhiri and Muhammad (2008) investigated the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. They used switching regime ARCH methodology to assess the impact of stock market openness to foreign investors on the market returns and analysed its observed irregular performance using recently developed methodologies. They reported that, the change in the volatility pattern and the irregular behaviour of the stock market came as a result of the introduction of a new regulation allowing foreign investors to participate in the UAE stock markets. This had created an unprecedented high level of volatility and could explain to some extent the sluggish performance of the markets. Furthermore based on the non linear threshold autoregressive methodology, they identified a significant leverage effect such that a stock price decrease would have a greater impact on subsequent volatility than a stock price increase with the same magnitude.

Long (2008) studied the characteristic of the stock return volatility in the Vietnam stock market (VSM) and showed, how it changes when regime changes were taken into consideration. Further the effects of financial liberalization on volatility were also examined and analysed. First, he tested the commonly known hypothesis of highly persistent volatility of stock return by using a (generalized) autoregressive conditional heteroskedasticity (ARCH/GARCH) model. The VSM stock return volatility was found to be evident. Next, the iterated cumulative sums of squares (ICSS) algorithm was used to identify the break points (shocks) that lead to the changes in the stock return rate variances. Following that, the control for the VSM return volatility regimes was incorporated into the ARCH/GARCH model by using a set of dichotomous dummy variables. The volatility regimes and their lifetimes were reported. All the events that were possibly related to these volatility regimes were identified, and their causes and effects were analyzed. Specifically, it was found that financial liberalization had a negative influence on the volatility of stock return in VSM. As for the effects of financial liberalization, the results showed that, when the equity market became more open, there were increases in stock return volatility.

Aggrawal *et al.* (2009) analysed volatility in emerging stock markets. The study examined what kind of events caused large shifts in the volatility of emerging stock markets. The authors first determined when large changes in the volatility of emerging stock markets occurred and then examined the global and local events during the period of increased volatility. An iterated cumulative sum of squares (ICSS) algorithm was used to identify the points of shocks/ sudden changes in the variance of returns in each market and how long the shift lasted. Both increases and decreases in the variance were identified, after which events around the time period when shifts in volatility occurred were identified. The high volatility in emerging stock markets was marked by several shifts. The large changes in the volatility were found to be related to the country - specific political, social and economic events. The

October 1987 crash was the only 'global event' during 1985 to 1995 which caused a significant jump in the volatility of several emerging stock markets.

GARCH models have been extensively used by the authors for forecasting volatility. Many studies have revealed that effect of local events and economic policies of the government are the basic factors affecting volatility in the developing stock markets. The nature of volatility in developing stock markets is more country specific. Volatility in developing stock markets has been influenced by global issues only rarely. Some studies evidenced the effect of liberalization on developing stock market. It has also been proved that when the equity market becomes more open, there are increases in stock return volatility.

2.3 Volatility of the Indian stock market

The most prominent stock markets in India are the National Stock Exchange and Bombay Stock Exchange. Bombay Stock Exchange is the oldest stock exchange in Asia with a rich heritage, now spanning three centuries in its 134 years of existence. The BSE Index, known as SENSEX, is India's first stock market index that enjoys an iconic stature, and is tracked worldwide.

NSE was promoted by leading financial institutions at the behest of the Government of India and was incorporated in November 1992. Today NSE is known as a major stock exchange in the country in terms of value and volume of trade. The most prominent index of the NSE is the S&P CNX Nifty index. Besides these two national stock exchanges, there are 21 regional stock exchanges in India. The abstract of various studies related to volatility in the Indian stock market is discussed in this section.

Kalimipalli and Ramachand (2002) aimed at documenting changes in returns, volatility and liquidity on the local market following foreign capital raising events by Indian firms. Study was based on examination of Indian firms that raised capital through equity listing and/or ADR issue abroad. Study showed that subsequent to gaining foreign exposure, firms experienced a decline in returns (though not statistically significant), volatility of returns, high/ low price ranges and volatility of the daily price range on the local (Indian) market. Firms gaining foreign exposure in fact experienced a smaller decline in volatility of returns as well as volatility of the daily high/low price range compared to firms issuing equity only on the local market. The results revealed that foreign issue of equity did not improve liquidity in the Indian market anymore than domestic issue.

Kirankumar and Mukhopadyay (2002) investigated the short run dynamic linkages between NSE Nifty in India and NASDAQ Composite in US, using intra-daily data, which determine the daytime and overnight returns. The study carried out a comprehensive analysis of movement and volatility transmission between US and Indian stock markets. Granger causality results indicated unidirectional Granger causality running from the US stock markets (both NASDAQ Composite and S & P 500 indices) to the Indian stock market, NSE Nifty index. And, the previous daytime returns of both NASDAQ Composite and NSE Nifty had significant impact on the NSE Nifty overnight returns.

Shenbagaraman (2003) assessed the impact of introducing index futures and options contracts on the volatility of the underlying stock index in India. Study explored the impact of the introduction of derivative trading on cash market volatility using data on stock index futures and options contracts traded on the S & P CNX Nifty. The results suggested that futures and options trading have not led to a change in the volatility of the underlying stock index, but the nature of volatility seemed to have changed post-futures. Analysis did not find evidence of any link between trading activity variables in the futures market and spot market volatility.

Lamba (2004) conducted a detailed, large sample analysis of the dynamic relationships between-the South Asian markets of India, Pakistan and Sri Lanka and the major developed markets using a multivariate co-integration framework and vector error-correction modelling. Study revealed that the Indian market is influenced by the large developed equity markets including the US, UK and Japan and that this influence has been strengthened during the more recent time period. Further, the author did not find any influence of Indian market on the Pakistani and Sri Lankan markets. Analysis found that Pakistan and Sri Lankan markets were relatively isolated from the major developed markets during the study period.

Badrinath and Apate (2005) examined the stock market, foreign exchange market and the call money market in India for evidence of volatility spillovers using multivariate EGARCH models which facilitate the study of asymmetric responses. Results indicated the existence of asymmetric volatility spillovers across these markets. The results also indicated that either the information assimilation across markets was slow or that the spillovers were on account of contagion. Study stressed the need of the dynamic structure of correlation in order to design appropriate risk hedging strategies.

Banerjee and Sarkar (2006) reported that the change in volume of trade in the market directly affects the volatility of asset returns. Further, the presence of Foreign Institutional Investors (FII) in the Indian stock market did not appear to increase the overall market volatility. Using intra - day data collected at five-minute intervals, the authors attempted to model the volatility in the daily return of National Stock Exchange. Study observed that the asymmetric GARCH models provided better fit than the symmetric GARCH model, confirming the presence of leverage effect. It was observed that the Indian stock market experienced volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like historical average, moving average etc.

Kumar (2006) forecasted volatility of the Indian stock and foreign exchange markets. He considered the Nifty index as a proxy for the stock market and accordingly the closing index values and the exchange rate data pertaining to the Indian rupee/US dollar exchange rate. Analysis attempted to evaluate the ability of ten different statistical and econometric volatility forecasting models in the context of Indian stock and forex markets. These competing models were evaluated on the basis of two categories of evaluation measures – symmetric and asymmetric error statistics. Based on an out of the sample forecasts and using a majority of evaluation measures the author found that GARCH and EWMA methods would lead to better volatility forecasts in the Indian stock market and the GARCH would achieve the same in the forex market. The same models performed better on the basis of asymmetric error statistics also.

Janakiramanan (2007) studied underpricing and long run performance of initial public offering in Indian stock market. The study used various methods to ascertain the significance of the over or underperformance of IPOs. The effect of various benchmarks on the return measurements was also studied, to elucidate the possibility that the magnitude of the performance is benchmark dependent. Study showed that the results on long-run underperformance of the IPOs depended very much on the choice of technique. The long-term performance of companies showed that investment in Indian IPOs provided positive abnormal return by the end of 60 days. The abnormal return was greater for investment in smaller companies compared to investment in larger companies. Study revealed that investment in IPOs generally provided positive benefit to Indian investors.

Kumar and Rakesh (2007) investigated the volatility in Indian stock market of daily and monthly return. Study was done at three different points - volatility of daily return in a year, volatility of daily return in a month, and volatility of monthly return in a year with respect to economic growth.The analysis was based on the adjusted opening and closing price of the Bombay Stock Exchange listed index BSE 100. Interpretations and testing of volatility in purview of different economic environment was part of the study. The study reported that both long and short-term volatility were declining in the Indian stock market over a period of time. It was evident that Indian stock market exhibited expected response to the growth rate of the economy. During the recession, volatility of both daily and monthly returns were high, on the other hand, during the period of growth, it was low. And in the decline phase it was comparatively lower than the recession phase.

Mishra *et al.* (2007) explored volatility spillovers between the Indian stock and foreign exchange markets. Results indicated that there existed a bidirectional volatility spillover between the Indian stock market and the foreign exchange market with the exception of S&P CNX Nifty and S&P CNX 500. It was revealed that both the markets moved in tandem with each other and there was a long run relationship between these two markets. The results suggested that there was an information flow (transmission) between these two markets and both these markets are integrated with each other.

Nathani (2007) used E-GARCH model and other quantitative techniques for forecasting volatility of Nifty with S&P CNX Nifty daily closing data. The actual realised market volatility was computed using Risk metrics. This realised volatility was compared with the model's computed volatility. Results showed a lot of variations in the computed volatility and the volatility could change drastically in a few days due to many factors. E- GARCH model had been able to capture the market volatility. And rolling five day forecast would be a good forecast of the direction of the volatility in the market.

Rao and Tripathy (2008) examined the volatility of Nifty to understand the behaviour of the Indian stock market. Study explored the daily Nifty movements as well as wide range of economic events in the study period. The results showed that the stock market volatility was the highest during certain years. While analysing to find the logical reasons for the excess or under returns on a specific day for the market, it was revealed that the market would react very sharply to economic, political and policy issues.

Compared to the studies on volatility in developed stock markets, the studies in emerging stock markets and that of Indian stock market are limited in number. Studies tracking sector – wise volatility of Indian stock market are not available. Hence an effort is made to forecast the volatility of the Indian stock market and its sector – wise volatility, using five forecasting models, viz., Random walk, Historical mean, Moving average, Simple regression and EWMA, drawing insights from the review of earlier studies.

Materials and Methods

CHAPTER 3

MATERIALS AND METHODS

The study on 'forecasting volatility of the Indian stock market' has been conducted with the main objectives of examining the volatility behavior of the Indian stock market, to forecast the sector- wise volatility of the Indian stock market and to identify the most efficient volatility forecasting model among the different models used.

This chapter narrates the methodology and data sources adopted in conducting the present study which are presented in the following sequence:

3.1 Sources of data
3.2 Selection of the stock exchange
3.3 Selection of the stock index and stocks
3.4 Statistical tools used for the study

3.1 Sources of data

The study has been conducted using secondary data on daily close prices of individual stocks from November 1994 to October 2008, and for NIFTY close value, from November 1995 to October 2008 from the website of National Stock Exchange, www.nseindia.com .

3.2 Selection of the stock exchange

National Stock Exchange, India's most trusted and Government recognized stock market was selected for the study. This stock exchange was purposely selected, because NSE is the market leader in terms of total turnover and volume of business among the stock markets across India. NSE was promoted by leading financial institutions at the behest of the Government of India and was incorporated in November 1992.

3.3 Selection of the stock index and stocks

Stock market indices are meant to capture the overall behaviour of equity markets. A stock market index is created by selecting a group of stocks that are representative of the whole market or a specified sector or segment of the market. An index is calculated with reference to a base period and a base index value. Here for the study, S&P CNX Nifty index was selected. S&P CNX Nifty is a well diversified 50 stock index accounting for 25 sectors of the economy. It is used for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds. From the 50 companies listed in the Nifty, the top 10 companies based on market capitalization as on 31st October 2008 have been identified. Five companies representing five different sectors which have been continuously listed for the last three years among the top ten companies were selected for the study. Out of these selected top ten companies, a few newly listed companies were not selected, since they did not have the required data as in the case of other companies selected. In addition, some of them did not fit into the criteria of continuous listing for the last three years. Instead next company in terms of market capitalisation with uniform data was selected for the study. Table 3.1 depicts the market capitalisation of each company listed in to the NIFTY-50 index as on 31st October 2008.

Table 3.1 Market capitalisation of companies listed in NIFTY 50 index, 31 October 2008

Sl. No.	Name of the Company	Market capitalisation (Rs. in Cr.)	Weightage to total index (%)
1	Reliance Industries Ltd.	216467	12.11
2	ONGC	143114	8.00
3	Bharati Airtel	124091	6.94
4	NTPC	116344	6.50
5	Infosys	79517	4.45

6	SBI	70543	3.95
7	BHEL	63231	3.53
8	ITC	58499	3.27
9	TCS	52600	2.94
10	HDFC Bank	50195	2.81
11	Hind Unilever	48993	2.74
12	L & T	47212	2.64
13	Reliance Communication	45398	2.54
14	ICICI Bank	44388	2.48
15	HDFC Finance	43472	2.43
16	Wipro	39885	2.23
17	Reliance Petroleum	39885	2.23
18	DLF	37507	2.11
19	SAIL	34943	1.96
20	Power Grid Corporation.	29399	1.65
21	GAIL(I)	27228	1.52
22	Reliance Power.	24543	1.37
23	Cairn	24438	1.36
24	Sun Pharma.	22879	1.28
25	Satyam Computer	20517	1.15
26	Sterlite Industries.	20114	1.13
27	Maruti Suzuki.	16272	0.92
28	Tata Steel.	15328	0.86
29	Tata Power	15266	0.85
30	Hero Honda.	14886	0.83
31	Tata Communications.	13821	0.77
32	Cipla	13774	0.76
33	Punjab National Bank.	13265	0.74
34	Idea Cellular.	13191	0.73
35	HCL Technologies.	11562	0.64
36	ABB	11529	0.63
37	Reliance Infrastructure	10821	0.60

38	Hindalco	10606	0.59
39	BPCL	10380	0.58
40	NALCO	10264	0.57
41	Mahindra & Mahindra.	9683	0.54
42	Grasim Industries.	9406	0.52
43	Ambuja Cement.	9280	0.51
44	ACC	9270	0.50
45	Siemens	8927	0.49
46	Unitech	7857	0.43
47	Tata Motors.	7629	0.42
48	Zee Entertainment Ltd.	6673	0.37
49	Suzlon Energy	6652	0.36
50	Ranbaxy Laboratories	6313	0.35
	Total	**1788057**	**100.00**

Source- The economic times dated 1st November 2008.

As revealed by Table 3.1, the top ten companies listed in Nifty had an aggregate weightage of 51.23 per cent in the overall index.

Table 3.2 depicts the list of top ten companies listed in the NIFTY-50 index on the basis of market capitalisation, as on 31st October 2008, with their sectoral background.

Table 3.2 List of top ten companies based on market capitalization, 31 October 2008

Rank.	Name of the Company	Sector Type.
1.	Reliance Industries Ltd.	Diversified Sector.
2	ONGC	Oil and Gas Sector.
3	Bharati Airtel	Telecommunication Sector
4	NTPC	Power & Electricity
5	Infosys	Information Technology
6	SBI	Banking Sector
7	BHEL	Engineering Heavy - General

8	ITC	Fast Moving Consumer Goods
9	TCS	Information Technology
10	HDFC	Banking sector.

As evident from Table 3.2, out of top ten companies, four companies belong to the public sector and the rest to the private sector. Although both Reliance Industries Limited and ONGC operate in the petroleum sector, Reliance is considered as belonging to the diversified sector, since it is engaged in a wide variety of business, ranging from retail to textile.

Applying all the criteria for the selection of the companies, the following five companies were selected so as to avoid duplication of sectors and to represent five different sectors.

- Reliance Industries Limited (Diversified Sector)
- Infosys (Information Technology sector)
- State Bank of India (Banking sector.)
- BHEL (Engineering, Heavy – General sector)
- ITC (Fast Moving Consumer Goods sector)

Companies such as ONGC, Bharati Airtel, and NTPC were not considered for the study, since these companies did not provide uniform data required for the study, as they were listed at different times in the NSE. ONGC was listed on August 9, 1995, Bharati Airtel on June 19, 2006 and NTPC on November 05, 2004 and hence data was not available from November 1994. So preference was given to the next companies in the list, which were listed from November 03, 1994. Selected companies had an aggregate weightage of around 27.31 per cent as on 31st October 2008.

3.4 Statistical tools used for the study.

From the daily close values of Nifty and the close prices of the selected five stocks, monthly figures were arrived at and used for estimation of the model parameters. To forecast the volatility, five models viz. Random Walk, Historical

Mean, Moving Average, Simple Regression and Exponential Weighted Moving Average models were used.

3.4.1 Data description

In this study the Nifty index was used as a proxy for the stock market and accordingly the closing index values were collected from November 1, 1995 till October, 31 2008. In the case of individual stocks, data of close prices were collected over the period from November 3, 1994 till October, 31, 2008. The data were collected from the website of National Stock Exchange (www.nseindia.com).

In the case of individual stocks the data pertaining to November, 1994 till October 2008 totaling 125 monthly observations were used for estimation of the model parameters and the remaining observations were used for out of sample forecasts. For Nifty index, close values were collected from November 1995 up to October 2008, totaling 125 monthly observations for the estimation of the model parameters and the remaining observations were used for out of sample forecasting.

Therefore the first month for which out of sample forecasts are obtained is March 2006 for NIFTY and for other stocks April 2005 and the out of sample forecasts were constructed for 43 months till Oct 2008.

3.4.2 Computation of volatility

The daily observations on close price of individual stocks and close values of Nifty were converted into continuous compounded returns in the standard method as the log differences.

$$r_t = \ln\left(\frac{I_{t-1}}{I_t}\right)$$

where 'It' stands for the closing index value/close price of individual stock on day 't'; following Merton (1980) the monthly volatility is obtained as the sum of the squared daily returns in that month which is shown below.

$$\sigma^2 = \sum_{t=1}^{N} r_t^2$$

where 'r_t' is the daily return on day't' and 'N' is the number of trading days in the month under study.

3.4.3 Standard deviation as a measure of volatility

The following standard formula was used for computing standard deviation as a measure of volatility.

$$\sigma = \sqrt{(1/n-1)\sum(r_t - \bar{r})^2}$$

3.4.4 Skewness

The skewness for the normal distribution is zero, and any symmetric data should have skewness near to zero. Negative values for the skewness indicate data that are skewed left and positive values for skewness indicate data that are skewed right. Skewed left means the left tail is long as compared to the right tail. Similarly right skewed means the right tail is long as compared to left tail. For univariate dataY_1, Y_2,...., Y_N, the following formula was used for computing skewness:

$$skewness = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^3}{(N-1)s^3}$$

where 'Y' is the mean, 's' is the standard deviation, and 'N' is the number of data points.

3.4.5 Kurtosis

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. Data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. For univariate data $Y_1, Y_2, \ldots, Y_N$, the formula used for computing kurtosis was

$$kurtosis = \frac{\sum_{i=1}^{N}(Y_i - \bar{Y})^4}{(N-1)s^4}$$

where Y is the mean, s is the standard deviation, and N is the number of data points.

3.4.6 Line graphs

Line graphs were drawn for the daily close values and squared returns of Nifty and for close prices and squared returns of individual stocks.

3.4.7 Forecasting of volatility

The forecasting capabilities of the following models were examined and compared using root mean square error (RMSE)

- Random walk
- Historical mean
- Moving average
- Simple regression and
- Exponential weighted moving average

A brief description of all the models used is given in the following paragraphs.

3.4.7.1 Random walk model

As per this model, the best forecast for this period's volatility is the last period's realized volatility.

$$\therefore \sigma_t^2 = \sigma_{t-1}^2$$

Where t = 126...........168.

3.4.7.2 Historical mean model

Assuming the conditional expectation of the volatility constant, this model forecasts volatility as the historical average of the past observed volatilities.

$$\therefore \sigma_t^2 = \frac{1}{t-1}\sum_{i=1}^{t-1}\sigma_i^2$$

where t = 126...........168.

3.4.7.3 Moving average model

In the historic mean model the forecast is based on all the available observation and each observation whether it is very old or immediate is given equal weight, this may lead to stale prices affecting the forecast. This is adjusted in a moving average method which is a traditional time series technique in which the volatility is defined as equally weighted average of realized volatilities in the past 'm' months. It is an indicator which is frequently used in the technical analysis and shows the average value of security's price over certain period. As the securities price changes, its average price also moves up and down. Moving averages thus simply measures the average price over a specific time frame. Moving Averages are trend following indicators and are generally used for measuring momentum and for identification or confirmation of the trend. A moving average-also helps to define possible areas of support and resistance. Finally it is also a barometer of crowd behavior and defines the direction of the crowd movements and current trend.

The underlying purpose of the moving averages is to help the investor to track the trends of financial assets by the smoothing out the day to day fluctuation or noise.

$$\therefore \sigma_t^2 = \frac{1}{m}\sum_{i=1}^{m}\sigma_{t-i}^2$$

represent the moving average. The choice of 'm' is rather arbitrary and in this study four moving average models with periods 3, 6, 9 and12 months were used.

3.4.7.4 Simple regression (First order auto regressive model – AR(1))

In this method the familiar regression of actual volatilities on lagged values was run. In other words the first auto regression was performed on the first part of data which is meant for estimating the parameters and the estimates thus obtained were used for forecasting the volatility for the next month. Accordingly the first part involved running the following regression.

$$\sigma_t^2 = \alpha + \beta \cdot \sigma_{t-1}^2$$

'α' and 'β' are estimated over the 13 year period from November 1995 till October 2008 for Nifty and for the individual stocks it was done for 14 years period from November 1994 to October 2008.

3.4.7.5 Exponential weighted moving average

Exponential smoothing is an adaptive forecasting method that gives greater weight to more recent observations so that the finite memory of the market is represented. This method adjusts the forecasts based on past forecast errors and the forecast is calculated as a weighted average of the immediate past observed volatility and the forecasted value for that same period i.e.,

$$\sigma_t^{2} = \alpha \cdot \sigma_{t-1}^2 + (1-\alpha) \cdot \hat{\sigma}_{t-1}^2$$

Here α is known as smoothing factor and is constrained to $0 < \alpha < 1$. The smoothing factor determines the weight that is given to actual volatility observed in the immediate past month and as $\alpha \rightarrow 1$ it means more recent observations get more weight and α can be chosen based on the analyst's intuitive judgment or can be objectively determined so as to produce the best fit by minimizing the sum of the squared deviation between actual and forecasted volatilities in the estimation period.

3.4.8 Evaluation measures

The forecasting performance of different models were compared using Mean absolute error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R^2 etc. They are calculated as follows.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{\sigma}_i - \sigma_i\right|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\sigma}_i - \sigma_i)^2}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|(\hat{\sigma}_i - \sigma_i)/\sigma_i\right| \ *100$$

Finally, based on the average monthly squared returns for the sample period for the stock index and the selected stocks, the confidence limits for each of them were calculated as Mean ± S.E.

Results and Discussion

CHAPTER 4

RESULTS AND DISCUSSION

After the onset of liberalisation and economic reforms, Indian economy is getting geared up for global integration. The integration process is slow but steady. Direct result of this integration is mainly observed across the stock markets in India, which are affected by the sentiments of investors and risk probabilities in global scenario. Stock market in India is also affected by the external flows and the volatile behaviour of the Foreign Institutional Investors FIIs). The volatile behaviour of FIIs can seriously impact economic stability at the grass root level. When FIIs withdraw suddenly, the stock markets come crashing down wiping away small investors' wealth. The high volume of FII purchases or sales and their extreme volatile behaviour can plunge the stock markets into an inexplicable crisis.

Index reflects the changing expectations of the stock market about future dividends of India's corporate sector. When the index goes up, it implies that the stock market thinks that the prospective dividends in the future will be better than previously thought. When prospects of dividends in the future become pessimistic, the index drops. The ideal index gives instant-to-instant readings about how the stock market perceives the future of a country's corporate sector. The continuous chain of news about the economy and its reaction by the market participants, also determine the volatility of stock market.

Given the fact that stock markets exhibit volatility, the next step is how to forecast the extent of this volatility, so that the market participants can reap profits by forecasting volatility of a stock or an index. The review of literature has already revealed the available tools or models for forecasting volatility of the stock market. Hence the present study is an attempt to examine the volatility behaviour of the Indian stock market, taking the example of NSE, forecasting its sector–wise volatility, and identifying a suitable model for assessing volatility. The chapter starts with a discussion about the global and Indian stock markets, followed by the analysis and forecasting of volatility of the Indian stock market. With these objectives in view, the results and discussions are presented under the following five major sections namely,

4.1 Stock markets across the world – an overview

The history of stock exchanges can be traced to the 12^{th} century in France, when the first brokers are believed to have developed, trading in debt and government securities. Unofficial share markets existed across Europe through the 1600s, where brokers would meet outside or in coffee houses to make trades. The Amsterdam Stock Exchange, created in 1602, became the first official stock exchange when it began trading the shares of the Dutch East India Company. These were the first company shares ever issued. By the early 1700s there were fully operational stock exchanges in France and England, and America followed in the later part of the century. Share exchanges became an important way for companies to raise capital for investment, while also offering investors the opportunity to share in company profits. The early days of the stock exchange experienced many scandals and share crashes, as there was little or no regulation and almost anyone was allowed to participate in the exchange.

The idea of trading stocks came to America with English colonists. With the birth of the United States came the need to develop economic power in addition to military might. Alexander Hamilton, the first U.S. Secretary of the Treasury, had studied the stock exchanges in Britain and believed they were essential to building and maintaining a vital and robust economy. During his term from 1789 to 1795, he promoted the development of American stock exchanges.

Today, stock exchanges operate around the world, and they have become highly regulated institutions. Investors wanting to buy and sell shares must do so through a share broker, who pays to own a seat on the exchange. Companies with shares traded on an exchange are said to be 'listed' and they must meet specific criteria, which varies across exchanges. Most stock exchanges began as floor exchanges, where traders made deals face-to-face. The largest stock exchange in the world, the New York Stock Exchange, continues to operate this way, but most of the world's exchanges have now become fully electronic. Most prominent markets are located in developed countries.They are having their own sophisticated market systems and market standards. As most of the capital turnover occurs across these stock markets, it puts indirect impact on other stock markets in the developing countries. A brief description about major stock markets from around the world is given in the ensuing paragraphs.

4.1.1 National Association of Securities Dealers Automated Quotations (NASDAQ)

While the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) represent the history of stock markets in the United States, the NASDAQ, which stands for "National Association of Securities Dealers Automated Quotations," represents the future, or, perhaps, the present, depending on one's point of view. Unlike the NYSE or AMEX, NASDAQ never had a real trading floor. It is a "virtual" stock market, meaning all trades are done electronically. Saying that NASDAQ is an electronic, computer-driven stock market seems perfectly normal these days, but, when it was founded in 1971, it was an incredibly advanced concept. Run by the National Association of Securities Dealers (NASD), it was founded in a day when there was no internet and computers were huge machines that filled entire floors of office buildings but had less computing power than a state-of-the-art laptop does these days. While its main exchange is in the United States, it also has exchange branches in Canada and Japan and associations with exchanges in Hong Kong and Europe, making it a global stock market. In 1999, it passed the NYSE in volume to become the largest stock market in the world.

4.1.1.1 Over the Counter (OTC)

NASDAQ operates by buying and selling what are called over-the-counter (OTC) stocks. These stocks are bought and sold outside the organized stock markets. Over-the-counter trading is the single largest securities market in the United States today, including almost all government securities and municipal and corporate bonds. NASDAQ provides price quotations on approximately 5,000 of the more actively traded OTC stocks. The exchange includes all types of companies, but is traditionally home to many high-tech stocks. The big ones include Microsoft, Intel, Dell, and Cisco.

4.1.2 New York Stock Exchange (NYSE)

Trading approximately 1.46 billion shares each day, the New York Stock Exchange (NYSE) is the leading stock exchange in the world. The exchange trades stocks for some 2,800 companies, ranging from blue chips to new high growth companies. Each listed company has to meet strict requirements, as the NYSE works to maintain its reputation of trading strong, high quality securities.

Operating as a continuous auction floor trading stock exchange, the major players on the floor of the New York Stock Exchange are specialists and brokers. Brokers are employed by investment firms and trade either on behalf of their firm's clients or the firm itself. The broker moves around the floor, bringing buy and sell orders to the specialists. Each specialist stands in one location on the floor and deals in one or several specific stocks, depending on their trading volume. The specialist's job is to accept buy and sell orders from brokers and manage the actual auction. It is also the specialist's job to ensure that there is a market for their specified stocks at all times, which means that they will invest their own firm's capital at times to keep the market active and maintain the shares' liquidity. Specialists and brokers interact to create an effective system that provides investors with competitive prices based on supply and demand.

4.1.3 London Stock Exchange (LSE)

The London Stock Exchange is the most important exchange in Europe and one of the largest in the world. It lists over 3,000 companies and with 350 of the companies coming from 50 different countries, the LSE is the most international of all exchanges. The London Stock Exchange is comprised of two different stock markets: the Main Market and the Alternative Investment Market (AIM). The Main Market is solely for established companies with high performance, and the listing requirements are strict. Approximately 1,800 of the LSE's company listings trade on the Main Market. The Alternative Investment Market on the other hand trades small-caps, or new enterprises with high growth potential. Over 1,060 companies are listed on this market. The LSE also has a new and growing exchange for equity derivatives called EDX London, created in 2003. In 2004, EDX traded an average of 3, 82,599 contracts per day. Its aim is to become the leading derivatives market in the world.

4.1.4 Hong Kong Stock Exchange (HKSE)

Although the trade of securities began in the middle of the 19th century, Hong Kong Stock Exchange was established at the end of the century. Local institutional and retail investors are the main contributors of market turnover (56%). The exchange also has a leading derivatives market in the Asia-Pacific region. With its total securities market capitalization of a record sum of HK$ 8,260.3 billion (US$ 1,063.9 trillion), the HKSE ranks eighth place by market capitalization in the world.

In 2000, the Stock Exchange of Hong Kong Limited, Hong Kong Futures Exchange Limited together with Hong Kong Securities Clearing Company Limited merged under a single exchange HKEx. The trading system of the Exchange is an order-driven system. HKEx securities market operates on two trading platforms - the Main Board and the Growth Enterprise Market (GEM). Each trading platform has a different set of requirements. The Main Board is the market for capital growth by established companies that meet profit requirements. Meanwhile, the Growth Enterprise Market provides a fund raising venue for 'high growth, high risk' companies. It promotes the development of technology industries and venture capital investments.

In October 2000, HKEx developed a trading system AMS/3 consisting of four components - Trading Terminal, Multi-Workstation System ('MWS'), Broker Supplied System ('BSS'), and Order Routing System ('ORS') that investors can choose among. The ORS allows investors to place requests electronically. In addition to trading through terminals in the Trading Hall, exchange participants are enabled to trade from their offices through installed off-floor terminals.

-The HKSE has the leading index the Hang Seng for shares traded on the Hong Kong Stock Exchange that was introduced in 1969. The Hang Seng index consisting of the 33 largest companies traded on the exchange represent around 70 per cent of the value of all stocks traded on the HKSE.

4.1.5 Tokyo Stock Exchange (TSE)

The Tokyo Stock Exchange is one of the more important world exchanges, trading an average of 1,540 million shares per day. It is the largest of the five exchanges in Japan. Most of the TSE's listings are domestic, although it also trades shares for 30 international companies. TSE uses an electronic, continuous auction system of trading. This means that brokers place orders online and when a buy and sell price match, the trade is automatically executed. Deals are made directly between buyer and seller, rather than through a market maker. The TSE uses price controls so that the price of a stock cannot rise or fall below a certain point throughout the day. These controls are used to prevent dramatic swings in prices that may lead to market uncertainty or stock crashes. If a major swing in price occurs, the exchange can stop trading on that stock for a specified period of time.

Stocks listed on the TSE are assigned to one of three markets: the First Section, Second Section, or Mothers. The highest listing criteria must be met for the First Section and all newly listed stocks begin on the Second Section, with less strict requirements. Stocks for high growth, emerging companies are listed on the Mothers market. The exchange undergoes a review at the end of each year, where the decision of whether any stocks will be moved either up or down is made.

The Tokyo Stock Exchange also has a significant market for derivatives, which has been operating for twenty years. The TSE lists futures and options in indexes, equities, and Japanese government bonds.

4.1.6 Singapore Exchange (SGX)

With Singapore now a leading financial center in the Asia-Pacific, the Singapore Exchange has become one of the premier exchanges in its region. It is a highly international exchange, with 40 per cent of its market capitalisation coming from foreign companies. The SGX divides its company listings into the SGX Main board and the SGX SESDAQ. The Main board lists companies that meet certain requirements including market capitalization, pre-tax profits, and operating track record. The SESDAQ, on the other hand, is for newer companies and there are no quantitative requirements for listing. Companies listed on the SESDAQ may apply to be moved to the Main board if they have been listed for at least two years and meet the minimum quantitative requirements.

The Singapore Exchange is a fully electronic exchange, using the Central Limit Order

Book (CLOB). Brokers place orders online and when a buy and sell order match, the system automatically executes the order and notifies the brokers. Trades that are not executed by the end of the day are terminated. Shares are typically traded in lots of 1000.

The Singapore Exchange is also well known for its trading in a variety of derivative securities via SGX-DT. It is the first exchange in Asia to offer equity index futures, and now offers the world's widest range of Asian index futures.

4.1.7 Shanghai Stock Exchange

The Shanghai Stock Exchange is the first and the largest stock exchange in China. The main indices used on the exchange are SSE 50 index, SSE 180 Index, SSE Composite Index and SHSE- SZSE 300 Index.

The Shanghai Stock Exchange works as a non profit institution administered by the China Securities Regulatory Commission. The exchange lists two different kinds of stocks: A and B shares. The difference between the two stocks is the currency that they are traded in. 'A' shares is traded in the local Renminbi yuan currency, whereas the 'B' shares are traded in U.S. dollars. Traditionally A shares were only traded within the country, but now both A and B shares may be traded world wide. The majority of the stocks listed on the exchange are 'A' shares.

4.2 Indian stock markets

The 'share mania' in India began when the American Civil War broke and the cotton supply from the US to Europe stopped. At the end of the war in 1874, the Dalal Street was identified as the place for share market. India's oldest and first stock exchange known as Bombay Stock Exchange (BSE) was established in Mumbai in 1875. The regulatory agency which oversees the functioning of stock markets is the Securities and Exchange Board of India (SEBI), which is also located in Mumbai. At present, there are 23 stock exchanges in India. Among them two are national level stock exchanges, namely, Bombay Stock Exchange and National Stock Exchange of India (NSE). One is Over the Counter Exchange of India (OTCEI) which is an electronic national stock exchange in which small and medium sized companies are listed. The rest 20 are Regional Stock Exchanges (RSE). The names of 23 stock exchanges are listed below:

- Bombay Stock Exchange
- National Stock Exchange
- OTC Exchange of India
- Ahmedabad Stock Exchange
- Bangalore Stock Exchange
- Bhubaneshwar Stock Exchange
- Calcutta Stock Exchange
- Cochin Stock Exchange
- Coimbatore Stock Exchange
- Delhi Stock Exchange
- Guwahati Stock Exchange
- Hyderabad Stock Exchange
- Jaipur Stock Exchange
- Ludhiana Stock Exchange
- Madhya Pradesh Stock Exchange
- Madras Stock Exchange
- Magadh Stock Exchange
- Mangalore Stock Exchange
- Meerut Stock Exchange
- Pune Stock Exchange
- Saurashtra Kutch Stock Exchange
- Uttar Pradesh Stock Exchange
- Vadodara Stock Exchange

Out of the 20 regional exchanges details of six prominent exchanges at Ahmedabad, Cochin, Bangalore, Kolkata, Pune and Delhi are given in the ensuing paragraphs, followed by that of BSE. The National Stock Exchange, the exchange under study is discussed as the last to have continuity with the further analysis of price movements and volatility.

4.2.1 Ahmedabad Stock Exchange (ASE)

The Ahmedabad Stock Exchange is the second oldest exchange of India. It was constituted in the year 1894 as a Public Charitable Trust. ASE was started under a banyan tree and therefrom progressed year after year. It holds a unique place in India. It got permanent recognition from the Government of India in 1982. The era of 80s and 90s saw some major focus in the exchange. A proper infrastructure was built up and the exchange was completely computerized. The exchange went live on screen-based trading on December12, 1996.

Currently there are 333 trading members in the exchange to serve the investors with one of the best transparent trading system in India. The trading of approximately 2000 nationally listed equities is done in the exchange. Over 200 high growth companies listed in the ASE or with other exchanges are also traded here.

4.2.2 Cochin Stock Exchange (CSE)

Cochin Stock Exchange is counted among one of the premier stock exchanges in India. It was established in 1978 and has undergone tremendous transformation over the years. In 1978, it had only five companies listed and had only 14 members. Currently, it has 508 members and 240 listed companies.

CSE went for computerization of its offices in 1989. To keep pace with the market, it took various initiatives; one such initiative was trading in dematerialised shares. It introduced the facility of computerised trading known as "Cochin Online Trading" (COLT) on March 17, 1997. It also became one of the promoters of the Interconnected Stock Exchange of India (ISE). The basic idea of ISE was to consolidate the smaller and fragmented markets which are less liquid into a national level integrated liquid market.

4.2.3 Bangalore Stock Exchange (BgSE)

Bangalore Stock Exchange (BgSE) started functioning from 1963 and it is currently the largest stock exchange in South India. There are 595 listed companies with more than 300 non-regional companies in it. Over 5000 companies from listed and permitted category can be traded at the Exchange at present. It is managed by the Council of Management which consists of members nominated by SEBI, public representatives, elected members and Executive Director. At present the exchange has 239 members of which nearly 25 per cent are corporate members.

4.2.4 Calcutta Stock Exchange (CSE)

CSE was incorporated in the year 1908 with 150 members. At present, the membership has reached above 900 with several corporate and institutional members. More than 3,500 companies have been listed on the exchange. With effect from April 14, 1980, CSE has been granted permanent recognition by the Central Government under the relevant provisions of the Securities Contracts (Regulation) Act, 1956.

4.2.5 Pune Stock Exchange (PSE)

PSE was established on 2nd September, 1982 with only 35 members. It is a company limited by guarantee. Initially, the exchange had only a few lakh rupees worth of business, but now it is having Rs.15-20 crores of business daily. More than 310 companies are listed with Pune Stock Exchange. Based on VECTOR (Versatile Engine for Centraliseed Trading and On-line Reporting), the exchange is successfully using a screen based Trading System. At present it covers, 185 broker members and nine workstations for the administration, market operations and surveillance activities of the exchange. Pune Stock Exchange is looking for the possibilities of widening its activities to several parts of Pune city and other cities like Satara, Sangli, Solapur, Kolhapur, Ahmednagar, Aurangabad, Nasik and Mumbai.

4.2.6 Delhi Stock Exchange (DSE)

The Delhi Stock Exchange Association Limited (DSE) was incorporated on June 25, 1947. The Exchange is an amalgamation of Delhi Stock and Share Brokers' Association Limited and the Delhi Stocks and Shares Exchange Limited. It is India's fifth exchange. The Exchange is one of the premier stock exchanges in India. The Delhi Stock Exchange is well connected to 50 cities with terminals in North India. The Exchange is having over 3,000 listed companies. It has received the market regulator's permission from BSE and has become its member. Now it facilitates the DSE members to trade on the BSE terminals. The Exchange is also considering the same from NSE.

4.2.7 Bombay Stock Exchange (BSE)

The Bombay Stock Exchange is known as the oldest exchange in Asia. It traces its history to the 1850s, when stockbrokers would gather under banyan trees in front of Mumbai's Town Hall. The location of these meetings changed many times, as the number of brokers constantly increased. The group eventually moved to Dalal Street in 1874 and in 1875 became an official organization known as 'The Native Share and Stock Brokers Association'. In 1956, the BSE became the first stock exchange to be recognized by the Indian Government under the Securities Contracts Regulation Act. Historically an open-cry floor trading exchange, the Bombay Stock Exchange switched to an electronic trading system in 1995. It took the exchange only fifty days to make this transition.

As the first stock exchange in India, the Bombay Stock Exchange is considered to have played a very important role in the development of the country's capital markets. The Bombay Stock Exchange is the largest of the 22 exchanges in India, in terms of listed companies, with over 6,000 listed companies. The Bombay Stock Exchange uses the BSE Sensex, an index of 30 large, developed BSE stocks. It has developed the BSE Sensex in 1986, giving the BSE a means to measure overall performance of the exchange which is closely followed around the world. Based on the Sensex, the BSE equity market has grown significantly since 1990. In addition to individual stocks, the BSE also has a market in derivatives, which was the first to be established in India. In 2000 the BSE used this index to open its derivatives market, trading Sensex futures contracts. The development of Sensex options along with equity derivatives followed in 2001 and 2002, expanding the BSE's trading platform. Listed derivatives on the exchange include stock futures and options, index futures and options, and weekly options.

The Bombay Stock Exchange is also actively involved with the development of the retail debt market. The debt market in India is considered extremely important, as the country continues to develop and depends on this type of investment for growth. Until recently, the debt market in India was limited to a wholesale market, with banks and financial institutions as the only participants. The Bombay Stock Exchange believes that a retail market will bring great opportunities to individual investors through better diversification.

4.2.8 National Stock Exchange (NSE)

Capital market reforms in India and the launch of the Securities and Exchange Board of India (SEBI) accelerated the incorporation of the second Indian stock exchange called the

National Stock Exchange (NSE) in Mumbai in the year 1992. After a few years of operations, the NSE has become the largest and the most advanced stock exchange in India in terms of total turnover and volume of transactions. NSE plays an important role in helping Indian companies to access equity capital, by providing a liquid and well-regulated market.

The NSE provides its clients with a single, fully electronic trading platform that is operated through a VSAT network. Unlike most world exchanges, the NSE uses the satellite communication system that connects traders from 345 Indian cities. The advanced technologies enable upto six million trades to be operated daily on the NSE trading platform. As a result of its hi- tech and transparent modes of operandi, NSE have become prominent player in the Indian capital market over the years.

The NSE is owned by a group of leading financial institutions such as Indian Bank and the Life Insurance Corporation of India. However, in the totally de-mutualised exchange, the ownership as well as the management does not have a right to trade on the Exchange. Only qualified traders can be involved in the securities trading.

The NSE is one of the few exchanges in the world trading all types of securities on a single platform, which is divided into three segments: Wholesale Debt Market (WDM), Capital Market (CM), and Futures & Options (F&O) Market. These three segments of the NSE trading platform were established one after another. The Wholesale Debt Market (WDM) commenced operations in June 1994 and the Capital Market (CM) segment was opened at the end of 1994. Finally, the Futures and Options segment began operating in 2000. Today the NSE takes the 14^{th} position in the top 40 futures exchanges in the world.

The National Stock Exchange of India has stringent requirements and criteria for the companies listed on the Exchange. Minimum capital requirements, project appraisal, and company's track record are just a few of the criteria. In addition, listed companies pay variable listing fees based on their corporate capital size. The companies listed includes from hi-tech to heavy industry, software, refinery, public sector units, infrastructure, and financial services. Trade data is distributed worldwide through various news-vending agencies. More importantly, each and every NSE listed company is required to satisfy stringent financial, public distribution and management requirements. High listing standards foster investor confidence and also bring credibility into the markets. Listing on NSE raises a company's profile among investors in India and abroad. NSE lists securities in its Capital Market (Equities) segment and its Wholesale Debt Market segment.

In 1996, the National Stock Exchange of India launched S&P CNX Nifty and CNX Junior Indices that make up 100 most liquid stocks in India. CNX Nifty is a diversified index of 50 stocks from 25 different economy sectors. The Indices are owned and managed by India Index Services and Products Ltd (IISL) that has a consulting and licensing agreement with Standard & Poor's. In 1998, the National Stock Exchange of India launched its web-site and was the first exchange in India that started trading stock on the Internet in 2000. The NSE has also proved its leadership in the Indian financial market by gaining many awards such as 'Best IT Usage Award' by Computer Society in India (1996 and 1997) and CHIP Web Award by CHIP magazine (1999).

4.2.8.1 Market capitalisation of NSE

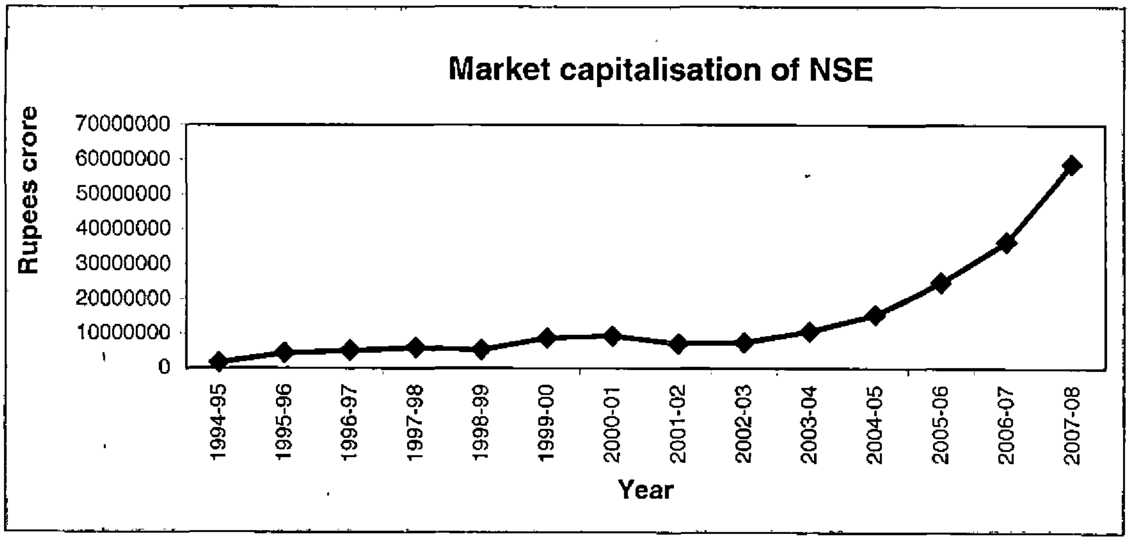
Market capitalisation, often called market cap, represents the aggregate value of a company or stock. It is an estimation of the value of a business that is obtained by multiplying the number of shares outstanding by the current price of a share. The outstanding shares are the actual shares in the hands of investors. Generally, the market recognizes three market cap divisions as large cap, mid cap , and small cap, although the cutoffs between the categories are not precise or fixed. Although the market cap of a company is an indication of the value of the company, it is only a temporary metric based on the current stock market. The true value of the company - its profits, product positioning, balance sheet, etc. - may not be reflected in the market cap. A company might be doing well, but still have a low market cap if its products and reputation have not caught the attention of the masses. The market capitalisation of NSE includes the sum total of the market capitalisation of all companies listed in NSE. Table 4.1 depicts the market capitalisation of NSE for the period 1994-95 to 2007-08. The same is graphically presented in Fig. 4.1.

Table 4.1 Market capitalisation of NSE, 1994 – 95 to 2007 -08

Year	Annual market capitalization (Rupees crore)	Annual Growth Rate (%)
1994-95	1710615	-
1995-96	4492716	162.64
1996-97	5130178	14.19
1997-98	6022696	17.40
1998-99	5296013	-12.07
1999-00	8718711	64.63
2000-01	9247468	6.06
2001-02	6966768	-24.66
2002-03	7398448	6.20
2003-04	10661885	44.11
2004-05	15575638	46.09
2005-06	24981438	60.39
2006-07	36587267	46.46
2007-08	58743645	60.56
CAGR		**0.287**

Source : www.rbi.org.in

Fig 4.1 Line graph of market capitalisation of NSE



As evident from Table 4.1 and Fig. 4.1, the market capitalisation of NSE is showing an increasing trend over the years. More and more companies got listed on the NSE after its inception. With the exception of the years 1998-99 and 2001-02 growth rate has always been positive. The steep decline in market capitalization in the year 2001-02 was due to the dotcom crash and global crisis. In initial years, due to low penetration of internet facility across the country with its high costs, NSE's reach was limited. From year 2003-04 onwards, there is steep increase and continuous increase in market capitalisation. With its advanced technology and transparent trading practices soon NSE became popular among market investors and the corporate sector. After year 2003-04 with increased penetration of internet and mobile telecommunication network NSE's reach increased in manifolds over a period of time. This phenomenon was seen in the ever increasing market capitalization of NSE. This trend is further supported with the bullish trend of the Indian stock market from year 2003-04 to 2007-08. But the Compound Annual Growth Rate of market capitalisation showed a lower annualised growth rate of 28.7 per cent over 14 years, implying a normal growth.

4.3 Volatility behaviour of the Indian stock market

The first objective of examining the volatility behaviour of the Indian stock market is done by analyzing the price movements in the stock market. The price movements are analysed for the S&P CNX Nifty, representing the NSE for the Indian stock market as a whole, and also for the five companies selected from Nifty based on market capitalisation, namely, Reliance Industries Limited (Reliance), Infosys Technologies Limited (Infosys), State Bank of India (SBI), Bharat Heavy Electricals Limited (BHEL) and Indian Tobacco Company (ITC) representing diversified, information and technology, financial, engineering heavy and fast moving consumer goods sectors respectively. A brief introduction about Nifty and profile of the five companies selected are also given as a prelude to the examination of their volatility behaviour. Since Foreign Institutional Investors (FII) have a major role in deciding the volatility of the Indian stock market, their investment in the Indian capital market is also discussed to start with, in this section.

4.3.1 Foreign Institutional Investors (FII) and stock market volatility

An important feature of the development of stock market in India in the last fifteen years has been the growing participation of institutional investors, both foreign institutional investors and the Indian mutual funds. The increasing role of institutional investors has brought both quantitative and qualitative developments in the stock market viz., expansion of securities business, increased depth and breadth of the market, and efficient pricing of the stocks.

Foreign Institutional Investors are investors, usually institutions or entities that invest money in the financial markets of a country different from where the institution or entity was originally incorporated. Due to the highly fluctuating nature of FII investments, it is termed as hot money in market circles. FII reactions, sentiments and behaviour against global developments, political developments, economic growth and industry performance garner more importance. So strong is the FII influence that domestic players and local fund houses can do little to negate a powerful FII trend. Sudden FII outflows are common. When FIIs withdraw suddenly, the stock markets come crashing down wiping away small investors' wealth. The high volume of FII purchases or sales and their extreme volatile behaviour can plunge the stock markets into an inexplicable crisis. The volatile behaviour of FIIs could seriously impact economic stability at the grass root level. Since they have emerged as one of the key index movers, it is quite pertinent to observe the extent of their investment in Indian stock markets, which is depicted in Table 4.2.

Table 4.2 Net investment by FII in the Indian capital markets, 1992-93 to 2007-08

Year	Net FII investment (Rupees crore)	Annual Growth Rate (%)
1992-93	14	-
1993-94	4.27	-69.50
1994-95	5444.60	127408.20
1995-96	4776.60	-12.27
1996-97	6720.90	40.70
1997-98	7386.20	9.90
1998-99	5908.45	-20.00
1999-00	-729.11	-112.34
2000-01	9765.13	1439.32
2001-02	9682.52	-0.85
2002-03	8272.90	-14.56

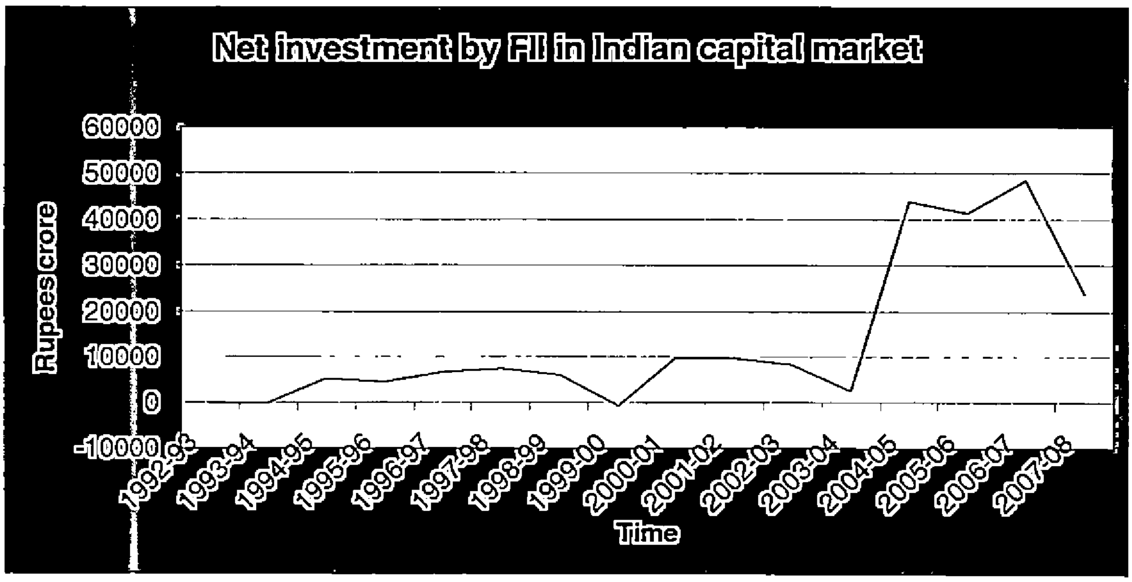
2003-04	2668.90	-67.74
2004-05	44000.03	1548.62
2005-06	41416.45	-5.87
2006-07	48650.04	17.47
2007-08	23754.05	-51.17
CAGR		**0.59**

Source : www.rbi.org.in

FIIs were allowed to invest in the Indian capital market securities from September 1992. However, investments were first made by them in January 1993. As evident from Table 4.2, the year 1995-96 witnessed the outflow of cash, thus showing negative annual growth rate. In the year 1994-95, for the first time, Indian capital market has seen manifold increase in investment through FIIs. The year 2006-07 market has seen maximum investment from FII. However because of global slowdown, FII investment declined by around 51 per cent in the year 2007-08. India was among the markets that saw the largest pullouts by FIIs in 2008. The Compound Annual Growth Rate of the investment of FIIs showed a normal annualised growth of 59 per cent over 17 years.

The net investment of FIIs in the Indian capital market is graphically presented by means of line graph in Fig. 4.2.

Fig.4.2 Line graph of net investment by FII in Indian capital market.



It is evident from the Figure 4.2 that the net investment by FII in Indian capital markets shows an overall increasing trend. From year 1992-93, up to year 1998-99, it had gone up and again came down to its initial levels. Hereafter upto year 2002-03 it was increasing first and later came down again but this time remained at higher level as compared to year 1998-99. This sharp increase was because of strong growth rate of the Indian economy and overall bull trend in the world market. A country like India with its stable central government, favouring the Indo-US bilateral relationships was the ideal choice for the FII. As a result, later in year 2003-04 it shows sky rocketing growth, which again came down in year 2005-06. Finally after increase in 2006-07, it came down drastically in the year 2007-08 due to the global slowdown.

Funds from United States, Canada, United Kingdom, Malaysia, Australia and South Korea along with 150 other global pension funds have invested in Indian stocks. The increasing interest of FIIs into the Indian markets is working as a catalyst for volatile Indian stock markets. The effect of their dominance is enthusiastic as well as a cause of concern for retail investors. The over dependence on FII and lack of balancing investment by Domestic Institutional Investor (DII) make Indian stock markets highly volatile. This in turn makes the market more linked to global sentiments rather than strong domestic fundamentals of economy. Hence, prediction of future volatility of the Indian stock market, gains utmost significance from the point of an ordinary investor.

4.3.2 Profile of the sample

The sample selected for the study includes the S&P CNX Nifty for examining and forecasting the volatility of the Indian stock market as a whole. In addition to Nifty, five companies listed top in the Nifty and representing five different sectors were selected for examining and forecasting the sector –wise volatility of the Indian stock market. A brief introduction about the samples selected forms the content of this section.

4.3.2.1 Standard & Poor's CRISIL NSE Index 50 (S&P CNX Nifty) -

The Standard & Poor's CRISIL NSE Index 50 or S&P CNX Nifty nicknamed *Nifty 50* or simply *Nifty*, is the leading index for large companies on the National Stock Exchange of

India. The Nifty is a well diversified 50 stock index accounting for 25 sectors of the Indian economy. The 50 companies are selected out of approximately 1,300 companies listed on the NSE, based on the criterion of market capitalisation. It captures approximately 60 per cent of its equity market capitalisation and is a true reflection of the Indian stock market. In other words, Nifty tracks the behaviour of a portfolio of blue chip companies, the largest and most liquid Indian securities. It is an indicator of all the major companies of the NSE. Just like the Sensex represents the top stocks of the BSE, the Nifty represents the top stocks of the NSE. The index has been trading since April 1996 and is well suited for a variety of purposes such as benchmarking fund portfolios, index based derivatives and index funds.

The S&P CNX Nifty index is owned and managed by the India Index Services and Products Ltd. (IISL), with which Standard and Poor's has a consulting and licensing agreement. IISL is a joint venture between NSE and Credit Rating Information Services of India Ltd. (CRISIL). S&P CNX Nifty is maintained by IISL's Index Policy Committee, which manages policy and guidelines for all CNX (CRISIL/NSE) indices. This Index Policy Committee follows a clear published set of rules for index revision and meets quarterly to consider their application. Additionally, the IISL's Index Maintenance Sub-Committee reviews decisions about additions and deletions to the index on a quarterly basis.

The criteria for inclusion in the Nifty include market capitalisation, public float, weighting and liquidity. Each company must have a market capitalization equal to or exceeding Rs. 5 billion for the preceding six months. It should have at least 12 per cent of it outstanding shares available for public trading. The index is computed using the market capitalization weighted method. For the purpose of inclusion in the NSE, liquidity is measured by impact cost. Each company must have traded at an average impact cost of 75 per cent or less for the preceding six months for 90 per cent of the trades. Impact cost measures the difference between the ideal selling price of a security and the actual price. The more liquid a security, the greater the chance that its shares trade at prices close to the ideal price. Highly liquid securities have very low impact cost. In addition, a company which enters the market with an IPO, can be reviewed for inclusion in the index if it meets the above criteria for three months.

Companies that substantially violate one or more of the criteria for index inclusion and companies involved in merger, acquisition, or significant restructuring such that they no longer meet the inclusion criteria will be removed from the index.

4.3.2.2 Reliance Industries Limited (RIL)

India and Reliance Industries rely on each other. The Company is India's largest petrochemical firm and one among the country's largest companies. Oil refining and the manufacture of polyolefin account for a major portion of Reliance's sales. It also makes textiles and explores for oil and gas, though these businesses are comparatively small. In 2009 the Company agreed to merge with its oil and gas refining subsidiary, Reliance Petroleum, in order to boost the operational and financial synergies of Reliance as a major refining company.

In the year 1998, the Company completed its ambitious project of building world's largest refinery, six months ahead of schedule. Reliance Jamnagar is the world's largest grassroots refinery and aromatics complex. As size and scale are both on its side, the Company enjoys lower input costs and constantly records the highest gross refining margins. Thus the profit figures of the Company got real momentum only after this project became operational.

On the backdrop of increasing crude oil prices, and commencement of its new petroleum refinery at Jamnagar, adjacent to its old site, which has the status of 100 percent export oriented special economic zone giving tax holiday for 15 years, Reliance had garnered hefty profits in the year 2007-08, though it had to shut down its petrol pumps across the country in the same year. As the public sector companies were selling the subsidised petroleum products, private companies like Reliance were forced to sell the products at the same rate. This resulted in big losses for the Company. Losses were certainly unbearable for longer term. When Government of India did not agree to compensate the losses made by private companies, Company officially declared the closure of its nation wide petrol pumps. This decision reversed the equation, and actually helped the company by reducing anticipated losses. The export oriented business policy of the Company paid much better rewards with increasing global demand and petroleum prices.

Due to all these reasons the Company's market cap has grown tremendously, even after its demerger in the year 2006. Investors continued to make bee line for Reliance stock in the market.

4.3.2.3 Infosys Technologies Limited (Infosys)

Infosys emphasizes every aspect of information technology. One of India's leading technology services firms, Infosys Technologies provides software development and engineering through a network of development centers in Asia, Europe and North America. It also provides data management, systems integration, project management, support, and maintenance services. Its subsidiaries, Infosys BPO offers business process outsourcing (BPO) services, and US-based Infosys Consulting provides strategic consulting. Infosys has rapidly expanded its presence in international markets, particularly in North America, which accounts for more than 60 per cent of sales. The Company has offices in more than 20 countries.

Infosys Technologies was listed on the NASDAQ stock exchange on March 11, 1999. It was the first Indian registered company to become listed on an American stock exchange. Listing on the NASDAQ enabled Infosys Technologies to institute an employee stock option plan through the use of American Depository Receipts (ADRs).

4.3.2.4 State Bank of India (SBI)

State Bank of India is the nation's largest commercial bank. The bank operates through more than 15,000 branches within India. SBI has more than 80 offices in nearly 35 other countries, including multiple locations in the US, Canada and Nigeria. The Bank has other units devoted to capital markets, fund management, factoring and commercial services, credit cards, and brokerage services. The Reserve Bank of India owns about 60 per cent of the capital of State Bank of India.

Its strong branch network supported with latest technology, and proper management has outperformed many private and international players in the market. Proper segmentation of the business along with its new ventures paved the way for its unique position into the Indian market. Its strategic expansion in recent years has helped in increasing the market reach of the bank. Along with increasing profits, the tag of a public sector bank made this stock more lucrative for the investors. Due to insulation of public sector undertaking and strong management control, the Bank was not affected by the US sub prime crisis. Thus its leadership position is to remain unchallenged in coming years, as before.

*4.3.2.5 **Bharat Heavy Electricals Limited (BHEL)***

Bharat Heavy Electricals Limited (BHEL) is an engineering and manufacturing company which produces capital goods for its two segments - power and industry sectors. It is one of the world's largest vendors of power generation equipments. BHEL's principal activities are to manufacture and distribute electrical, electronic, mechanical and nuclear power equipments. BHEL manufactures more than 180 products under 30 major product groups, including electronic, mechanical, and nuclear power equipments. The Company derives over 70 per cent of its revenues from its power business. BHEL sells its products to clients located in more than 70 countries around the world.

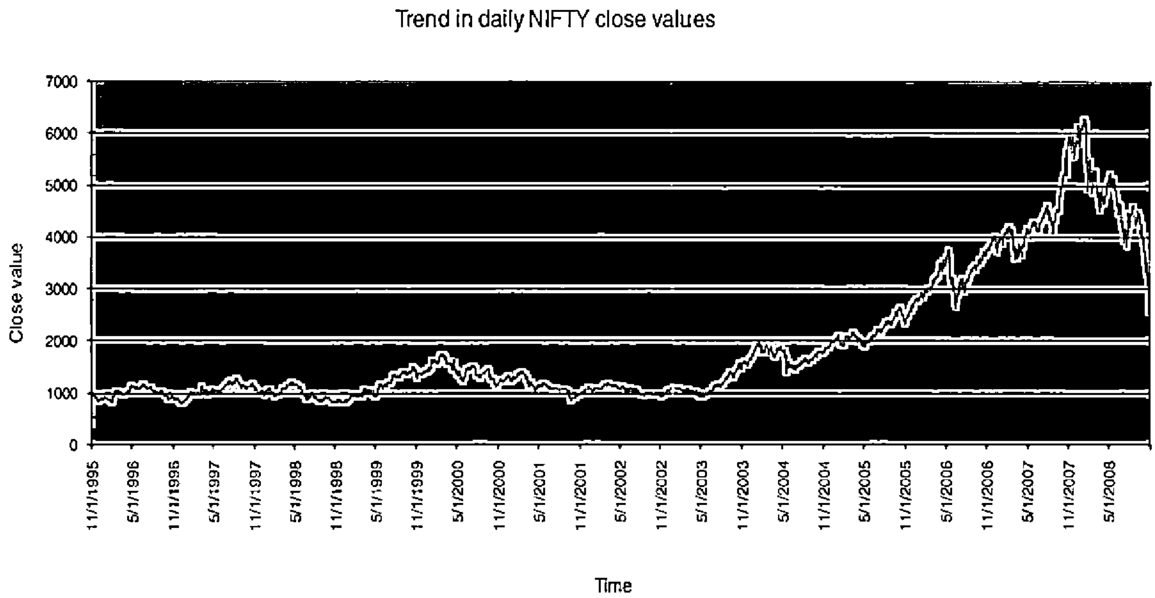
*4.3.2.6 **Indian Tobacco Company (ITC)***

Indian Tobacco Company (ITC) walks with the other giants of the Indian business world, Tata and Reliance. Primarily, the Company makes cigarettes and tobacco, as well as papers and packaging. It manages lines of branded apparel, personal care products, and prepackaged food. ITC also runs hotels and exports agricultural commodities (including rice, wheat, and lentils). ITC is India's second-largest exporter of agri-products. Its major brands include India Kings, Insignia, Navy Cut, Scissors, and Gold Flake (cigarettes); Wills Sport and John Players (clothing); Kitchens of India and Aashirvaad (prepackaged food); and Expressions (greeting cards). It is also parent to one of India's leading technology companies, ITC Infotech.

4.3.3 Trend in daily price movements

The volatility behaviour of the Indian stock market is examined from two angles – one, from the point of view of the stock market as a whole, taking the daily close values of S&P CNX Nifty and secondly of the sector – wise, taking daily close prices of five stocks representing five different sectors, from the Nifty. The close values of Nifty and close prices of the five stocks selected are collected from the website of NSE, www.nseindia.com for the period 3rd November 1994 to 31st October 2008 and used for analysing the price movements. First the trend in the price movements of Nifty is depicted in Fig. 4.3, followed by that of Reliance, Infosys, SBI, BHEL and ITC in Fig. 4.4, 4.5, 4.6, 4.7 and 4.8 respectively. Prices are plotted on the XY chart, where X- axis represents the time in days and Y- axis represents the close values or prices.

Fig.4.3 Trend in daily price movements of NIFTY close values



It is evident from the Figure 4.3 that the close values of NIFTY-50 index, under the study period is having an increasing trend in general. For the period from November 1995 up to February 2000, it is steadily increasing, and reached up to 1753.5 mark for the first time. Thereafter till 2nd May 2003 a steady downward trend is noticed, the index value reaching as low as 938, which is followed by a straight upward trend up to 9th January 2008, when Nifty touched the mark of 6272 points. This was followed by a sudden decreasing trend, with Nifty dipping to a low level of 2885.6 on 31st October 2008, due to the slowdown of the global economy and sudden exit of FIIs from the Indian stock market.

Fig 4.4 Trend in daily price movements of Reliance Industries Limited.

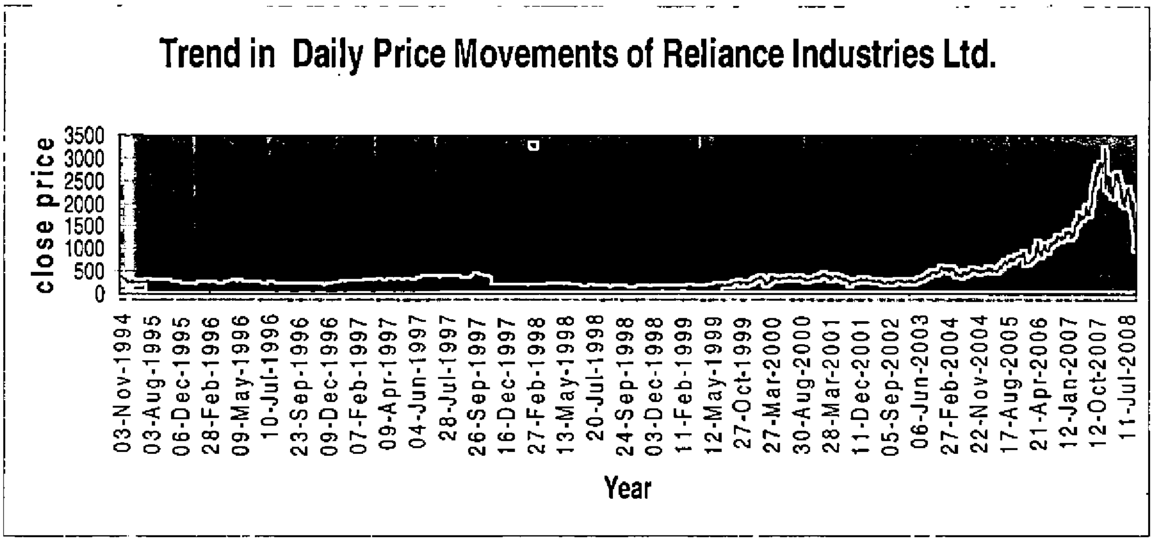


Fig. 4.4 reveals an overall clustered trend for Reliance upto 14th July1999, after which a slow increasing trend is noticed till 27th October 2003. After the death of patriarch Dhirubhai Ambani, Reliance was demerged on 25th January 2006. But the loss of its patriarch did not adversely affect the Company since he had made necessary arrangements for its future before his death. Post demerger stock of the Company witnessed sky-rocket increase in the prices. As noted in the case of Nifty (Fig. 4.3), there was sharp increasing trend upto 15th January 2008. Reasons like surge in crude oil prices and exploration of new petrochemical reserves by the Company could be attributed for making this darling company of the Dalal Street, dearer to the investor. It is to be noted that Reliance with all its advantages was not an exception to the aftereffects of the slowdown of the global economy since 2008.

Fig 4.5 Trend in daily price movements of Infosys.

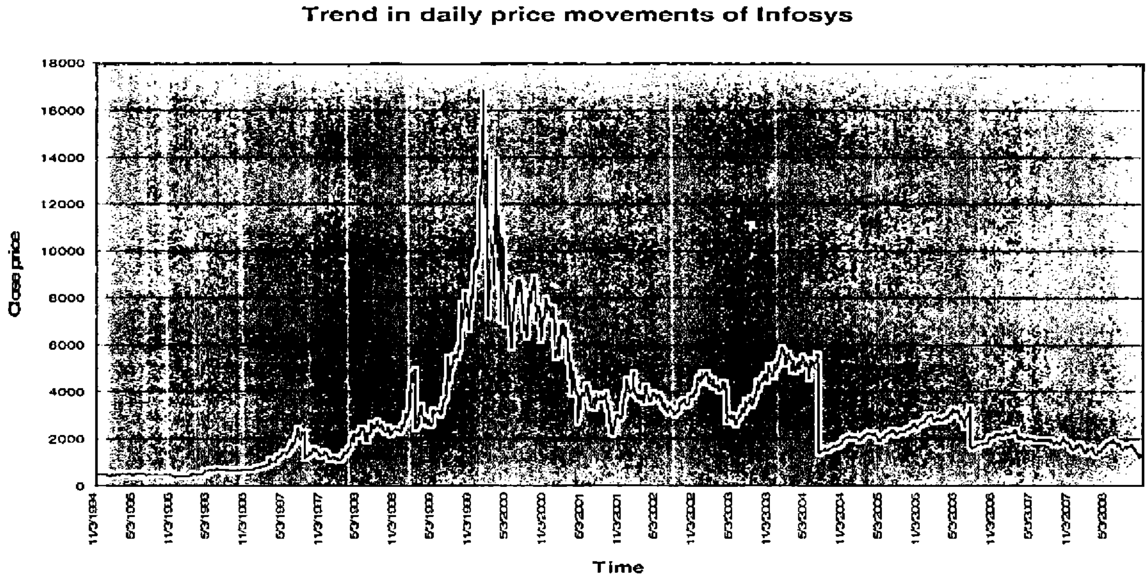
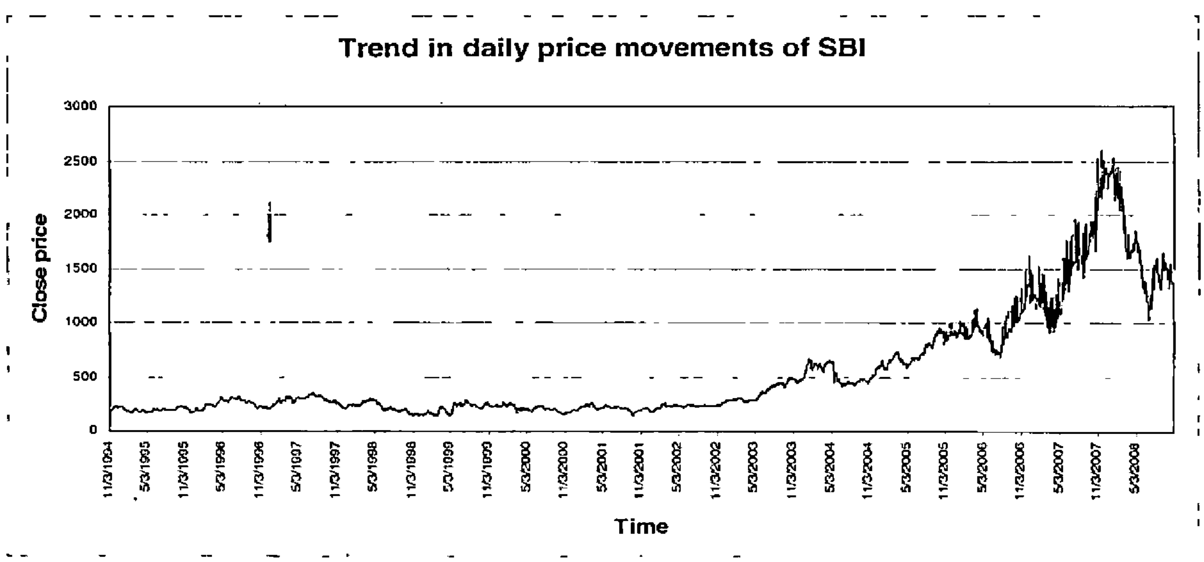


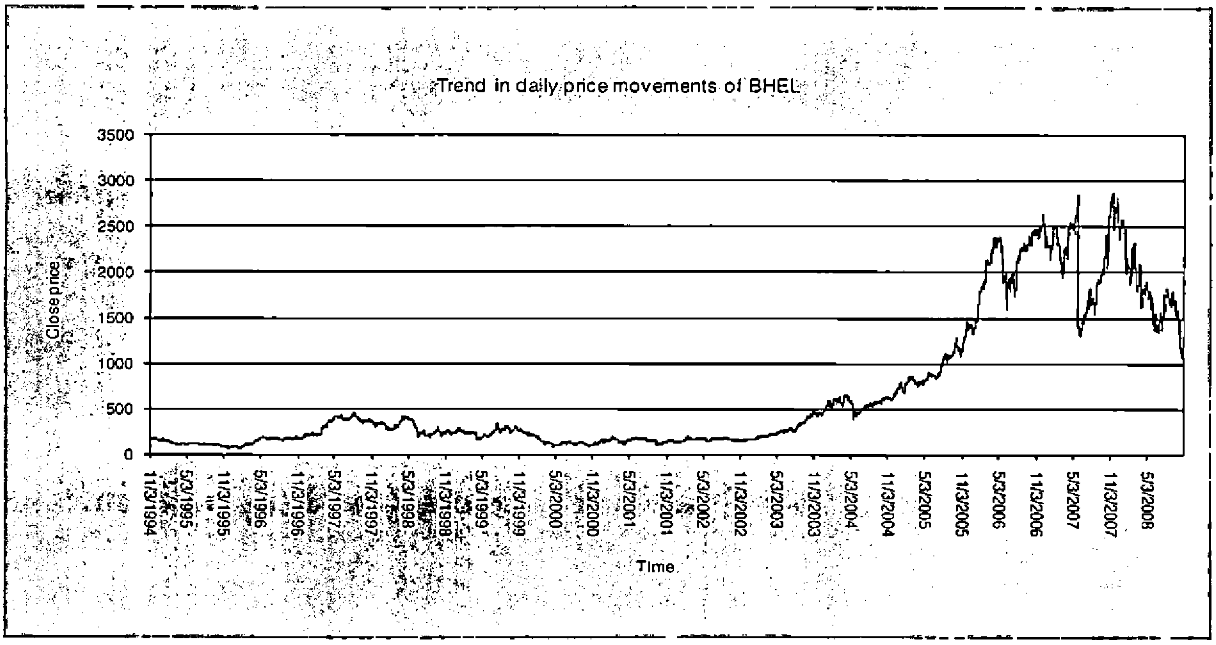
Fig. 4.5 depicts an overall fluctuating trend in the close price of Infosys during the study period. Between 3rd November1994 and 17th July 1997, very slow, but steady rise in close prices is seen, reaching first time high of Rs 2412. The stock reached a high of Rs 5001 on 09th February 1999. Later, on the backdrop of global boom in IT stocks, the stock witnessed an immense upward trend in close prices, and on 4th January 2000, reached its all time high value of Rs16870.85. But the stock price tumbled down to Rs. 2701.10 on 12th April, 2001 following the bursting of dot com bubble. The downward trend continued till 12th July 2004, taking the prices further down to Rs1376.15. Although it started recovering, it stumbled again along with other stocks and Nifty reaching a low close price of Rs1388.95 as on 31st October 2008.

Fig 4.6 Trend in daily price movements of SBI.



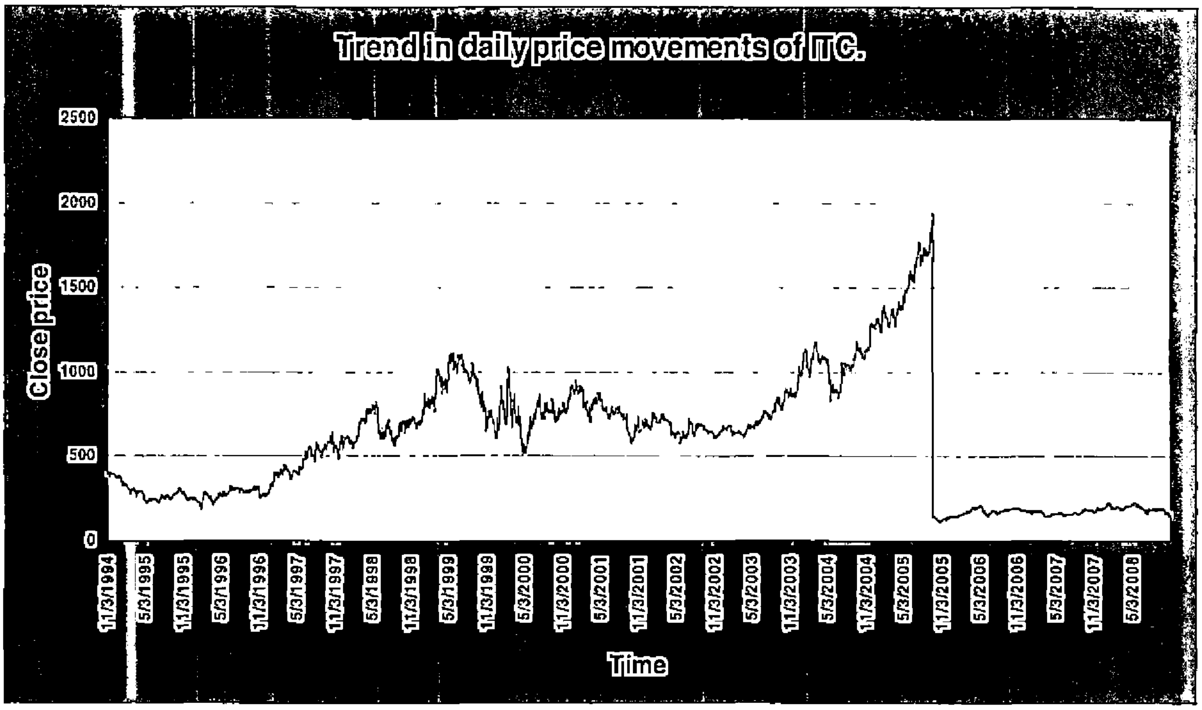
The close prices of State Bank of India under the study period show an overall consistent trend, from 3rd November 1994 to 17th May 2004, after which a sharp increasing trend is noticed up to 20th November 2007 due to increased banking business, along with overall swing in stock markets. As in the case of other stocks and Nifty discussed above, decreasing trend on the back drop of 'sub prime crisis' in US resulting in stock market crash all over the world is noticed in the case of SBI also, since the early 2008.

Fig.4.7 Trend in daily price movements of BHEL



From Fig. 4.7 it is clear that there is an overall consistent trend from 3rd November1994 to18th November 2002 in the case of BHEL. Thereafter a sharp increasing trend in the price is clearly visible upto 14th November 2007 due to increased industrialisation and most of the projects of BHEL running on a stream. This was followed by sharp decreasing trend upto 31st October 2008 because of market correction, effect of increased fuel prices and increased commodity prices in the global markets which affected the overall demand and profits of the company, along with the global slowdown.

Fig. 4.8 Trend in daily price movements of ITC



After a normal increase with fluctuations, sharp increasing trend is seen since late 2003, reaching an all time high on 20th September 2005. In the face of new highs for the stock, company declared the share split and bonus to the investors. In effect the number of total outstanding shares increased significantly, increasing stock's liquidity with lower priced shares, which often reduced the bid/ask spread. This resulted in the increased volume of trade. Along with this, profit booking sell dipped the ITC share to very low prices after the date of stock split. As a result of market correction for the stock split and bonus declared, on 21st September 2005 stock has slumped down drastically. However, stock never recovered fully and witnessed general fluctuation in prices up to 31st October 2008.

The analysis of the price movements of Nifty and selected stocks have revealed that all were adversely affected by the global slowdown from the year 2008. Besides this general and common factor, stocks were positively as well as negatively affected by industry specific and company specific factors, revealing their volatility behaviour.

4.4 Forecast of the sector - wise volatility of the Indian stock market

Volatility in financial markets has attracted growing attention of academicians, policy makers and practitioners during the past two decades. Volatility receives a great deal of concern from policy makers and financial market participants because it can be used as a measurement of risk. Second, the volatility in the stock, bond and foreign exchange markets raises important public policy issues about the stability of financial markets and the impact of volatility on the economy. Third, from a theoretical perspective, volatility plays a central role in the pricing of derivative securities.

Since the flow of information and the time used in processing that information varies with the individual (sectors) markets, one should expect different volatility patterns across (sectors) markets. Additionally, volatility spillovers are usually attributed to changes in common information and cross-market hedging, which may simultaneously alter expectations across (sectors) markets.

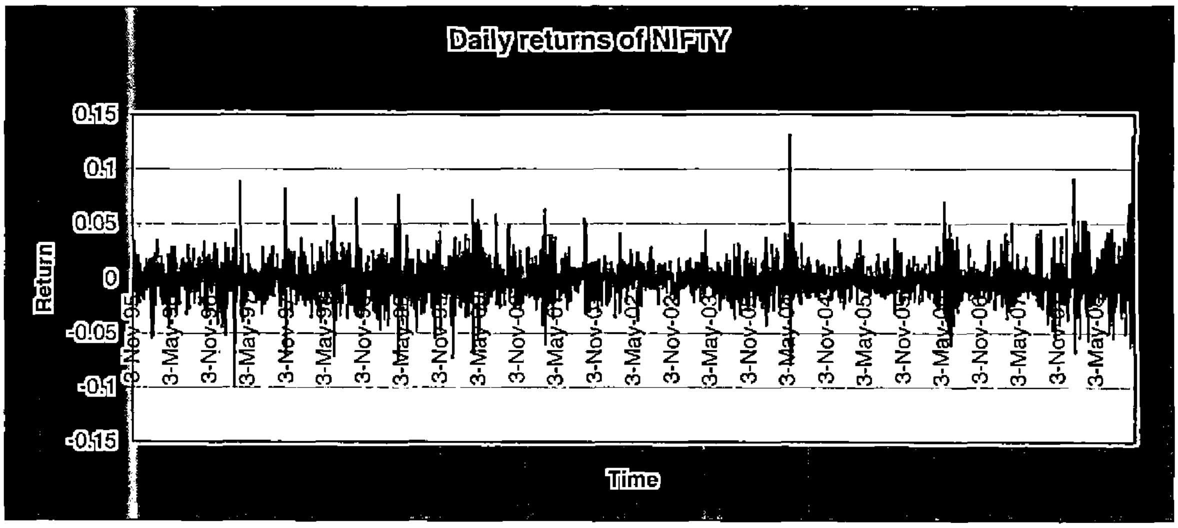
Every index is constituted by different companies representing different sectors, such as automobile, petroleum, banking, pharmaceuticals, fast moving consumer goods etc. All sectors are interrelated with one another. This link is well seen in the trade of securities constituting the index. Generally one major sector leads the market rally or fall, while other sectors just adjust their position to the changing ground. For example, when metal price rises, stocks of metal companies start soaring, eventually heating the stocks of automobile sector. As metal is major raw material for the automobile sector, price hike in such input will result in the shrinkage of profits thus giving out poor quarterly or yearly financial performance. Such scenario disappoints the investors, resulting in less demand, with heavy sell of securities in automobile sector. This results in the flow of money from one sector to the other sector, as a balancing act.

In each index, a different sector carries different weightage. Further these sectors are represented by the most prominent companies in that sector. The share prices of these companies do fluctuate as per the market sentiments, representing current status of the volatility in each sector. But the market values of individual shares are not a clear cut reflection of the true worth of the companies involved, but the state of demand for those shares relative to their supply .The indirect impact of actual public holding of the company along with the net investment by FII plays the crucial role.

Sector wise volatility is also affected by the activity in other markets. The relationship of a particular sector with other market, decides the scale of sector wise volatility in the capital markets. In case of India, the exchange rate of Rupee against US dollar directly affects the profits of Indian information and technology sector companies. When Rupee appreciates, it reduces the earnings of IT sector companies. So when Indian currency appreciates it takes toll on IT companies stocks. Similarly, when rupee depreciates, IT stocks become hot favourite for the investors. Strictly speaking, the sector wise volatility is a contribution of factors like market within the market, one sector's linkage with other market, and overall investment outlook of the investor. Reflection of sector specific volatility into the overall index is limited to proportionate weightage of each sector in the index. Except for some volatility breaks which occur at the same time in all the sectors, which are associated with global events, others do occur in all sectors at different times. Hence analysis of sector – wise volatility is of great significance from the investor's point of view, which is the content of this section.

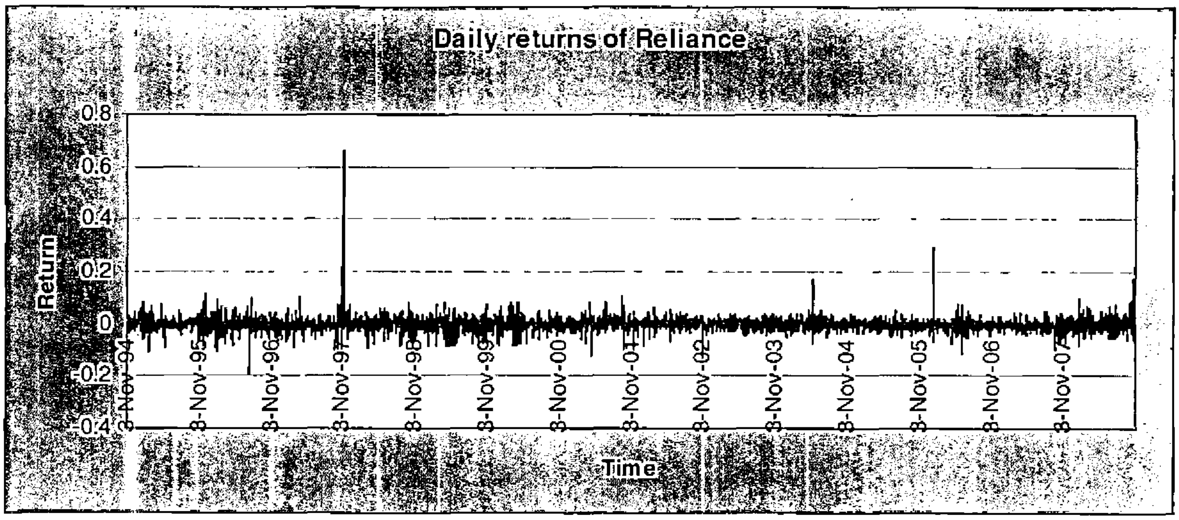
For forecasting volatility, five sectors are considered, namely, diversified sector, information and technology sector, financial or banking sector, engineering heavy sector and fast moving consumer goods sector. Along with the analysis of sector – wise volatility, the volatility of the Nifty representing Indian stock market as a whole is also forecasted. For forecasting, first, daily returns are plotted for Nifty and for five companies taking time along the X axis and daily price returns along the Y axis.

Fig 4.9 Daily returns of NIFTY.



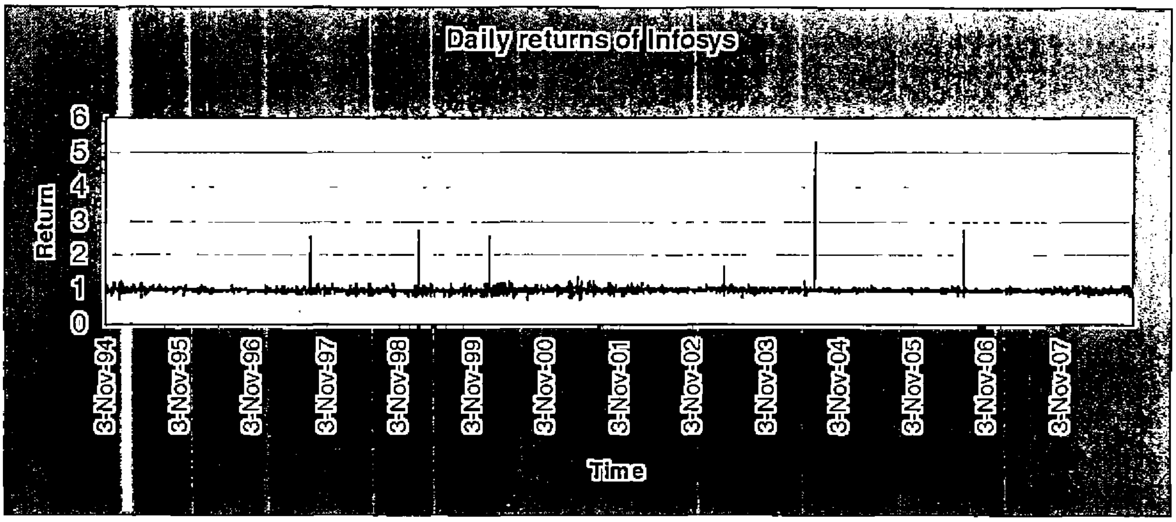
Daily returns of Nifty shows high fluctuating up and downs which direct that the market is volatile and if studied properly can be used to generate more profit. As the five companies included in the study constitutes more than 27 per cent weightage to the total index, the volatility of the index has major influence of these companies and remaining is contributed by 45 other companies which are not included in the study. Absence of major peak negative value of return implies the overall range bound stability of the volatility in the market.

Fig. 4.10 Daily returns of Reliance.



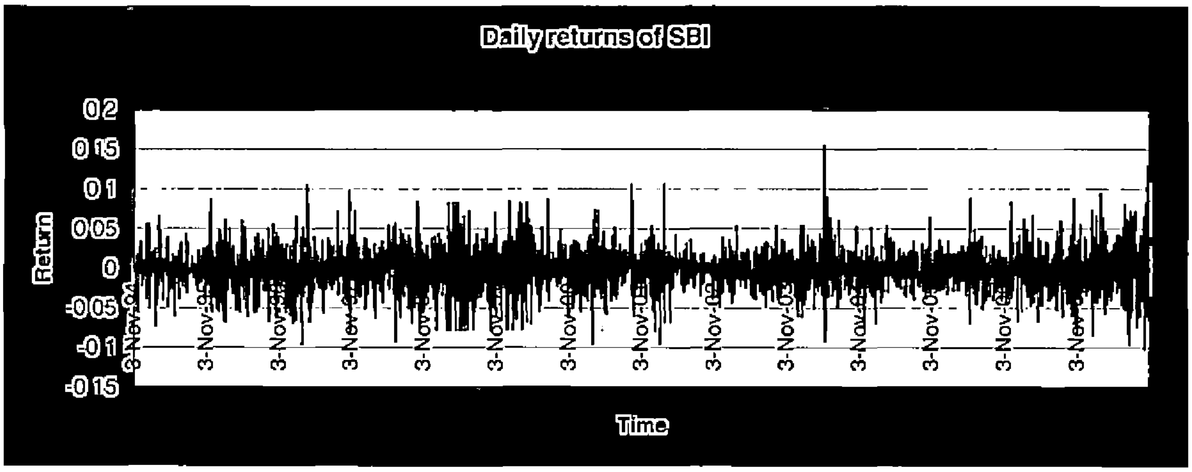
Reliance has the majority weightage in the stock market. It reflects the depth of investor's interest to the stock. Due to its large number of investors and comparatively limited number of shares available in the market, the stock remained successful to attract both price and investors. As a result Reliance stock generated low but consistent daily returns.

Fig. 4.11 Daily returns of Infosys



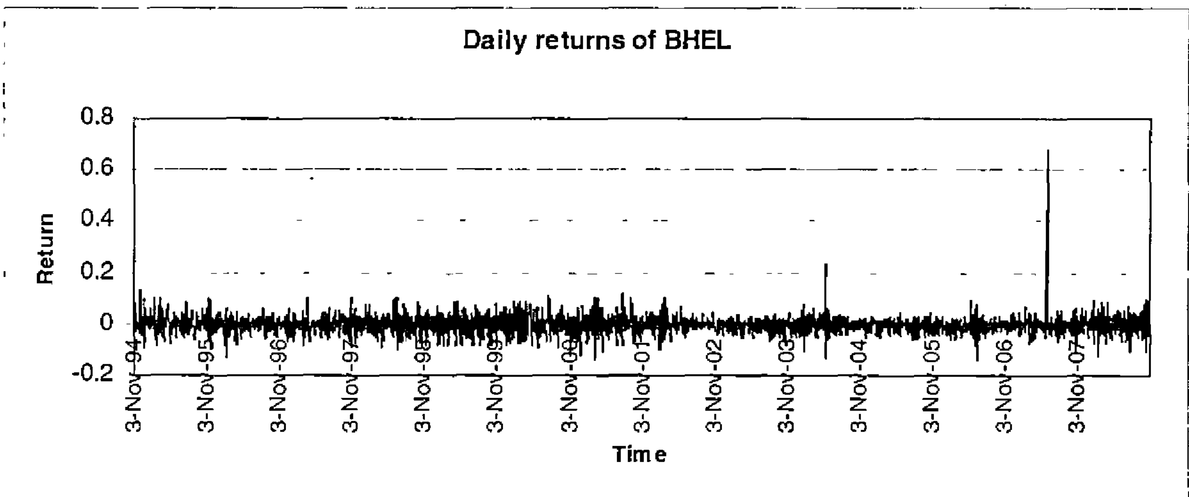
True to the reputation of IT baron, Infosys reported ever positive daily returns over the years. Due to its niche area of operating and less peer competition, the Company got all the benefits of being present in the right place at the right time. Further its business expansion strategy and decisions such as getting listed in the overseas stock markets attracted the investors from across the world. The growth rate of the Company assured the market acceptance and reputation to the stock which continuously kept the momentum going on in the same pace.

Fig.4.12 Daily returns of SBI.



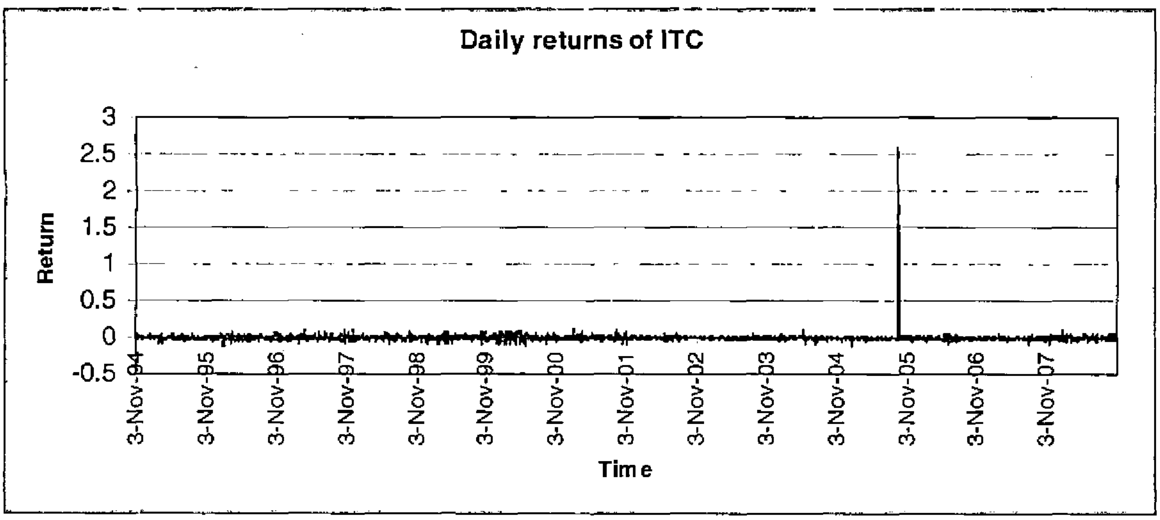
Most striking ups and downs in the daily returns of SBI stock suggest the presence of really high volatility. Considering the presence of number of competitors in the market and the overall weightage of this stock in the Nifty index, this trend is quite acceptable. Moreover, the tag of a public sector bank has made this stock lucrative for the investors.

Fig.4.13 Daily returns of BHEL.



Presence of two extreme positive peaks and absence of extreme negative peaks confirms the investors' faith in the stock. Its public sector background, and niche area of working together with constantly increasing market share is guaranteeing bright future prospects, for the Company and indirectly to the investors. It has enabled consistent daily returns over a period of time to the investors.

Fig.4.14 Daily returns of ITC.



Except one peak value, the graph of ITC shows a consistent level of very low daily returns. Considering the area of operation and total weightage in Nifty index, result is quite obvious. Due to its dominant market position and range of its portfolio, the Company is holding the leadership position in its sector. Because of low level of margin ratio and growth rate, ITC stock gives lower daily returns as compared to other stocks included in this study.

4.4.1 Volatility (Average monthly squared returns)

The daily squared returns for Nifty index and each company are calculated and average monthly squared returns are arrived at by taking the average of daily squared returns for a particular month. Line graphs are also drawn taking months along the X axis and average monthly squared returns (volatility) along the Y axis. After obtaining the monthly volatility series, the forecasting horizon has been decided. In this study one-month ahead forecasts are chosen. Furthermore, periods have been chosen for estimating parameters and for predicting volatility. The first 125 months of data are used to fit the models. Thus the first month for which an out-of sample forecast is obtained is March 2006 for Nifty and April 2005 for other companies. As the sample is rolled over, the models are re-estimated and sequential one-month ahead forecasts are made. Hence, in total 56 monthly volatilities are forecasted.

Table 4.3 Summary statistics of the squared returns series

Company	N	Mean	Standard deviation	Maximum	Skewness	Kurtosis	Variance
NIFTY	125	0.000254	0.0002563	0.0019	3.280	14.634	1.11278
Reliance	125	0.000862	0.0021764	0 .0240	9.815	104.172	3.80346
Infosys	125	1.006656	0.1510004	2.2184	1.944	49.019	0.01146
SBI	125	0.000645	0.0005645	0.0035	2.325	7.220	3.23557
BHEL	125	0.001002	0.0009405	0.0060	2.554	9.302	3.56333
ITC	125	0.000619	0.0005544	0.0029	1.948	4.269	2.64127

For analysing volatility, variation in squared returns of prices is studied using variance, skewness and kurtosis. All the companies under study were found positively skewed. Reliance showed highest positive skewness, followed by Nifty, BHEL, SBI, ITC, and Infosys. Positive skewness confirmed the presence of extremely high values of squared returns, which pulls the mean towards the right tail of the distribution. Kurtosis analysis revealed that Reliance has very high peaked values, followed by BHEL, Infosys, NIFTY, SBI, and ITC. The findings of Table 4.3 underline the presence of volatility in the market. Since Reliance showed high positive skewness, kurtosis and variance, it is inferred that

Reliance has the highest volatility when compared to other companies.

4.4.1.1 Histogram of volatility of Nifty and selected stocks

The histogram of the samples, viz., Nifty, Reliance, Infosys, SBI, BHEL and ITC are shown in Fig. 4.15, 4.16, 4.17, 4.18, 4.19 and 4.20.

Fig.4.15 Histogram of volatility of Nifty

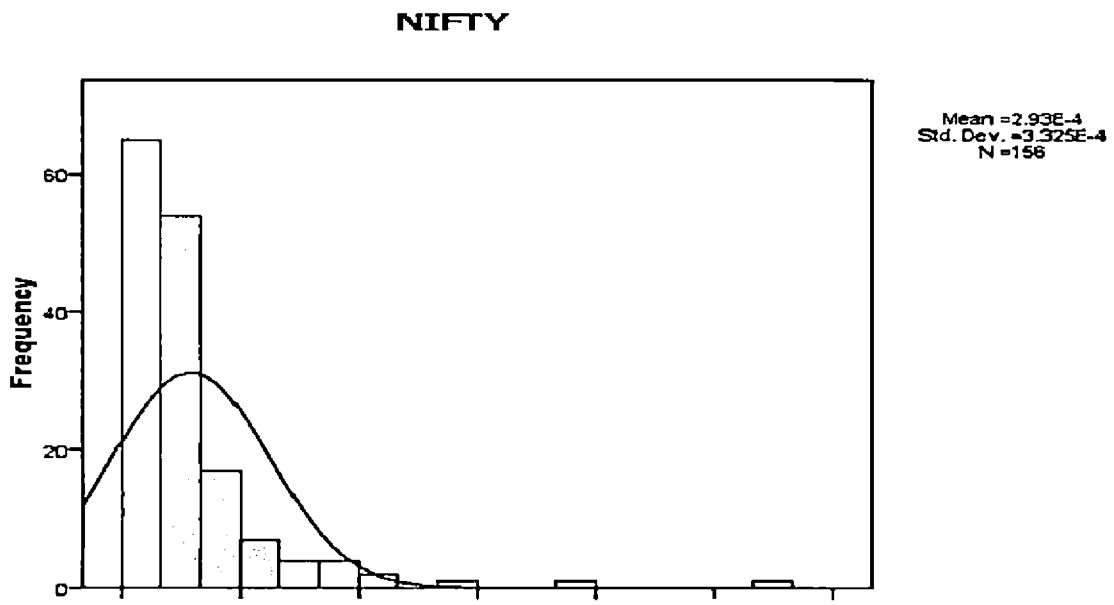


Fig. 4.16 Histogram of volatility of Reliance.

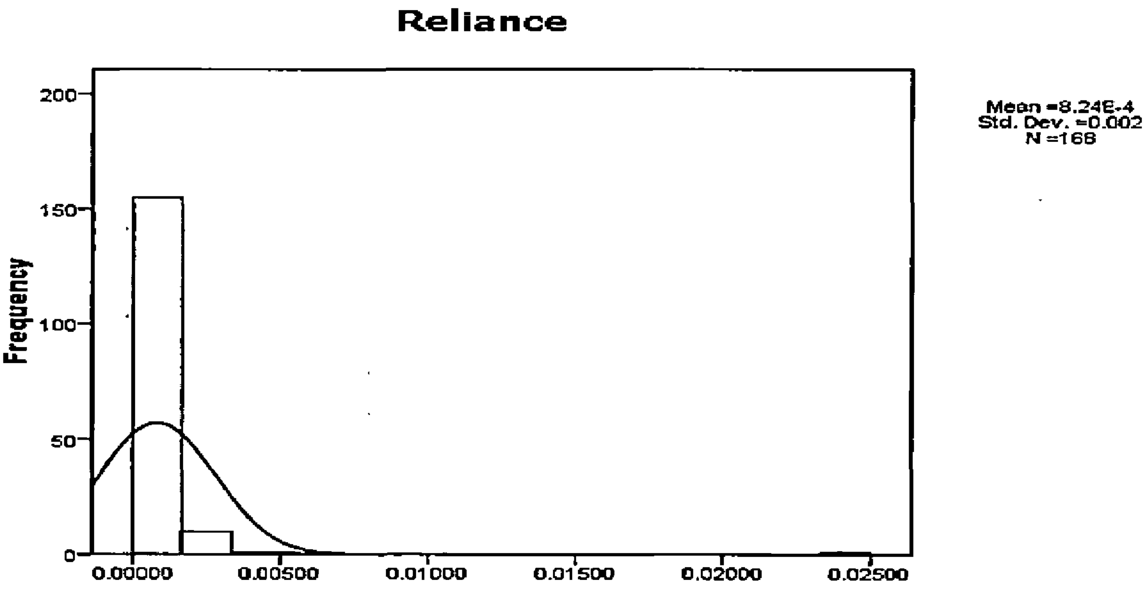


Fig.4.17 Histogram of volatility of Infosys.

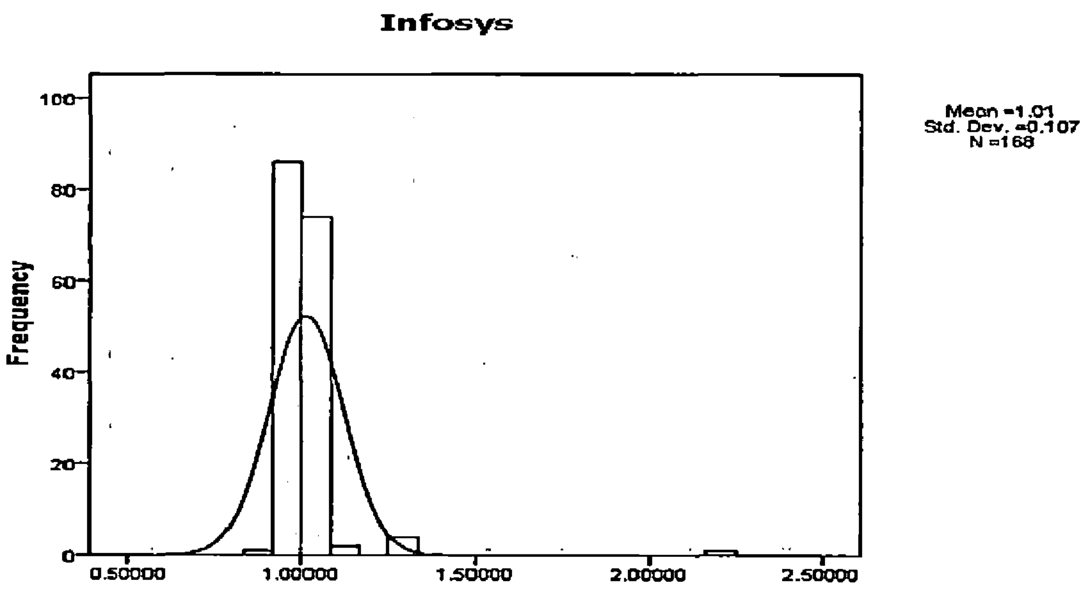


Fig.4.18 Histogram of volatility of SBI.

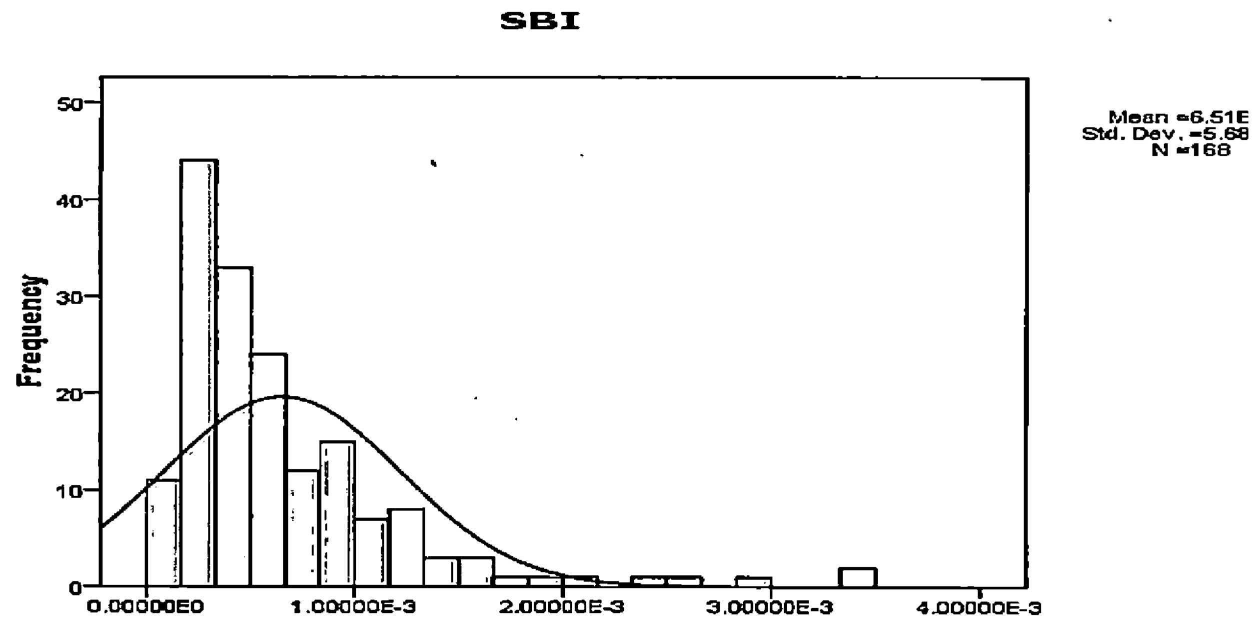


Fig 4.19 Histogram of volatility of BHEL

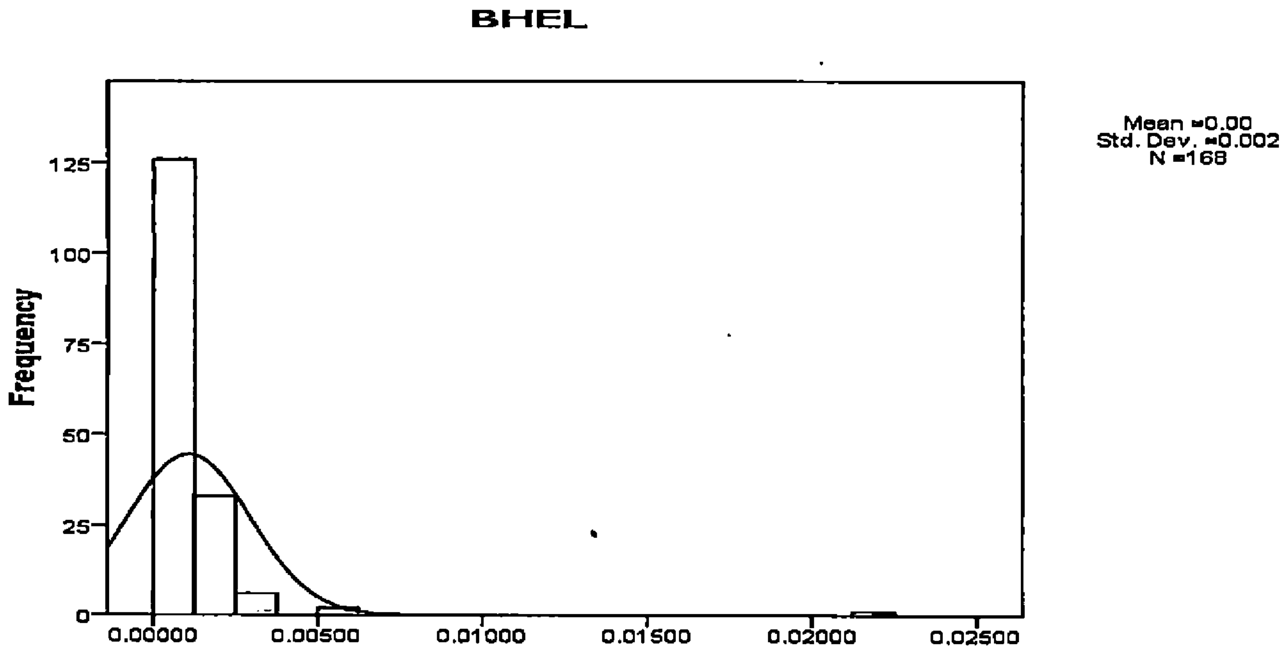
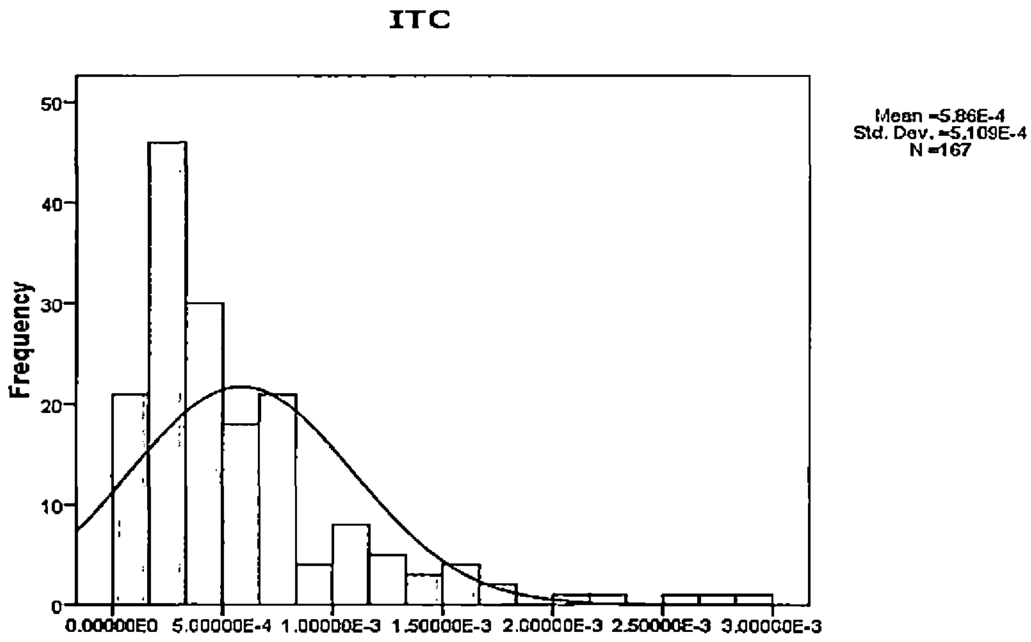


Fig.4.20 Histogram of volatility of ITC

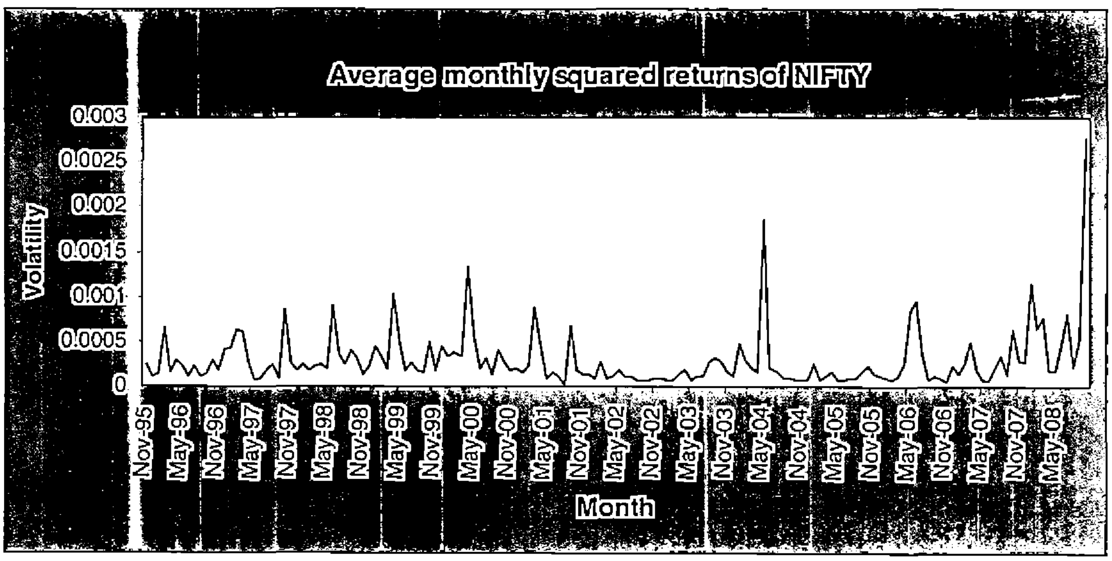


The skewness and kurtosis of the squared return series of Nifty and the stocks of selected companies are evident from the histograms.

4.4.1.2 Line graphs of average monthly squared returns (Volatility)

Line graphs were also drawn for Nifty representing the Indian stock market as a whole, and for the selected five companies representing five sectors viz., Reliance (diversified sector), Infosys (IT), SBI (Banking), BHEL (Engineering heavy) and ITC (FMCG) by taking months along the X axis and average monthly squared returns (volatility) along the Y axis.

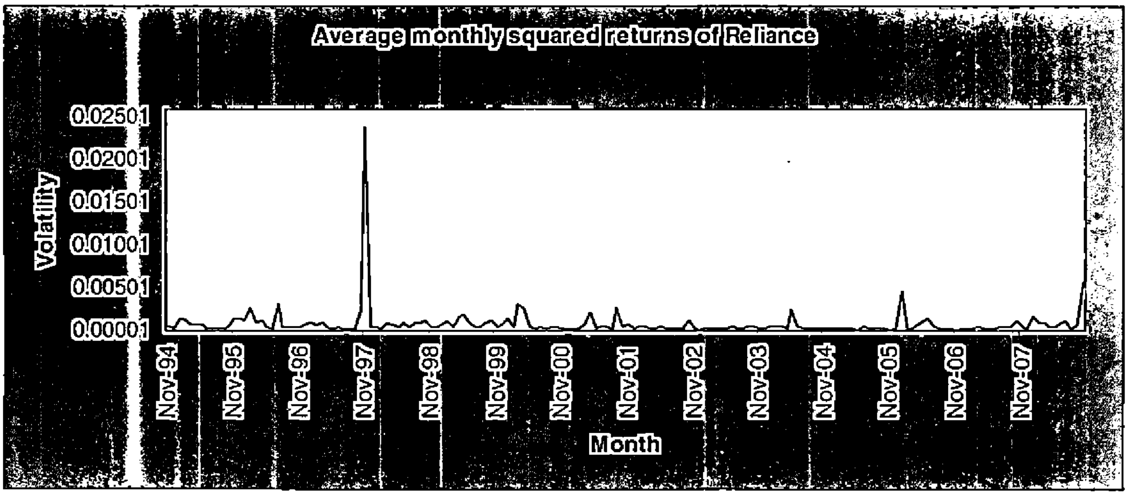
Fig. 4.21 Line graph of average monthly squared returns of Nifty



In total there are 156 monthly volatilities. Fig 4.21 plots the series. From Fig.4.21 two particularly volatile periods can be identified. The first one corresponds to May 2004, while the second one occurred in October 2008. First one was due to money poured by FII into the market, while other peak was on the eve of the global stock market boom before sub prime crisis.

Table 4.3 shows the mean, maximum, standard deviation, skewness and kurtosis of the entire sample. The sample maximum is 0.0019, mean is 0.000254, variance is 1.11278 and standard deviation is 0.002563. The sample skewness is 3.280 while kurtosis is 14.634 and suggests that the distribution of volatility is not a normal distribution. This is the evidence of volatility clustering and suggests that the volatility is predictable.

Fig. 4.22 Line graph of average monthly squared returns of Reliance (diversified sector)

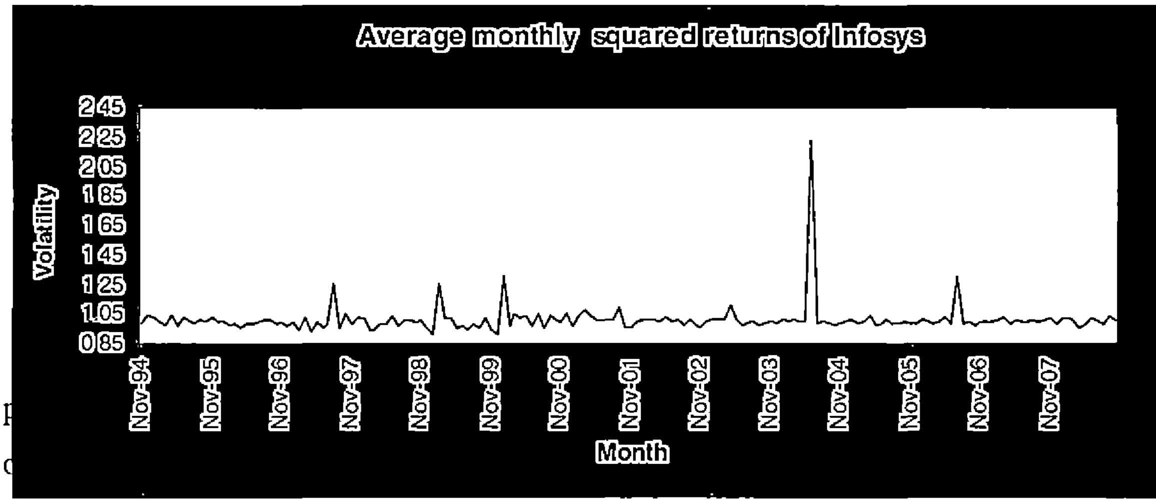


In total there are 168 monthly volatilities. Fig 4.22 shows one particular period which is highly volatile and it corresponds to November 1997. It was due to the fact that the Company announced a liberal bonus issue in the ratio of 1:1 on October 16, 1997, after a gap of 14 years. The book closure for the bonus was declared between November 29 and December 6, 1997. Around 57 lakh euro-convertible bonds of Reliance Industries Ltd were converted into equity shares ahead of the book-closure for the 1:1 bonus issue on November

29, 2007.

The maximum value of squared returns for the study period was 0.0240, mean was 0.00862, variance was 3.80346, the standard deviation was 0.00218, the sample skewness was 9.815 while kurtosis was 104.172 as provided by Table 4.3 and suggested that the distribution of volatility was not a normal distribution. This gives the evidence of volatility clustering and suggests that the volatility is predictable.

Fig. 4.23 Line graph of average monthly squared returns of Infosys (Information Technology)



atile
one
iced

during June 2004. The last one was in July, 2006.

The two major volatilities of 1997 and 1999 occurred in the initial phase of dot com bubble in stock markets. On 24th January 2000, Infosys opted for a share split at the value of Rs. 5 per share. As a result of the bonuses, each ADS became equivalent to one domestic share Further company proposed its shareholders a whopping 2,950 per cent dividend for 2003-2004, including the 290 per cent dividend already paid. On 14th April 2004, a 3:1 bonus issue (three bonus shares for every share held) for domestic shareholders and a 1:1 bonus for American Depository Share (ADS) holders were announced. The predictability of the volatility can be evidenced from the statistics given in Table 4.3 and the statistics of Infosys provides an unconditional distribution of volatility.

The maximum value of squared returns for the study period was2.2184, mean was1.006656, variance was0.01146, the standard deviation was0.1510004, the sample skewness was 1.944 while kurtosis was 49.019 as provided by Table 4.3 and suggested that the distribution of volatility was not a normal distribution.

Fig.4.24 Line graph of Average monthly squared returns of SBI (Banking sector)

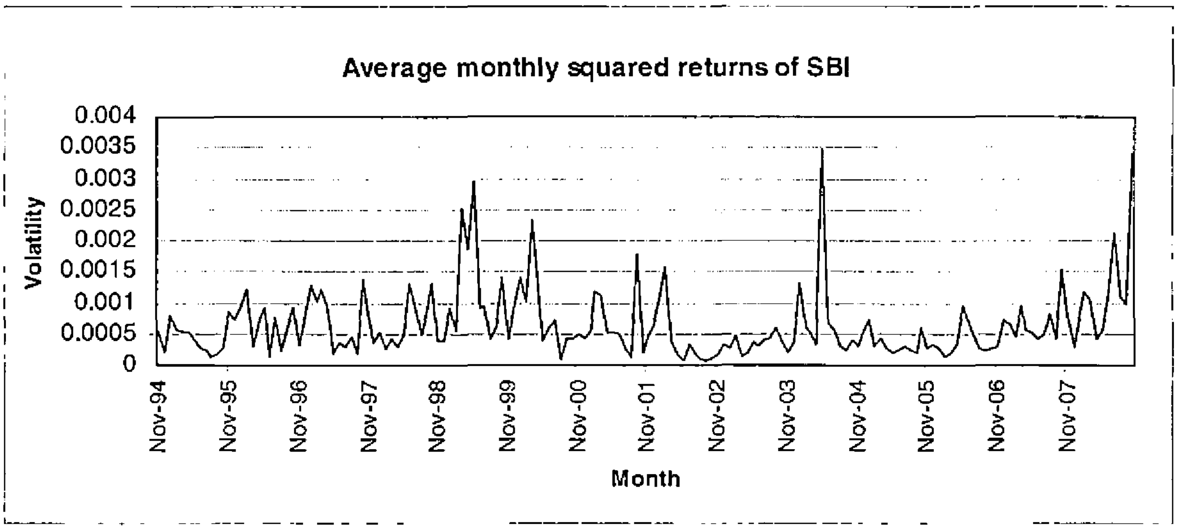
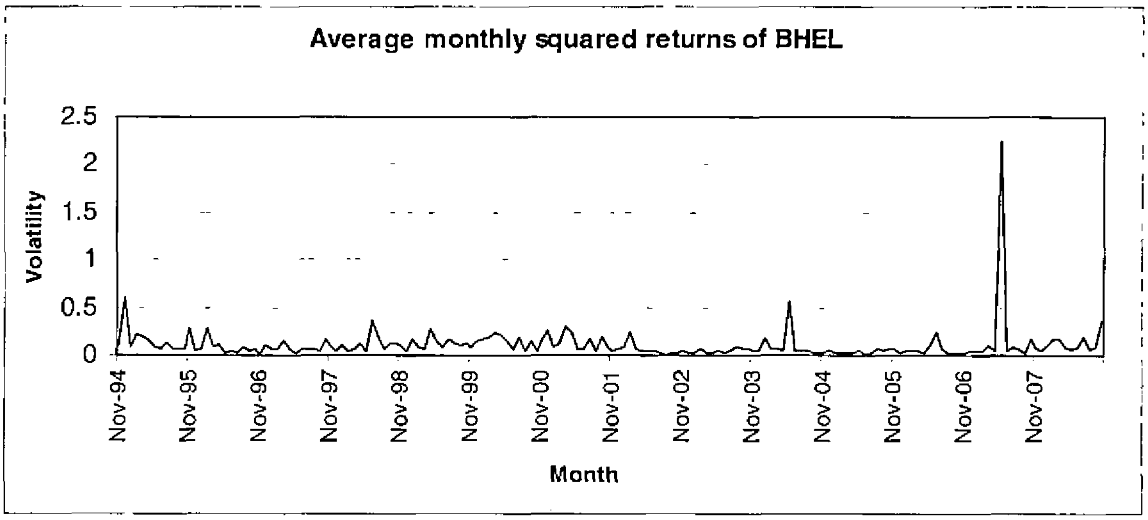


Fig 4.24 shows four particularly volatile periods. In total there are 168 monthly volatilities. The first one corresponds to May 1999, while the second one occurred in March 2000, third one in May, 2004, and the fourth in October, 2008. In the case of SBI also the predictability of volatility can be identified from Table 4.3. While looking at the statistics given by Table 4.3, it is clear that volatility of SBI follows an unconditional distribution and not a normal distribution. Hence there is evidence of volatility clustering and it paves the way for prediction or forecasting of volatility.

In April 2004, Supreme Court upheld the constitutional validity of the Securitisation Act, empowering the financial institutions to attach and sell assets of defaulting borrowers. This indirectly boosted the performance of the Bank. The SBI crossed $1.2 billion profit mark in the financial year 2003-04. The Board of Directors announced a dividend of 110 per cent, including a special dividend of 10 per cent; record date was set in May 2004. The fact that dividend was tax free (at that time) in the hands of investors, made it more attractive. In year 2008 SBI made a rights issue in to the market. With the global booming market trend, SBI stock witnessed the second highest market value in October 2008.

The maximum value of squared returns for the study period was 0.0035, mean was0.000645, variance was, the standard deviation was0.0005645, the sample skewness was 2.325 while kurtosis was 7.220 as provided by Table 4.3 and suggested that the distribution of volatility was not a normal distribution. This gives the evidence of volatility clustering.

Fig. 4.25 Line graph of Average monthly squared returns of BHEL (Engineering Heavy)



In total there are 168 monthly volatilities. Fig 4.25 plots the series. From this graph one particular volatile period can be identified. It corresponds to May 2007. The Company made a bonus issue of 1:1 share for which the record date was fixed as 1st June 2007. Further it recommended a final dividend of 60 per cent of the Company's post-bonus enhanced share capital. The sample maximum, mean, standard deviation, sample skewness and kurtosis are 0.0060, 0.001002, 0.0009405, 2.554, 9.302 respectively as detailed in Table 4.3. These statistics becomes the evidence of volatility clustering and suggests that the volatility is predictable.

Fig. 4.26 Line graph of Average monthly squared returns of ITC (FMCG sector)

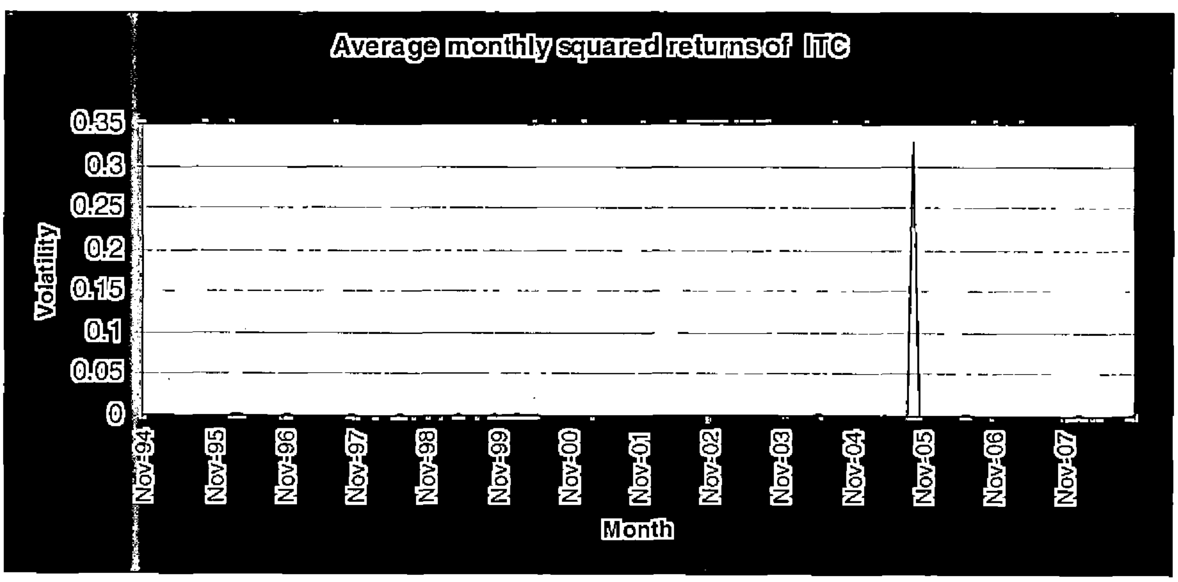
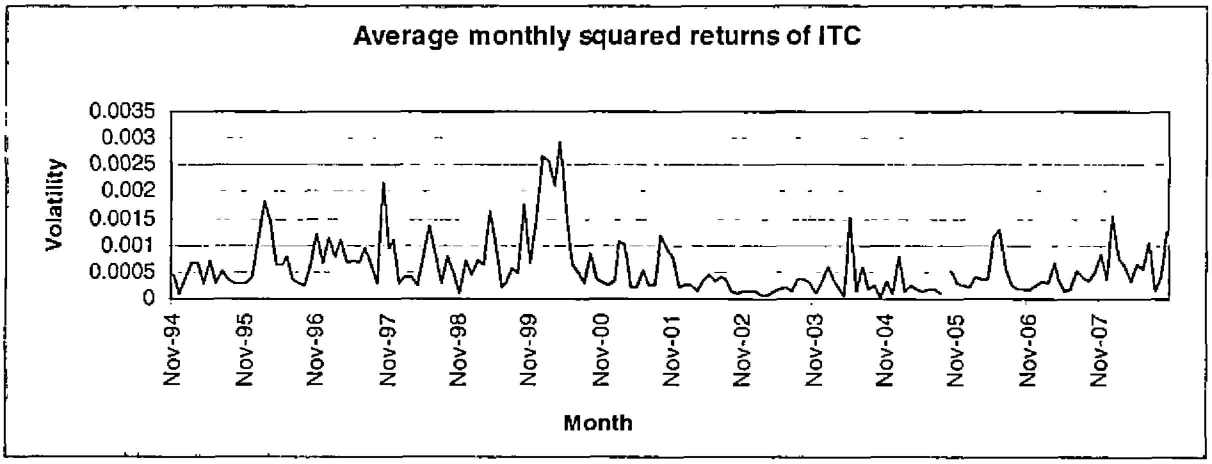


Fig. 4.27 Average monthly squared returns of ITC (excluding September 2005 monthly volatility figure)



In total there are 168 monthly volatilities. Fig 4.26 plots the series. From this graph one particular point which is highly volatile can be identified. It corresponds to September, 2005, when the Company declared a bonus issue in the ratio of one share for every two equity shares of Rs. 10 each and it also split the face value of shares from Rs. 10 to Re.1.The summary statistics of ITC provided by Table 4.3 gives an indication that the distribution of volatility is not normal and hence there is chances for the prediction of volatility in this sector.

To make graph of volatility of ITC more illustrative, another graph excluding September 2005 monthly volatility is drawn and depicted in Fig. 4.27. It clearly shows the major impact of volatility in September 2005 on the overall volatility of the ITC stock.

As provided by Table 4.3 the maximum value of squared returns for the study period was 0.0029, mean was 0.000619, variance was 2.64127, the standard deviation was 0.0005544, the sample skewness was 1.948 while kurtosis was 4.269. It suggested that the distribution of volatility was not a normal distribution.

4.4.2 Forecasting of volatility

Based on the earlier studies in the international context discussed in the review of literature, this work tries to examine the forecasting capabilities of five different models, viz., Random Walk, Historical Mean, Moving Average, Simple Regression and Exponential Weighted Moving Average models in predicting volatility of the Indian stock market.

4.4.2.1 Random Walk Model

Using the Random Walk Model the actual and predicted volatility of Nifty and of five sectors of Indian stock market, represented by five companies viz., Reliance, Infosys, SBI, BHEL and ITC are illustrated through Fig.4.28, 4.29, 4.30, 4.31, 4.32 and 4.33 respectively. As per this model, the best forecast for this period's volatility is the last period's realized volatility.

Fig. 4.28 Actual and predicted volatility of NIFTY using random walk model

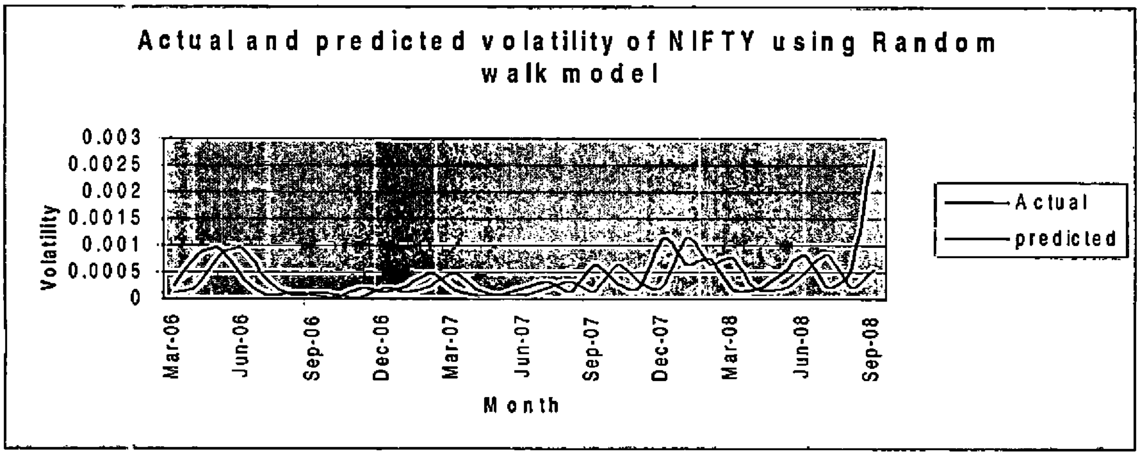


Fig. 4.29 Actual and predicted volatility of Reliance using random walk model.

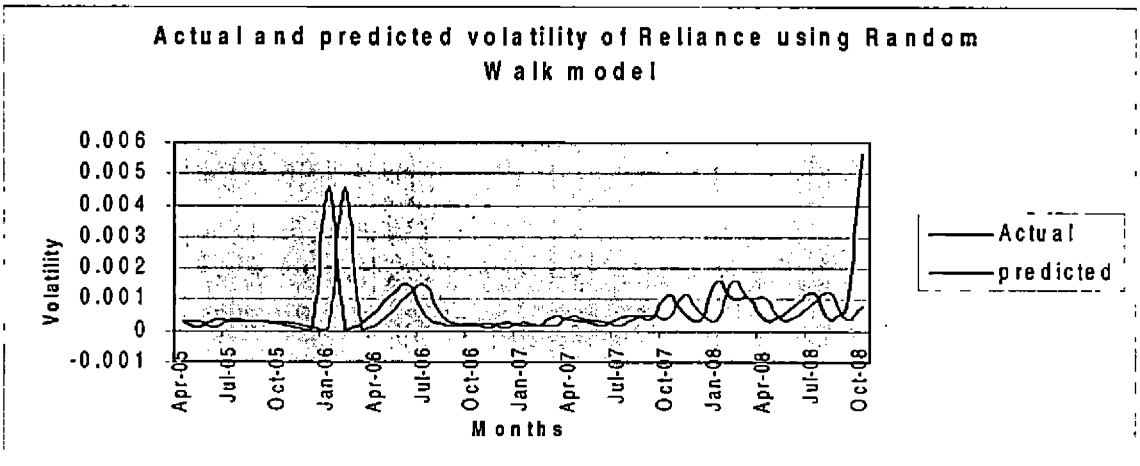


Fig.4.30 Actual and predicted volatility of Infosys using random walk model.

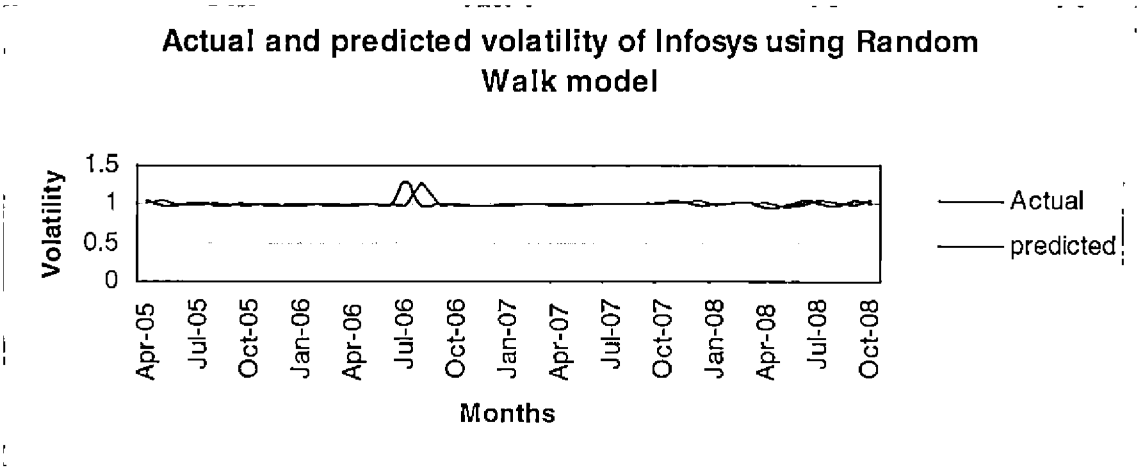


Fig. 4.31 Actual and predicted volatility of SBI using random walk model.

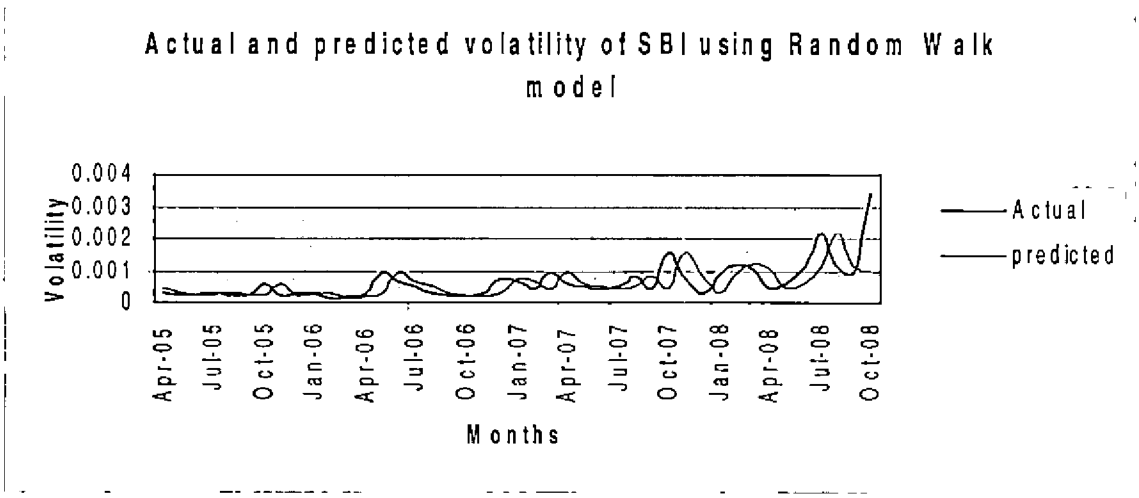


Fig.4.32 Actual and predicted volatility of BHEL using random walk model.

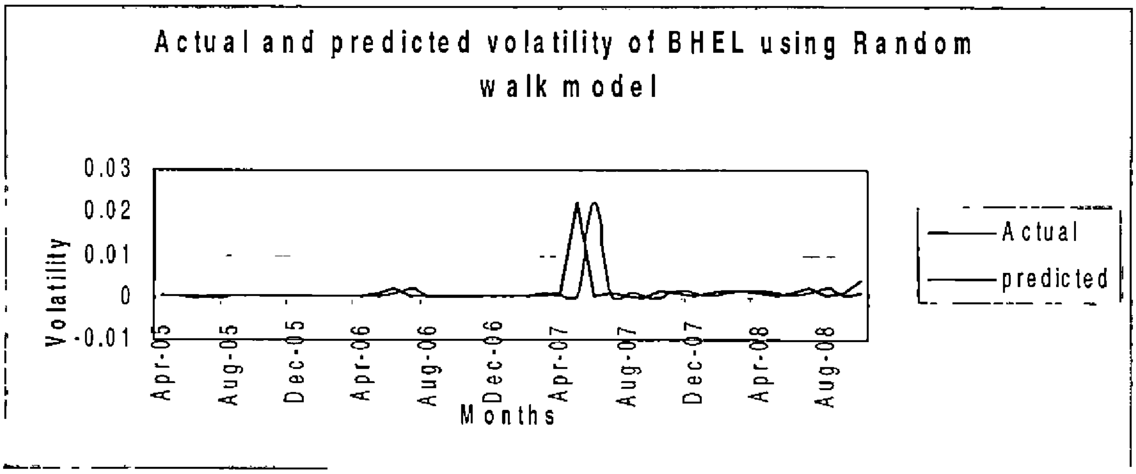
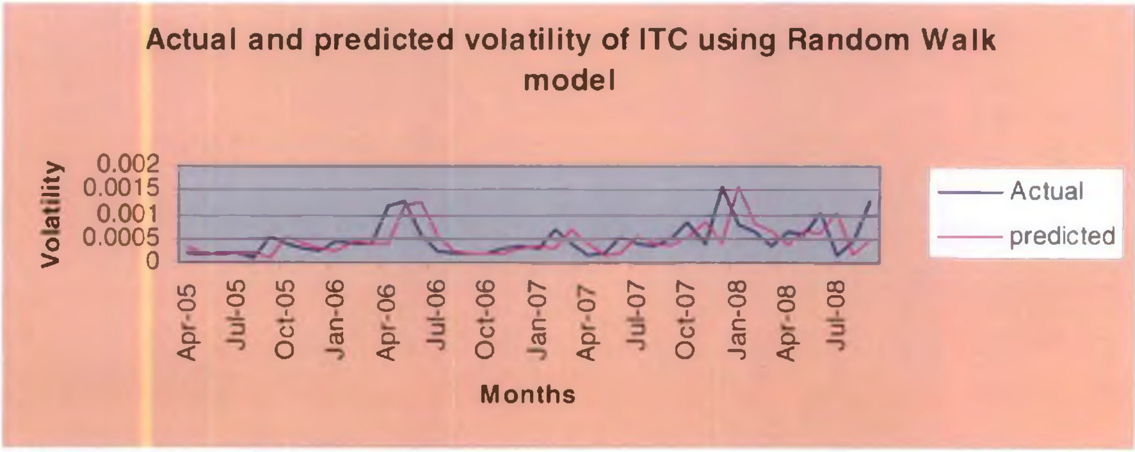


Fig. 4.33 Actual and predicted volatility of ITC using random walk model.



From the figures plotted above it can be concluded that Random walk model is suitable for the prediction of volatility for Infosys and BHEL only. For the other companies Random walk model is not suitable.

4.4.2.2 Historic Mean Model

The second model which is used for predicting the volatility is the Historic mean model. In the case of Historic mean model also, figures are plotted for the actual and predicted values and are depicted in Fig.4.34, 4.35, 4.36, 4.37, 4.38 and 4.39 for Nifty, Reliance, Infosys, SBI, BHEL and ITC respectively. Assuming the conditional expectation of the volatility constant, this model forecasts volatility as the historical average of the past observed volatilities.

Fig. 4.34 Actual and predicted volatility of Nifty using historical mean model.

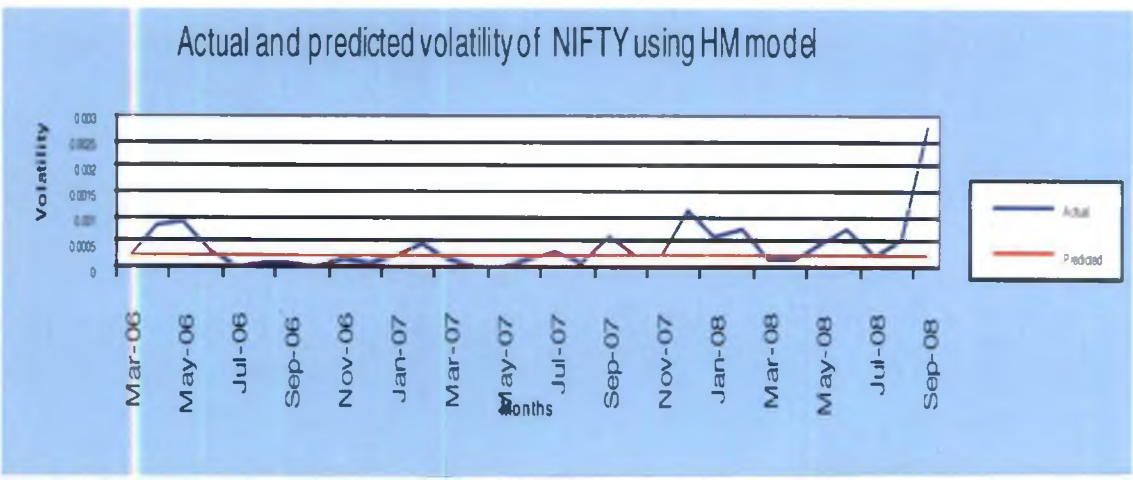


Fig.4.35 Actual and predicted volatility of Reliance using historical mean model.

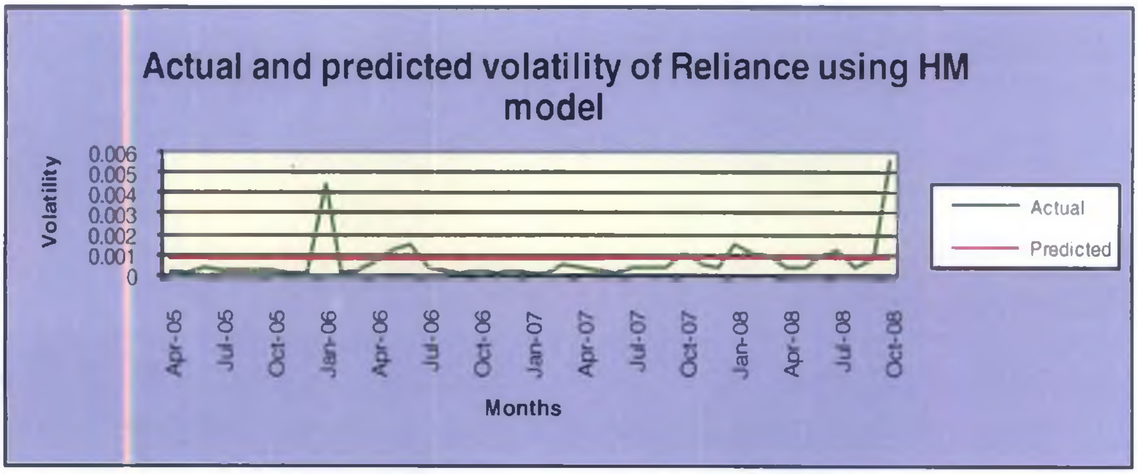


Fig. 4.36 Actual and predicted volatility of Infosys using historical mean model.

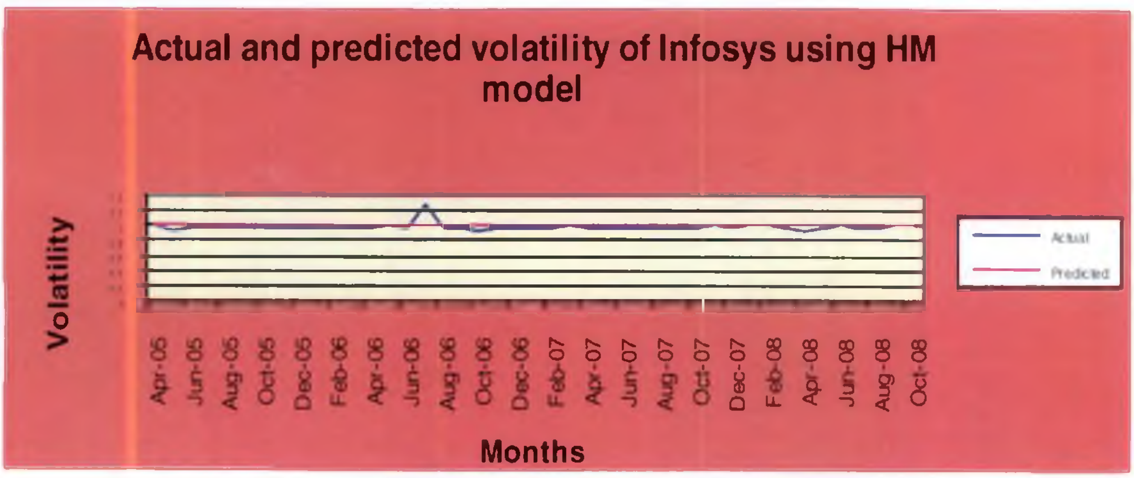


Fig. 4.37 Actual and predicted volatility of SBI using historical mean model.

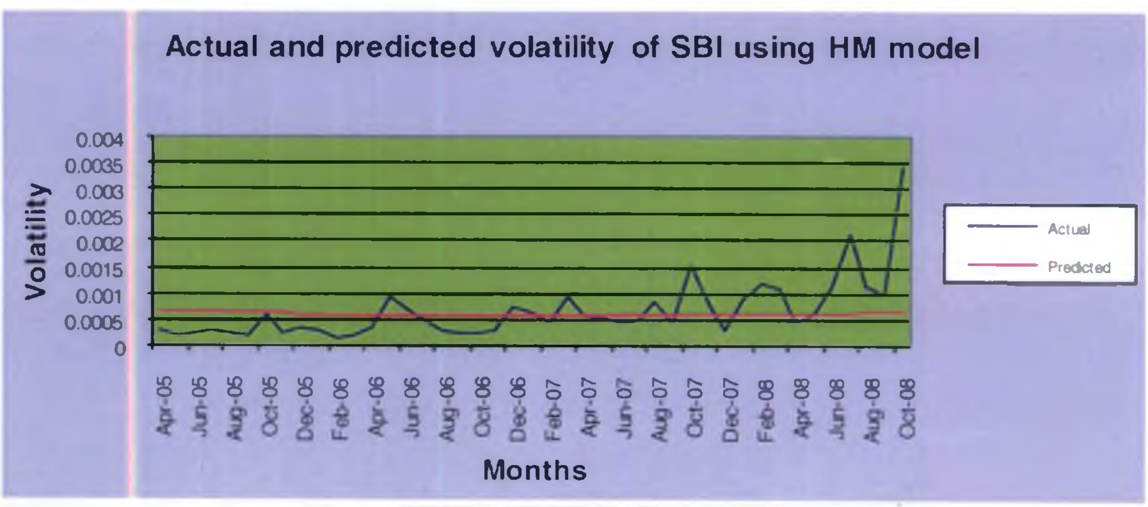


Fig.4.38 Actual and predicted volatility of BHEL using historical mean model.

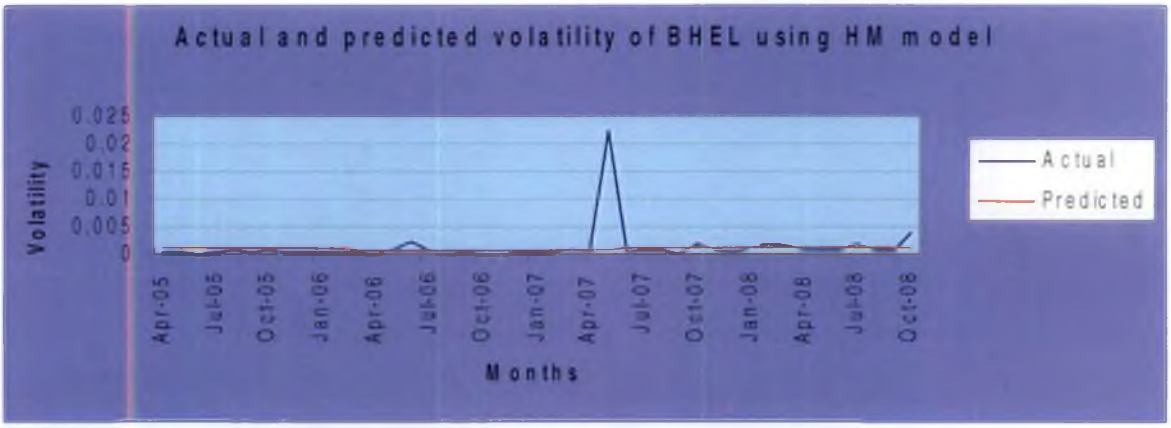
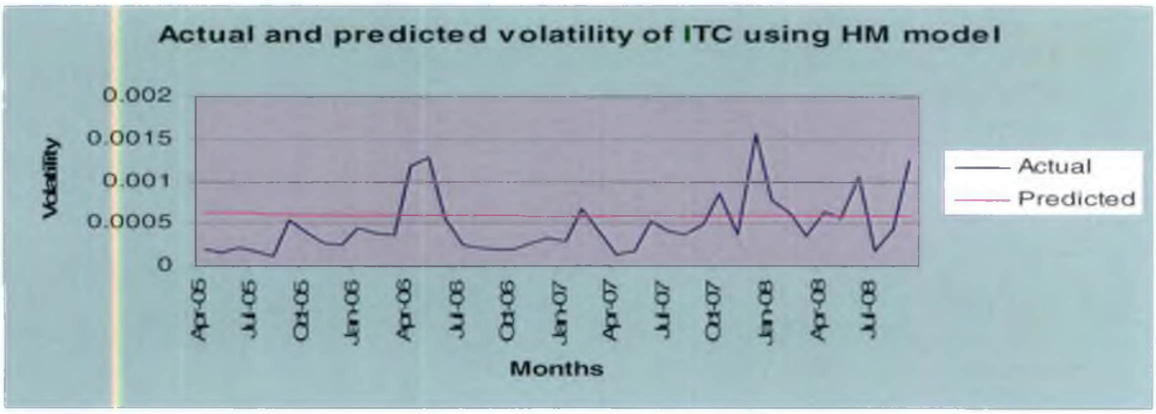


Fig.4.39 Actual and predicted volatility of ITC using historical mean model.



It is evident from all the above figures that Historic mean model is far below the capability of predicting with accuracy the volatility of the stock market for the Nifty and the five companies under observation.

4.4.2.3 Moving Average Model

Moving average method is a traditional time series technique in which the volatility is defined as equally weighted average of realized volatilities in the past 'm' months. Predicted and actual values of each company's volatility using moving average model are plotted and shown below in Fig. 4.40, 4.41, 4.42, 4.43, 4.44, and 4.45.

Fig. 4.40 Actual and predicted volatility of NIFTY using 3, 6, 9 & 12 monthly moving average.

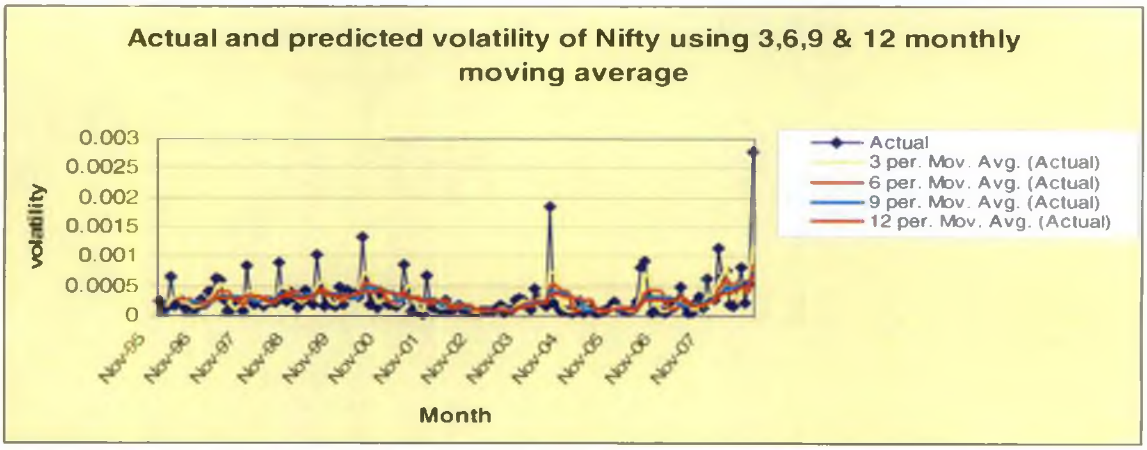


Fig. 4.41 Actual and predicted volatility of Reliance using 3, 6, 9 & 12 monthly moving average.

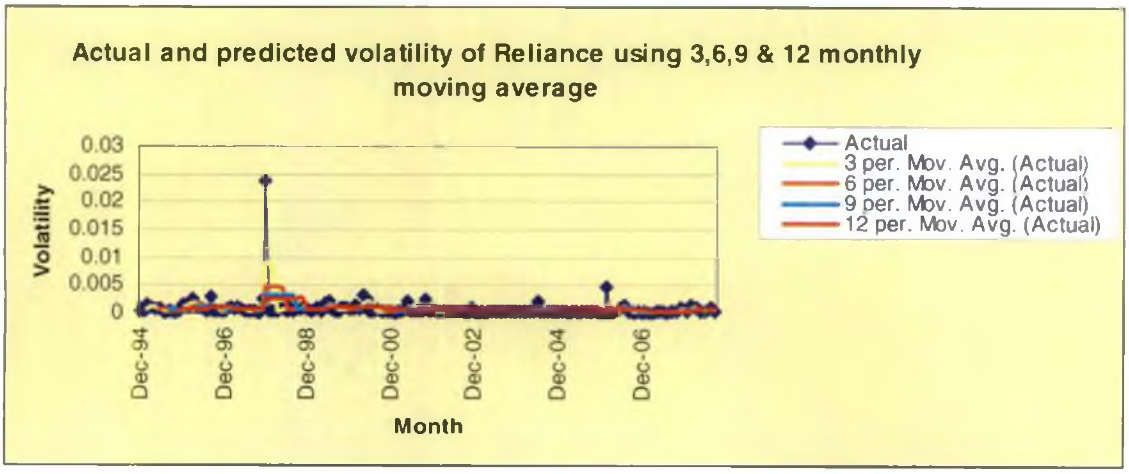


Fig. 4.42 Actual and predicted volatility of Infosys using 3, 6, 9 & 12 monthly moving average.

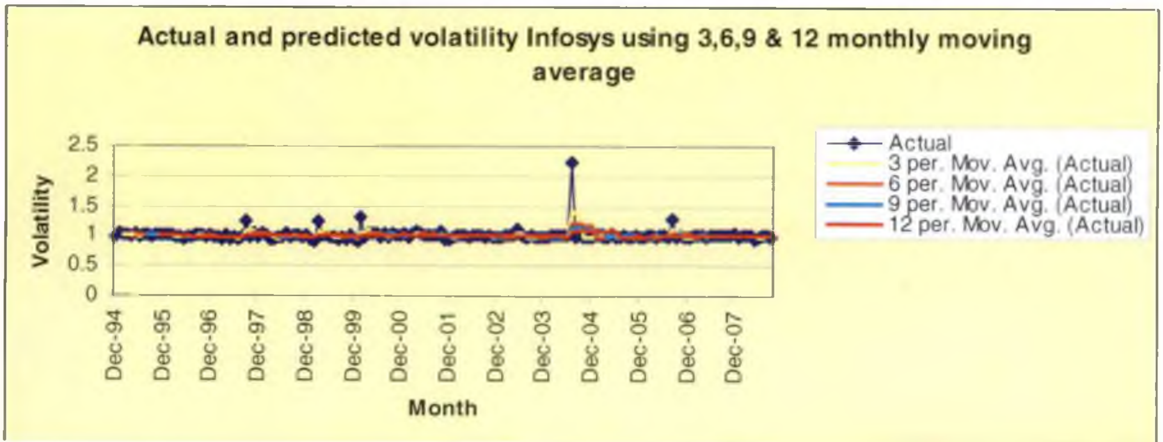


Fig. 4.43 Actual and predicted volatility of SBI using 3, 6, 9 & 12 monthly moving average.

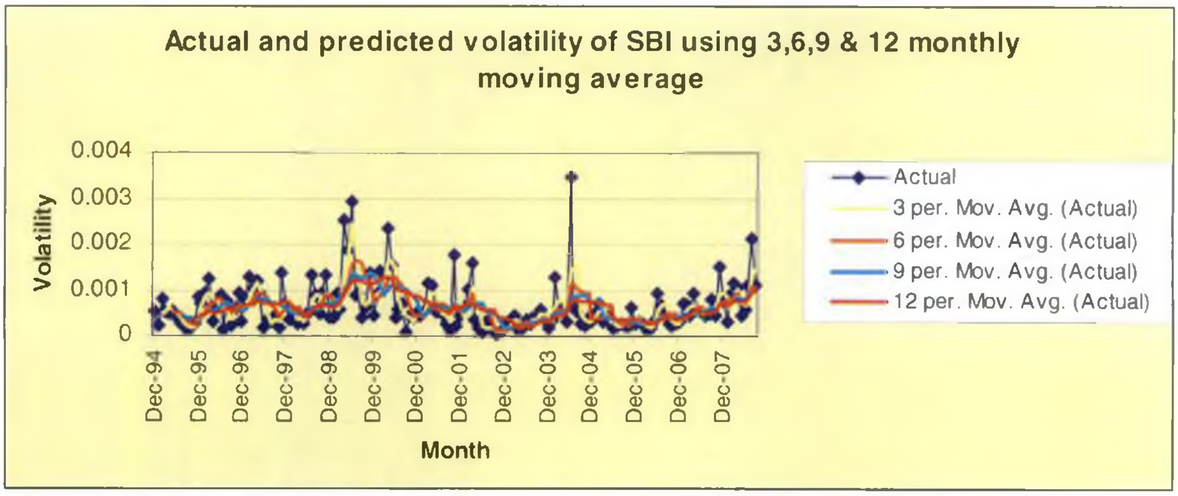


Fig. 4.44 Actual and predicted volatility of BHEL using 3, 6, 9 & 12 monthly moving average.

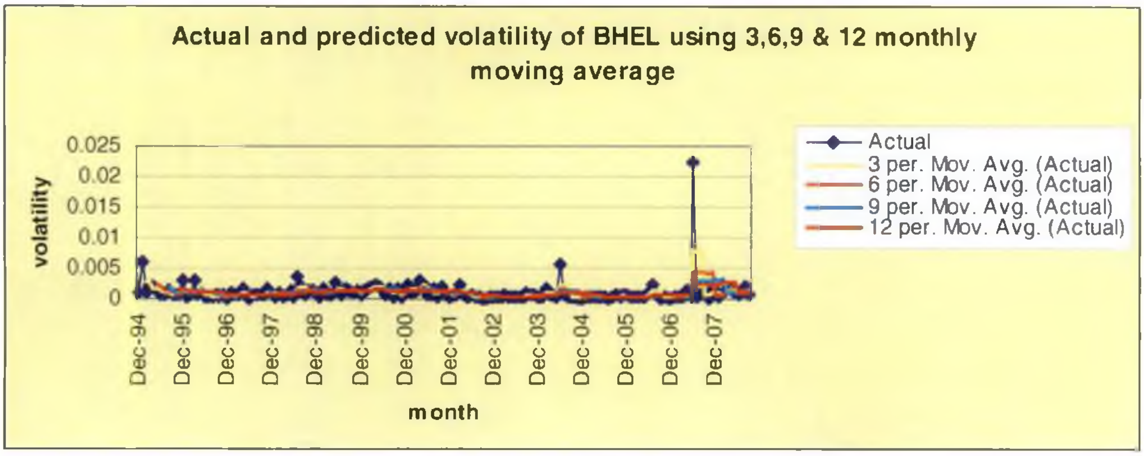
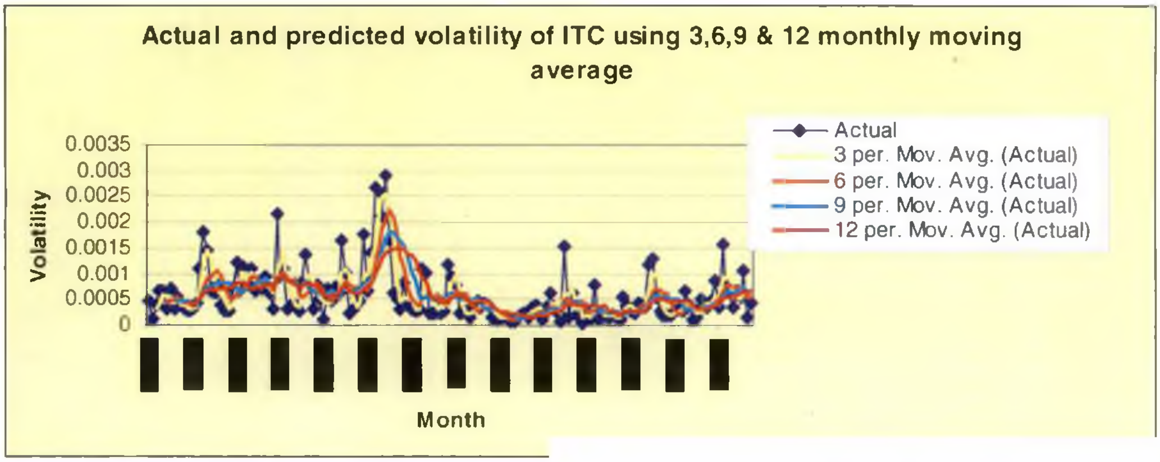


Fig.4.45 Actual and predicted volatility of ITC using 3, 6, 9 & 12 monthly moving average



Here three, six, nine and twelve monthly moving averages are taken for predicting the volatility, and it can be inferred from the above figures that three months moving average is most suitable for all the six observations for predicting the volatility.

4.4.2.4 First order Autoregressive Model (AR (1))

First order autoregressive model (AR (1)) is the fourth model which is used for predicting the volatility in the stock market for the six observations. In this method regression of actual volatilities, on lagged values is run. Table 4.4 depicts the summary statistics for AR (1) model.

Table 4.4 statistics for AR (1) model

Company	**Model fit statistics**					
	Adjusted R^2	RMSE	MAPE	MAE	MaxAPE	MaxAE
Nifty	83.1%	0.000	48.807	7.877E-5	582.261	0.000
Reliance	98.9%	0.000	50.058	0.000	451.957	0.001
Infosys	94%	0.030	2.236	0.022	8.705	0.094
SBI	61%	0.000	75.702	0.000	620.833	0.001
BHEL	69.5%	0.001	69.342	0.000	958.562	0.002
ITC	59.3%	0.000	71.054	0.000	537.816	0.002

From Table 4.5 it can be observed that Reliance is having the highest value of R^2 i.e. 98.9 per cent with RMSE and MAE =0, indicating the high predictability of the model. For Infosys also the value of R^2 is 94 per cent with a very low value of RMSE = 0.03 and MAE= 0.022. Then comes Nifty for which the value of R^2 is 83.1 per cent, with RMSE and MAE nearly equal to zero. So the prediction of volatility for Reliance, Infosys and Nifty can be effectively done using AR (1) model. For the other companies, prediction can be done with moderately high values of R^2.

Table 4.5 Forecasting models for Indian stock market using AR (1) model

Company	AR (1) Regression model	R^2
Nifty	$0.363\ Y^{**}t\text{-}1$ (0.089)	83.1%
Reliance	$0.384\ Y^{**}t\text{-}1 + 0.001$ (0.089)	98.9 %
Infosys	$0.076\ Y^{**}t\text{-}1 + 0.997$ (0.098)	94%
SBI	$0.412\ Y^{**}t\text{-}1 + 0.001$ (0.087)	61%
BHEL	$0.242\ Y^{**}t\text{-}1 + 0.001$ (0.092)	69.5%
ITC	$0.694\ Y^{**}t\text{-}1 + .001$ (0.66)	59.3 %

** Regression coefficient significant at 1% level of significance

From Table 4.5 it is again clear that the AR (1) regression model is most suitable for Reliance followed by Infosys, Nifty, BHEL, SBI and ITC. The actual and predicted values of volatility using the AR(1) regression model for Nifty and the five companies under study is illustrated in Fig. 4.46, 4.47, 4.48, 4.49, 4.50 and 4.51.

Fig. 4.46 Actual and predicted volatility of Nifty using AR (1) model.

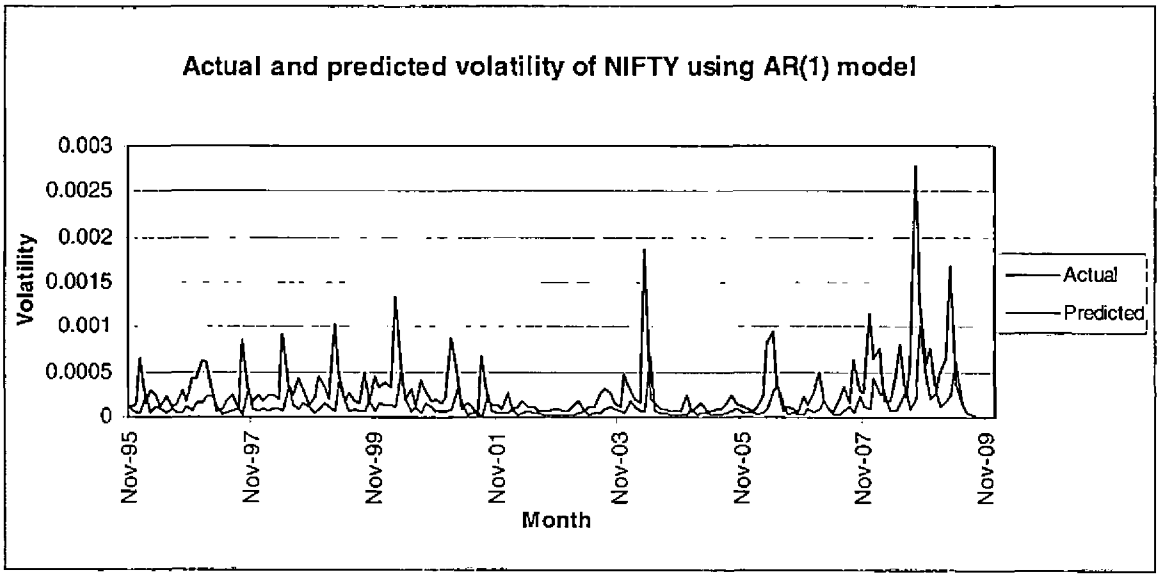


Fig. 4.47 Actual and predicted volatility of Reliance using AR(1) model.

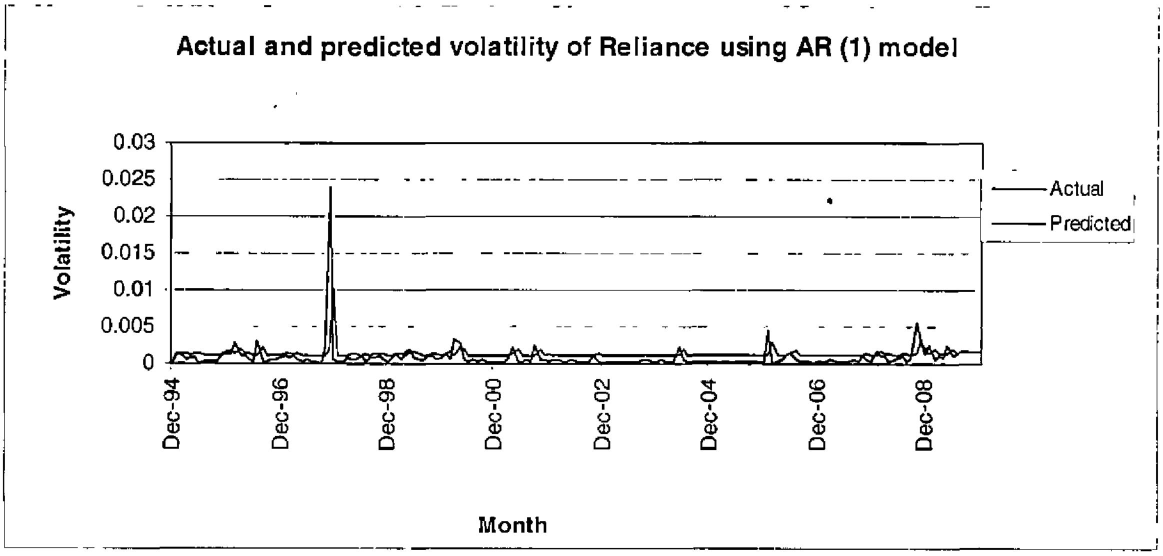


Fig. 4.48 Actual and predicted volatility of Infosys using AR (1) model.

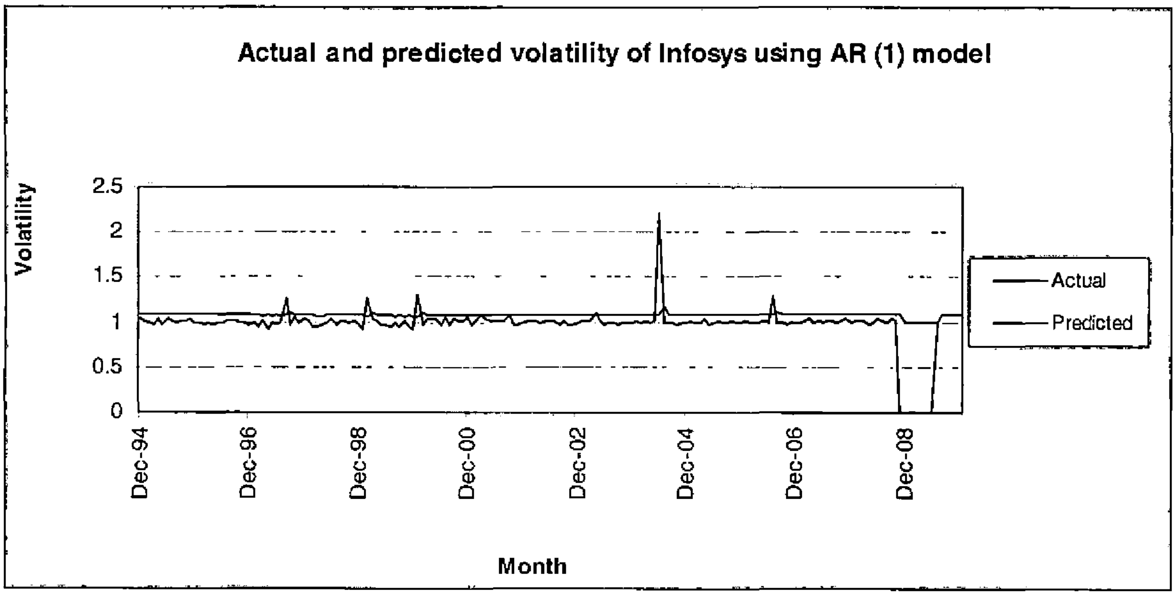


Fig. 4.49 Actual and predicted volatility of SBI using AR (1) model.

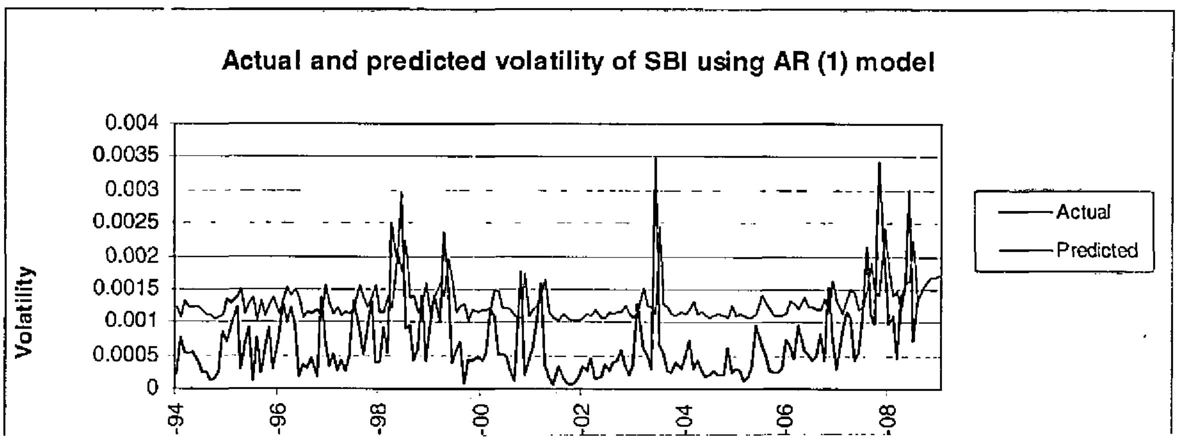


Fig. 4.50 Actual and predicted volatility of BHEL using AR(1) model

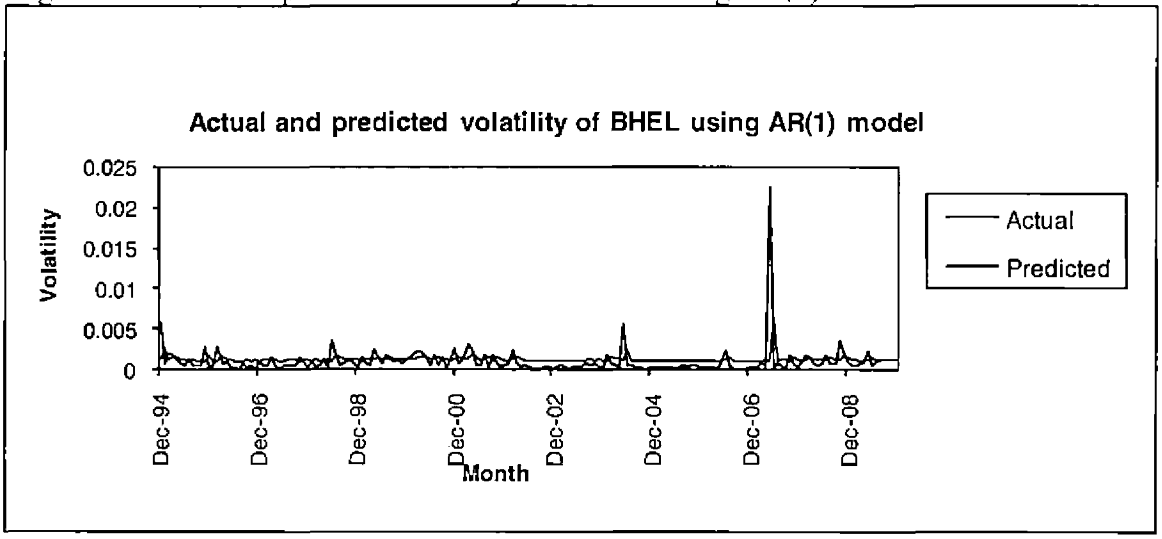
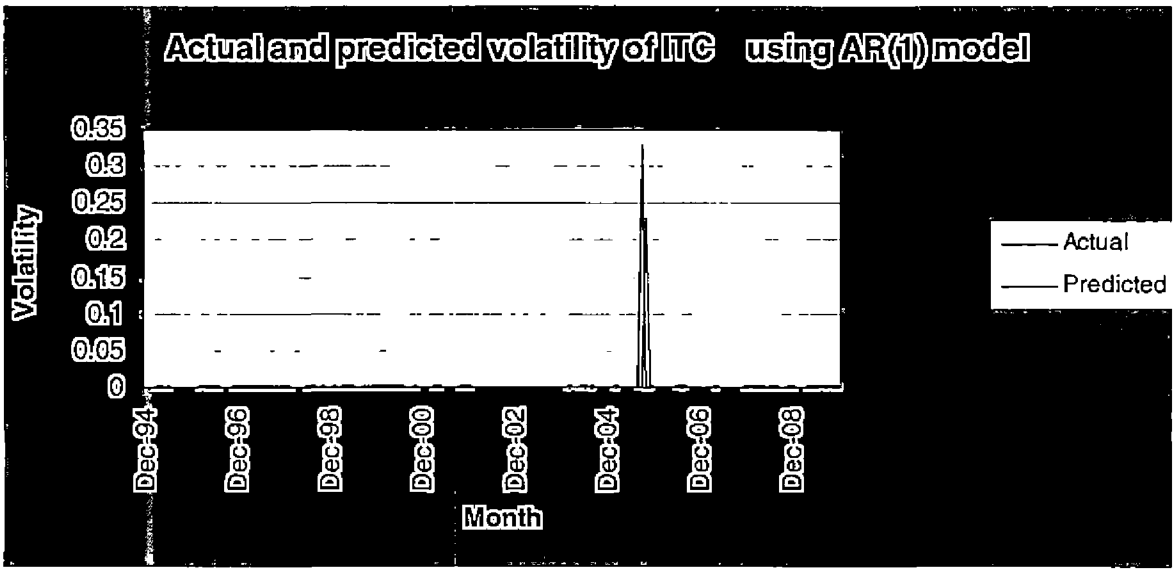


Fig. 4.51 Actual and predicted volatility of ITC using AR (1) model



The above plotted figures also strengthen the point that for Reliance and Infosys, the AR (1) model is very effective in prediction of volatility as compared to others. The actual and the predicted volatility graphs for these two companies move without much variability in the same direction.

4.4.2.5 Exponential Weighted Moving Average Model (EWMA)

Exponential smoothing is an adaptive forecasting method that gives greater weight to more recent observations so that the finite memory of the market is represented. This method

Exponential smoothing is an adaptive forecasting method that gives greater weight to more recent observations so that the finite memory of the market is represented. This method adjusts the forecasts based on past forecast errors and the forecast is calculated as a weighted average of the immediate past observed volatility and the forecasted value for that same period. This is the fifth model which is used in this study.

Table 4.6 Statistics for Exponential weighted moving average model

	Model fit statistics					
	Adjusted R^2	RMSE	MAPE	MAE	MaxAPE	MaxAE
NIFTY	90.9%	0.000	48.438	7.565E-5	557.378	0.000
Reliance	99.5%	0.000	41.108	0.000	356.278	0.001
Infosys	93%	0.055	3.778	0.038	14.883	0.146
SBI	72.7%	0.000	74.433	0.000	868.034	0.001
BHEL	82.6%	0.001	69.690	0.000	613.057	0.002
ITC	56.9%	0.000	71.490	0.000	579.272	0.001

Table 4.6 shows that volatility of Reliance can be predicted using exponential weighted moving average model with a value of R^2 = 99.5 per cent with RMSE = 0 and MAE =0, which is an indication of the best forecasting model. For Infosys and NIFTY the value of R^2 is 93 per cent and 90.9 per cent respectively, with very low values of RMSE and MAE. For BHEL, the value of R2 is 82.6 per cent.This shows the capability of the Exponential

weighted moving average model to forecast the volatility for the stock market and companies which are having the presence of high volatility clustering. Table 4.7 also helps clear understanding of the model fitted and the R^2 value.

Table 4.7 Forecasting models for Indian stock market using the exponential smoothing model.

Company	Exponential weighted smoothing regression model	Adjusted R^2
NIFTY	$Y_t = Y_{t-1} + 0.760\ \varepsilon^{**}_{t-1} - 0.000000088$ (0.066)	90.9%
Reliance	$Y_t = Y_{t-1} + 0.665\ \varepsilon^{**}_{t-1} - 0.0000027$ (0.078)	99.5%
Infosys	$Y_t = Y_{t-1} - 0.071\ \varepsilon^{**}_{t-1} + 0.008$ (0.97)	93.0%
SBI	$Y_t = Y_{t-1} + 0.823\ \varepsilon^{**}_{t-1} - 0.00000055$ (0.056)	72.7%
BHEL	$Y_t = Y_{t-1} + 0.819\ \varepsilon^{**}_{t-1} - 0.0000051$ (0.056)	82.6%
ITC	$Y_t = Y_{t-1} + 0.895\ \varepsilon^{**}_{t-1} - 0.0000016$ (0.047)	56.9%

The actual and predicted volatility for all samples of the Indian stock market using Exponential smoothing average model are depicted in Fig.4.52, 4.53, 4.54, 4.55, 4.56 and 4.57.

Fig. 4.52 Actual and predicted volatility of Nifty using exponential smoothing model.

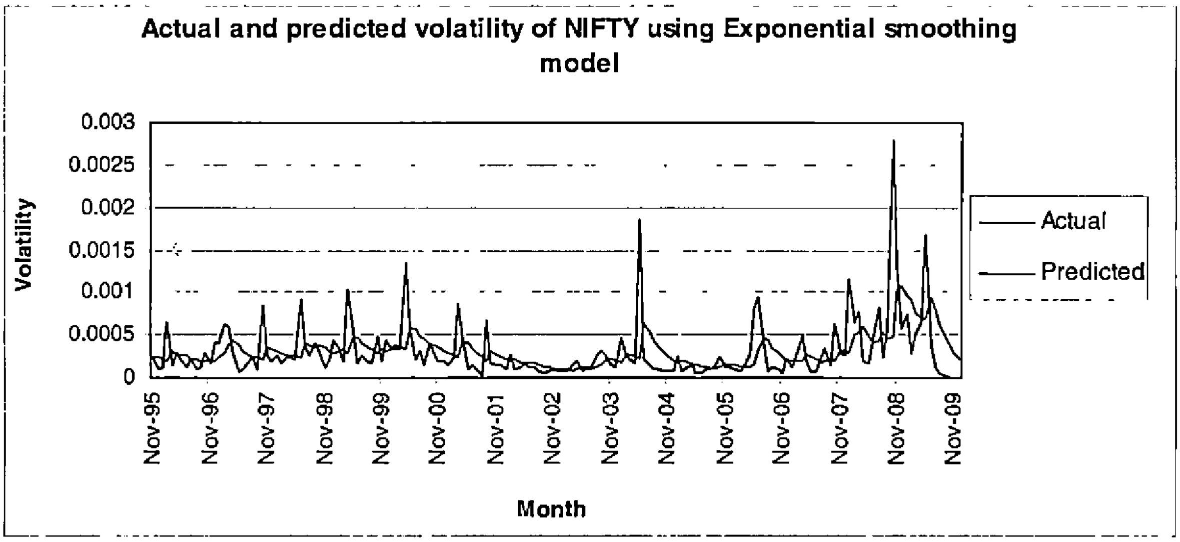


Fig. 4.53 Actual and predicted volatility of Reliance using exponential smoothing model.

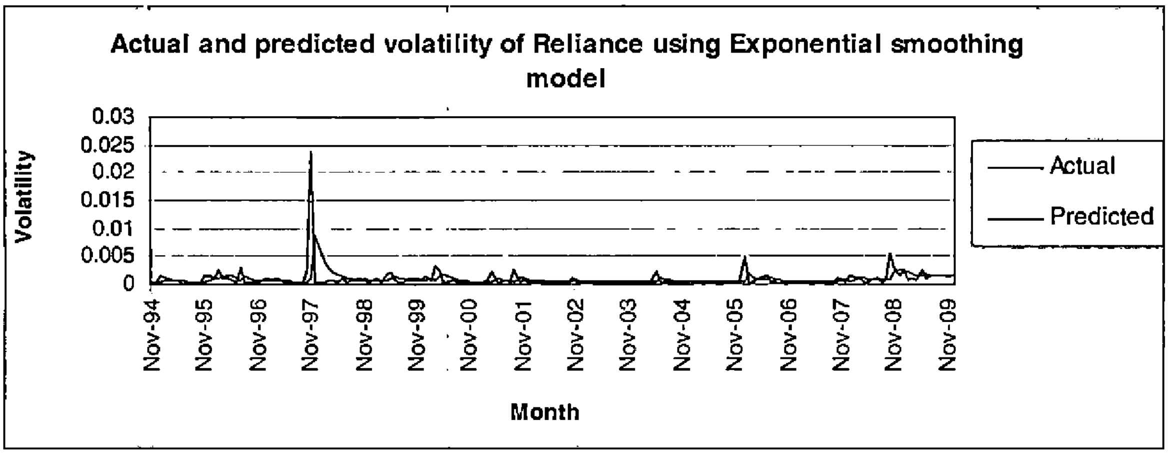


Fig. 4.54 Actual and predicted volatility of Infosys using exponential smoothing model

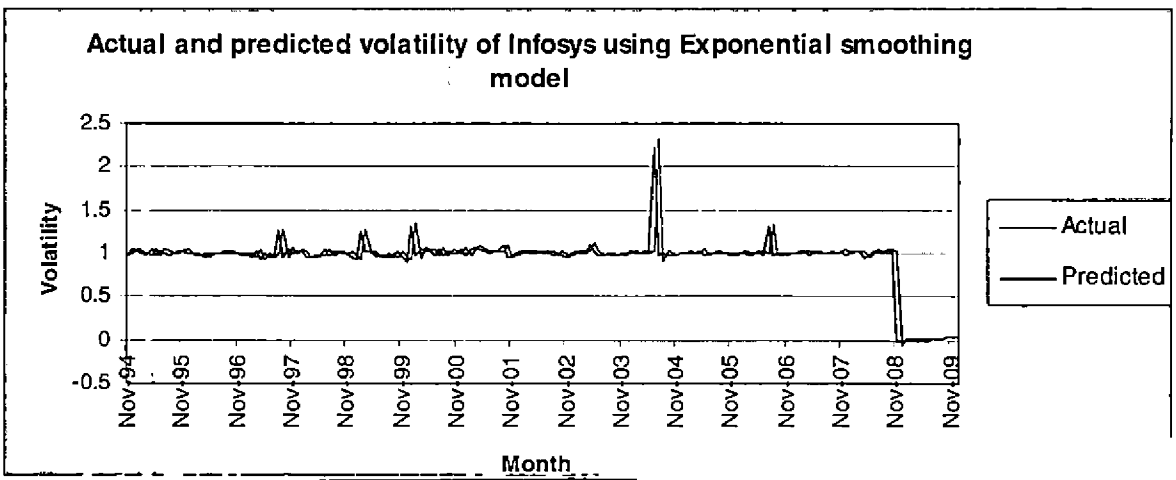
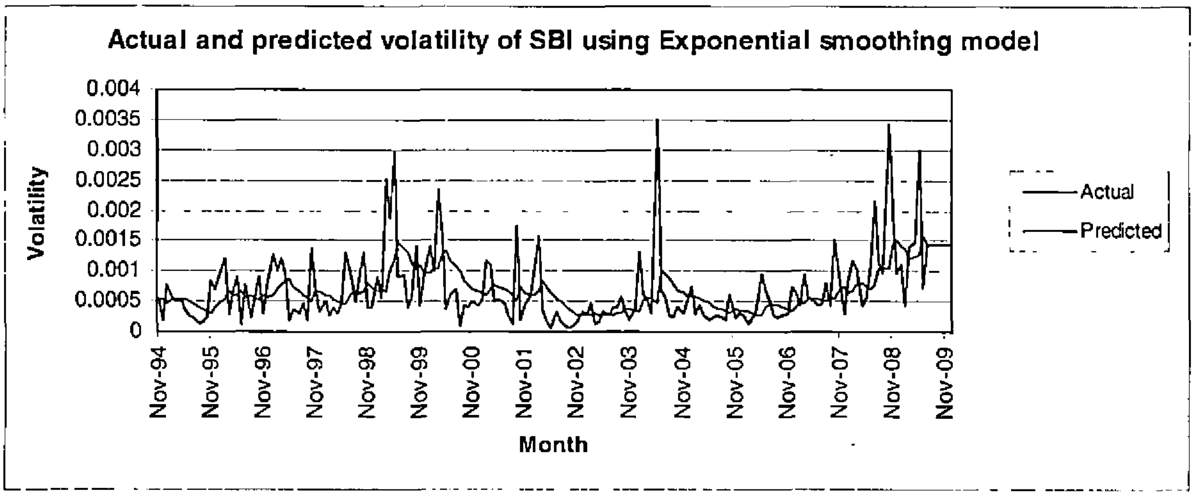
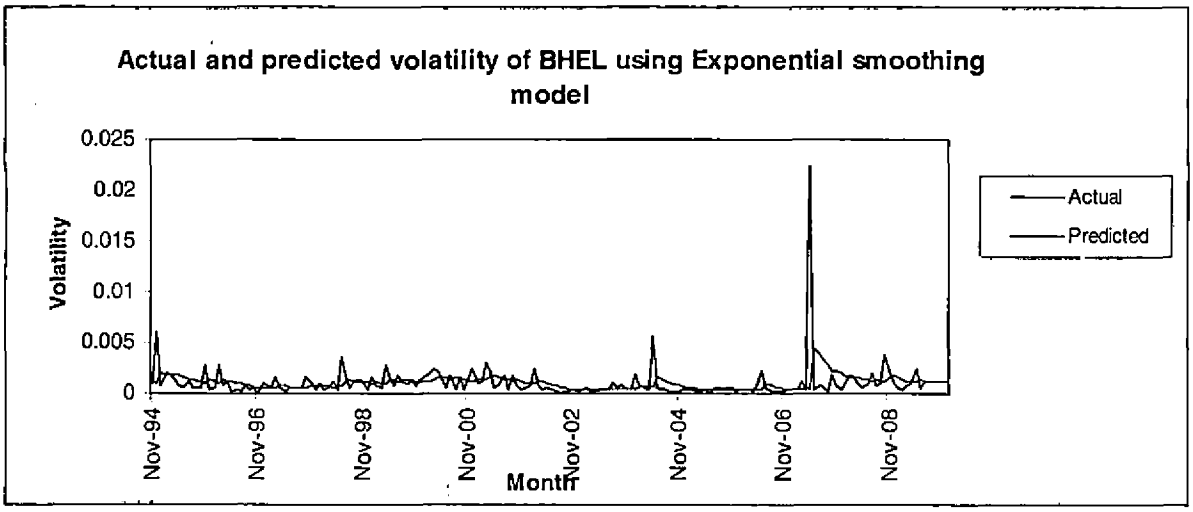


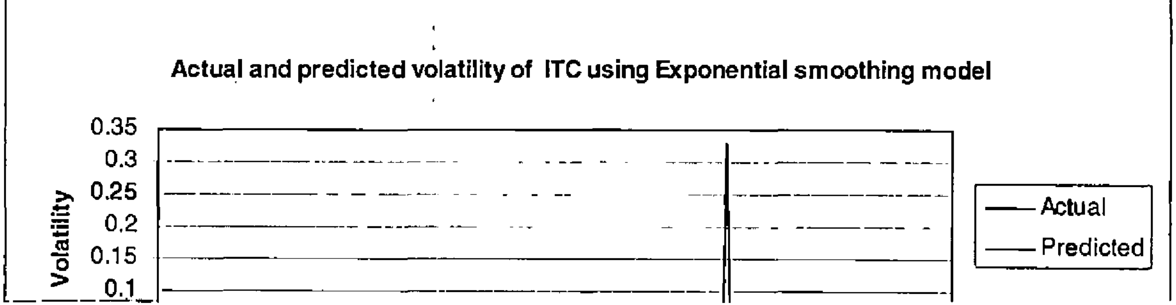
Fig. 4.55 Actual and predicted volatility of SBI using exponential smoothing model.



4.56 Actual and predicted volatility of BHEL using exponential smoothing model.



4.57 Actual and predicted volatility of ITC using exponential smoothing model.



The above figures depict that Reliance and Infosys have got highest predictability of the volatility in the stock market by using the exponential smoothing model.

The error that occur while predicting the volatility using the exponential smoothing model for each of the above samples are plotted in Fig.4.58, 4.59, 4.60, 4.61, 4.62 and 4.63.

Fig. 4.58 Forecasted error of volatility for Nifty using exponential smoothing model.

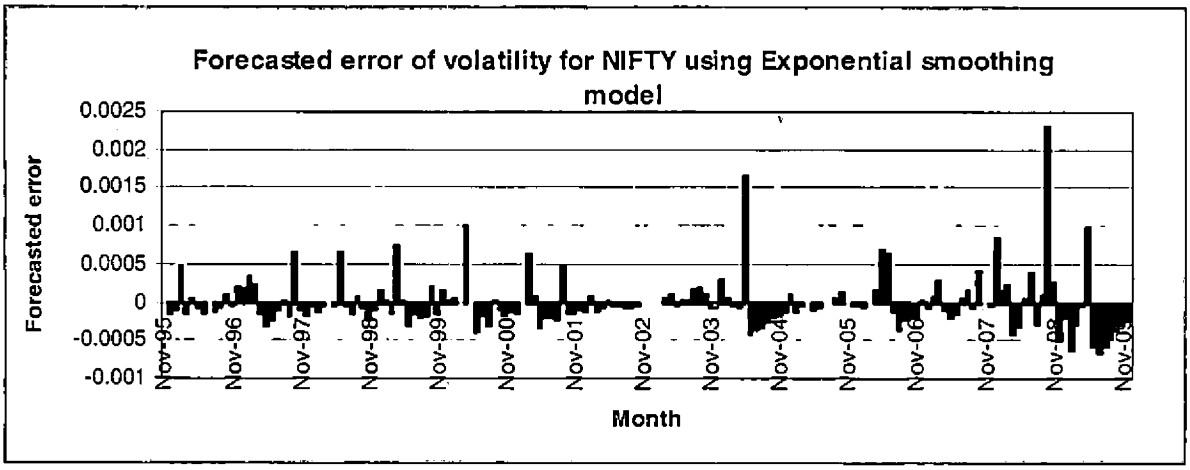


Fig. 4.59 Forecasted error of volatility for Reliance using exponential smoothing model

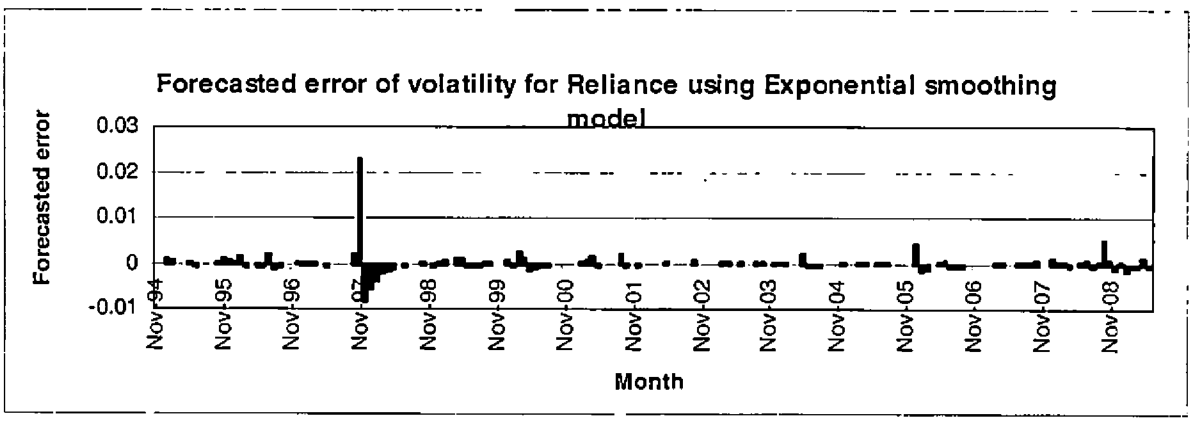


Fig. 4.60 Forecasted error of volatility for Infosys using exponential smoothing model

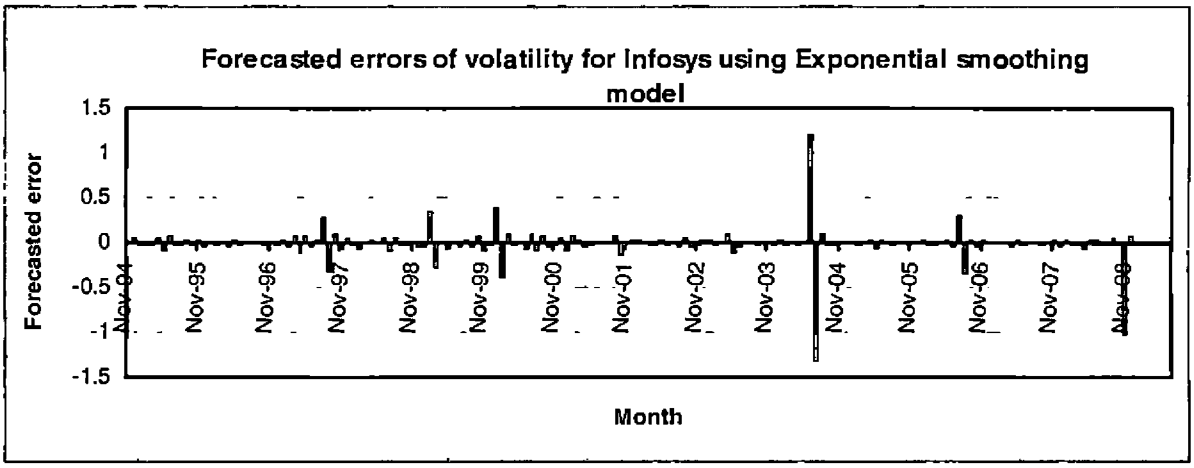


Fig. 4.61 Forecasted error of volatility for SBI using exponential smoothing model.

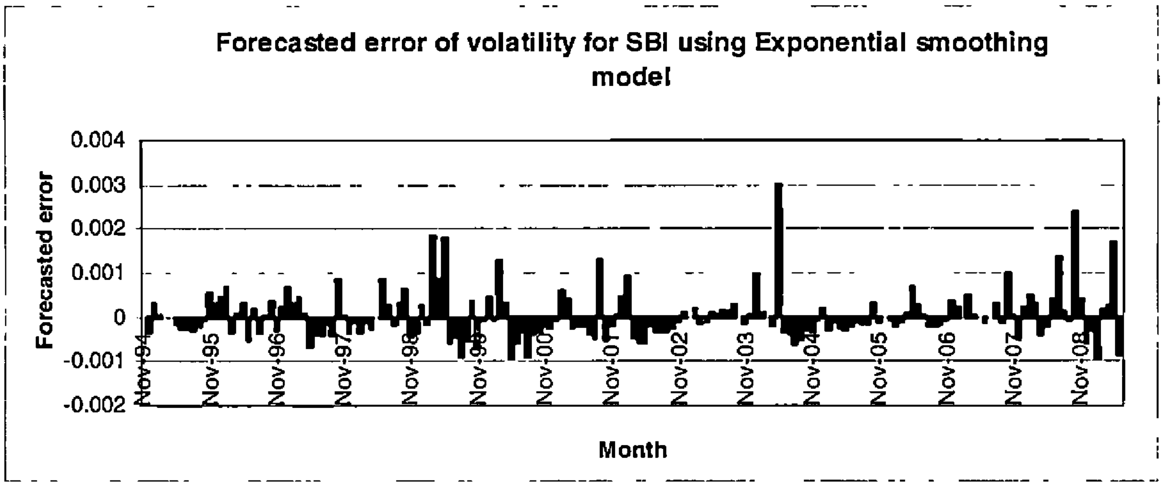


Fig. 4.62 Forecasted error of volatility for BHEL using exponential smoothing model.

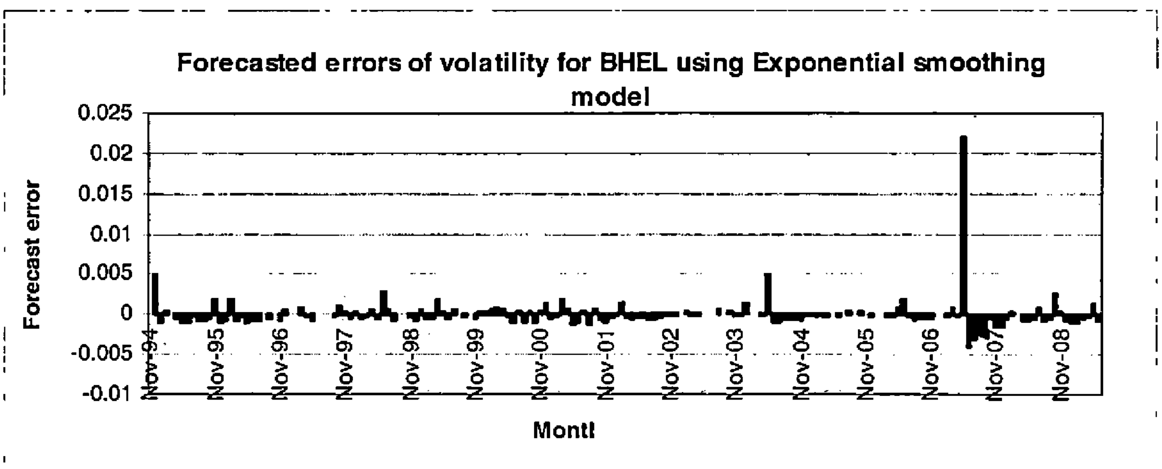
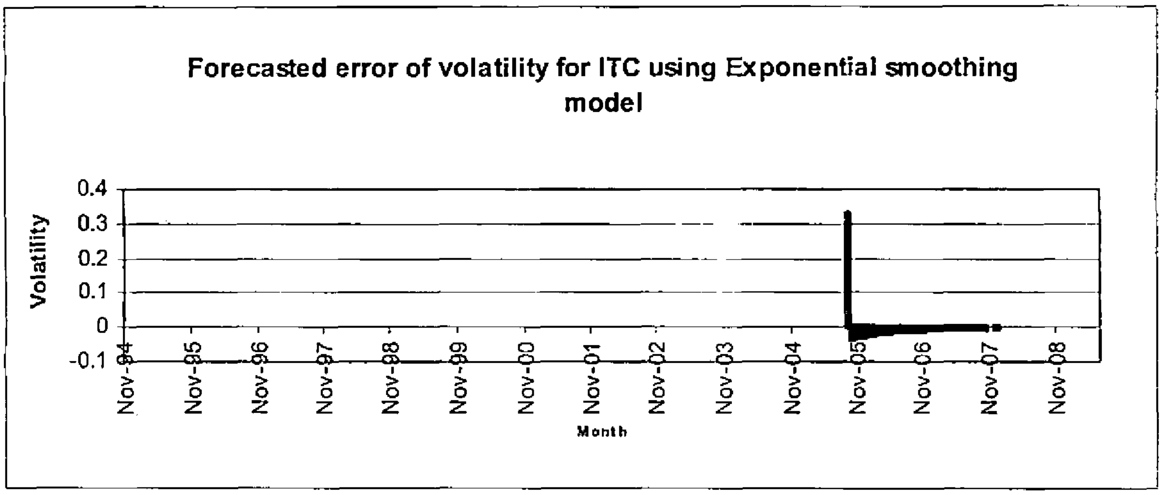


Fig. 4.63 Forecasted error of volatility for ITC using exponential smoothing model



It is clear from the figures that by using the exponential smoothing model the errors of prediction are very less in quantity for almost all the samples under study, thereby showing the efficiency of the model in predicting volatility of stock markets

4.4 Identification of the superior volatility forecasting model

Five models viz., Random walk model (RWM), Historic mean model (HMM), Moving average model (MA 3,6,9,12), AR(1)model, and Exponential weighted moving average model (EWMA) were fitted to forecast the volatility of squared price returns of the stock market as a whole and of the companies representing various sectors, viz; Nifty, Reliance, Infosys, SBI, BHEL and ITC. The efficiency or the predictive capability of different models are compared in this section using the statistics viz; Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R^2 etc. calculated for the data of sample period as well as, for the out of sample period. These statistics are available in Table 4.8

Table 4.8 Comparison of volatility forecasting models based on their performance for the sample period

Company	Model fit statistics for the sample period.														
	RWM			HMM			MA 3			AR(1)			Exp. Smoothing		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Nifty	0.0002	0.0003	73.22	0.0002	0	113.13	0.0001	0.0002	49.83	7.88E-05	0	48.81	7.57E-05	0	48.44
Reliance	0.0008	0.0030	114.26	0.0008	0	169.65	0.0005	0.0017	67.11	0	0	50.06	0	0	41.11
Infosys	0.0647	0.1753	5.7891	0.0409	0.1214	3.4281	0.0407	0.1019	3.6274	0.0220	0.030	2.2360	0.0380	0.0550	3.7780
SBI	0.0004	0.0007	86.51	0.0004	0	111.56	0.0300	0.0004	51.76	0	0	75.70	0	0	74.43
BHEL	0.0008	0.001245	93.749	0.0008	0	153.63	0.0005	0.0007	59.93	0	0.0010	69.34	0	0.0010	69.69
ITC	0.0004	0.000507	81.87	0.0004	0	138.19	0.0001	0.0003	51.98	0	0	71.05	0	0	71.49

Table 4.9 Comparison of volatility forecasting models based on the performance for out of sample period.

Company	Model fit statistics for out of sample period									
	RWM		HMM		MA3		AR(1)		Exp. Smoothing	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Nifty	0.0004	0.0007	0.0003	0.0006	0.0003	0.0002	0.0035	0.0006	0.0003	0.0005
Reliance	0.0006	0.0013	0.0007	0.0011	0.0007	0.0006	0.0009	0.0012	0.0006	0.0011
Infosys	0.0343	0.0712	0.0238	0.0479	0.0238	1.0076	0.2214	0.4054	0.0526	0.1591
SBI	0.0003	0.0005	0.0004	0.0006	0.0004	0.0002	0.0007	0.0008	0.0003	0.0006
BHEL	0.0015	0.0048	0.0011	0.0034	0.0011	0.0028	0.0012	0.0032	0.0011	0.0033
ITC	0.1547	0.0706	0.0096	0.0499	0.0096	0.0412	0.0117	0.0558	0.0127	0.047

Table 4.10 Ranking of volatility forecasting models based on the values of MAE

Company	RWM	HMM	MA3	AR(1)	EWMA
	MAE	MAE	MAE	MAE	MAE
Nifty	0.0004 (2)	0.0003 (1)	0.0003 (1)	0.0035 (3)	0.0003 (1)
Reliance	0.0006 (1)	0.0007 (2)	0.0007 (2)	0.0009 (3)	0.0006 (1)
Infosys	0.0343 (2)	0.0238 (1)	0.0238 (1)	0.2214 (4)	0.0526 (3)
SBI	0.0003 (1)	0.0004 (2)	0.0004 (2)	0.0007 (3)	0.0003 (1)
BHEL	0.0015 (3)	0.0011 (1)	0.0011 (1)	0.0012 (2)	0.0011 (1)
ITC	0.1547 (4)	0.0096 (1)	0.0096 (1)	0.0117 (2)	0.0127 (3)

Table 4.11 Ranking of volatility forecasting models based on the values of RMSE

Company	RWM	HMM	MA3	AR(1)	EWMA
	RMSE	RMSE	RMSE	RMSE	RMSE
Nifty	0.0007 (4)	0.0006 (3)	0.0002 (1)	0.0006 (3)	0.0005 (2)
Reliance	0.0013 (4)	0.0011 (2)	0.0006 (1)	0.0012 (3)	0.0011 (2)
Infosys	0.0712 (2)	0.0479 (1)	1.0076 (5)	0.4054 (4)	0.1591 (3)
SBI	0.0005 (2)	0.0006 (3)	0.0002 (1)	0.0008 (4)	0.0006 (3)
BHEL	0.0048 (5)	0.0034 (4)	0.0028 (1)	0.0032 (2)	0.0033 (3)
ITC	0.0706 (5)	0.0499 (3)	0.0412 (1)	0.0558 (4)	0.047 (2)

Table 4.12 Ranking of different forecasting models based on the values of MAPE.

Company	RWM	HMM	MA 3	AR(1)	EWMA
Nifty	73.22 (4)	113.13 (5)	49.83 (3)	48.81 (2)	48.44 (1)
Reliance	114.26 (4)	169.65 (5)	67.11 (3)	50.06 (2)	41.11 (1)
Infosys	5.7891 (5)	3.4281 (2)	3.6274 (3)	2.236 (1)	3.778 (4)
SBI	86.51 (4)	111.56 (5)	51.76 (1)	75.7 (3)	74.43 (2)
BHEL	93.749 (4)	153.63 (5)	59.93 (1)	69.34 (2)	69.69 (3)
ITC	81.87 (4)	138.19 (5)	51.98 (1)	71.05 (2)	71.49 (3)

Based on the values of MAE , RMSE and MAPE the different models are ranked according to their capability of prediction and with minimum information lost through error. The best identified model for forecasting the volatility of stock markets is the Exponential weighted moving average model. Then comes AR(1) followed by MA(3), RWM and HMM. Thus it can be concluded that out of the five models considered, superior models for predicting the volatility of stock markets are the Exponential weighted moving average model, followed by AR(1) and MA (3).

Prediction of volatility using the best model

Using the best performing model, ie, EWMA, the volatility of the next six months viz., July 2009 to December 2009, are predicted. Predicted squared returns or volatility of Nifty, Reliance, Infosys, SBI, BHEL and ITC are plotted in Fig.4.64, 4.65, 4.66, 4.67, 4.68 and 4.69 respectively.

Fig. 4.64 Predicted volatility of Nifty for July '09 to December '09

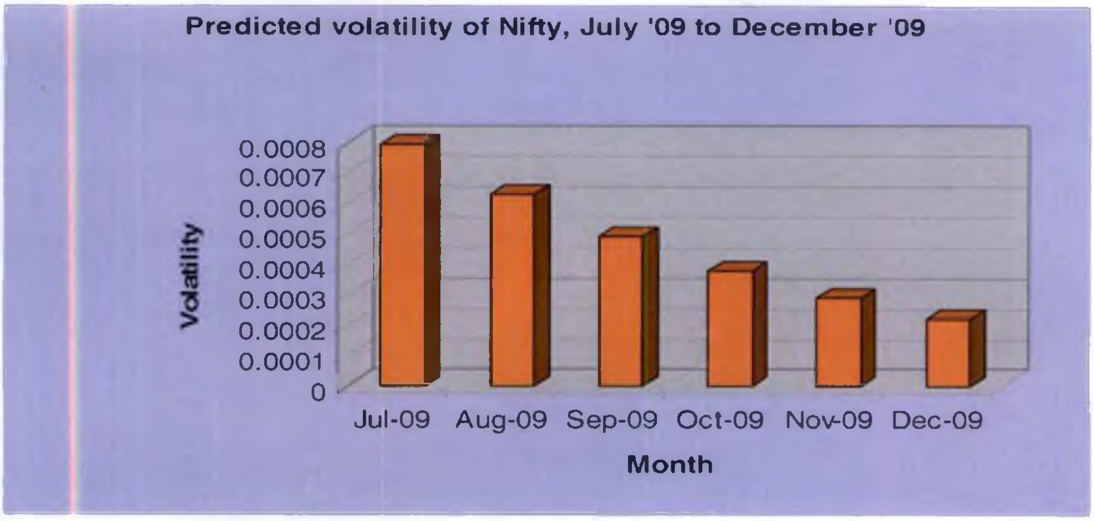


Fig. 4.65 Predicted volatility of Reliance for July '09 to December '09

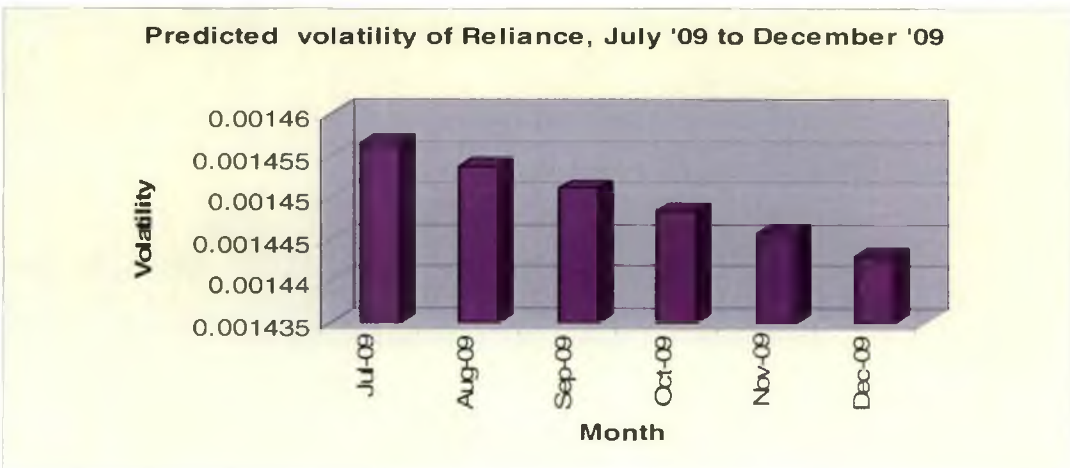


Fig. 4.66 Predicted volatility of Infosys for July '09 to December '09.

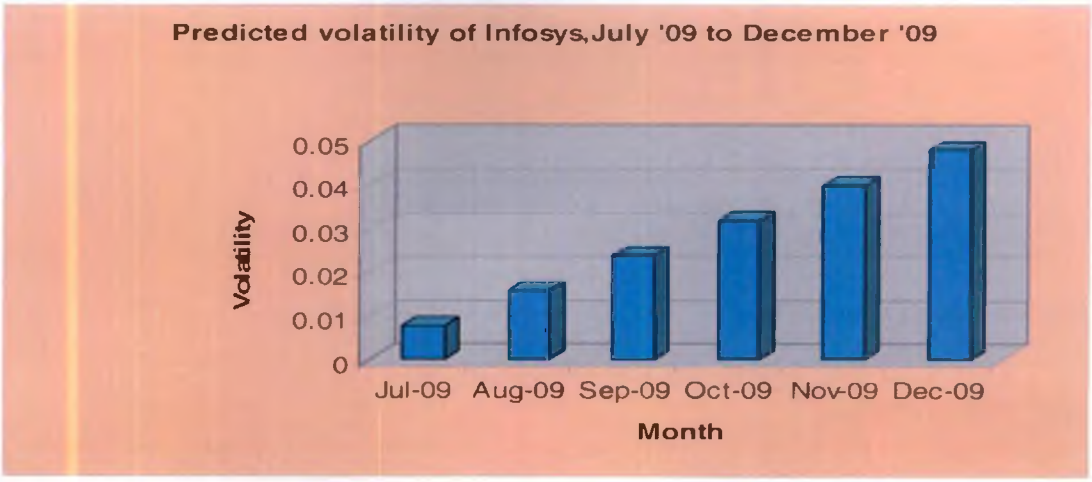


Fig. 4.67 Predicted volatility of SBI for July '09 to December '09.

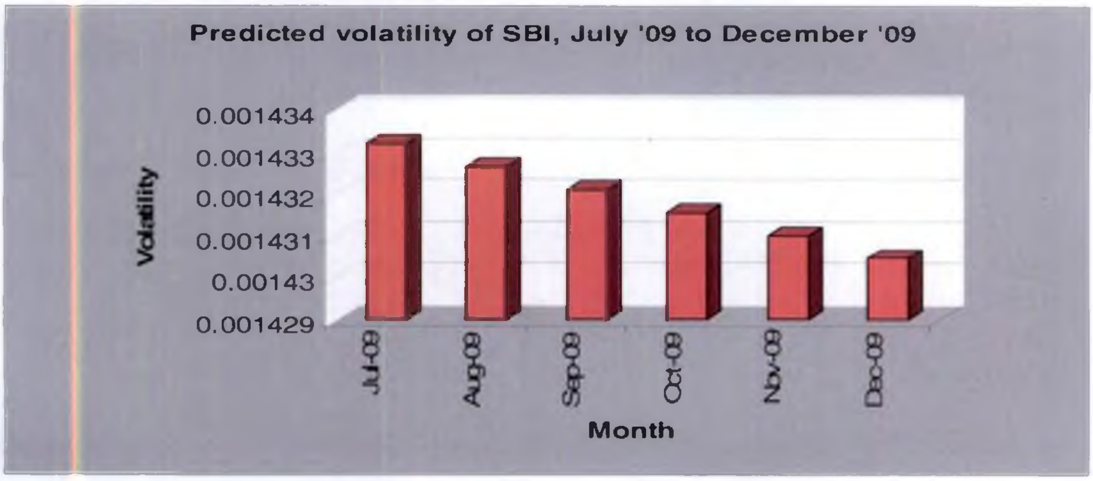


Fig. 4.68 Predicted volatility of BHEL for July '09 to December '09.

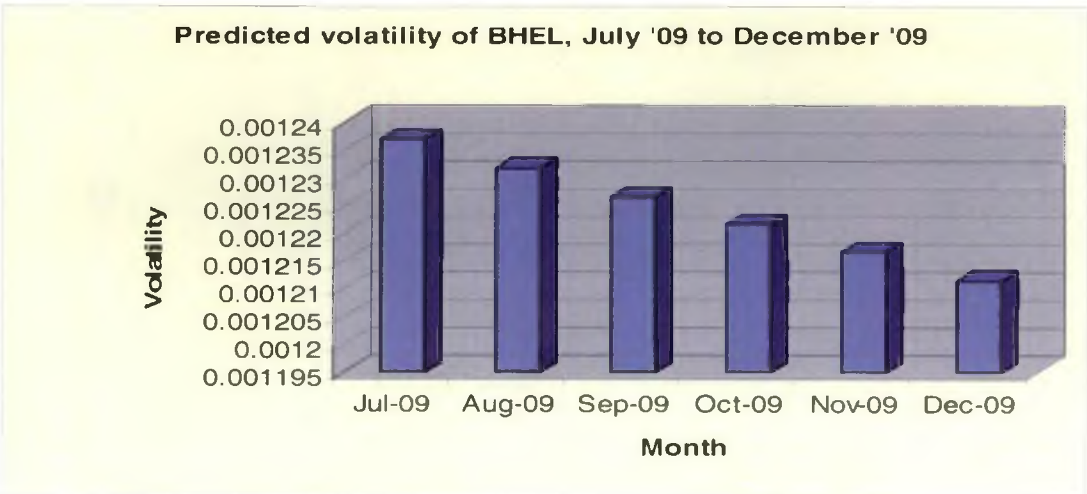
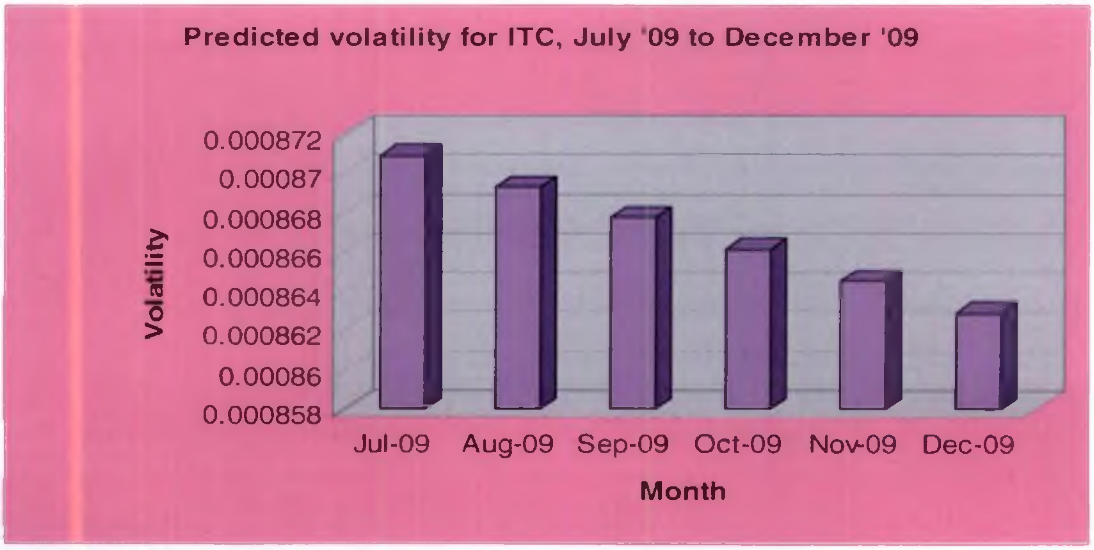


Fig. 4.69 Predicted volatility of ITC for July '09 to December '09.



Graphical representation of predicted volatility for all stocks indicates decreasing trend of volatility for the next six months, except for Infosys. The increasing trend of volatility for Infosys is advantageous as well as risky for the investors. A peak in volatility will be followed by a definite steep decline and the investors should be alert to hold or sell off the stocks.

Infosys is the only company, which earns majority earnings through export business. Due to current slow down, when most of the FIIs made exit from the Indian market, exchange rate of Indian Rupee against the US Dollar depreciated. This boosted up the expectation of better performance by the IT giant Infosys. So investor may consider this stock for higher returns.

In the case of other stocks and Nifty as a whole, deepening economical crisis across the world, resulted in the increasing numbers of lay offs, and drop outs across the world. This affected the global demand of day to day items as well as luxury. The market crash was so big that, it did not spare even big players in the market. All these factors affected the companies, whose stocks showed decreasing trend of monthly squared returns. In the case of Reliance sudden fall in crude oil prices and overall demand worried the investors. Financial waiver scheme for farmers announced by Government, took the toll on the SBI stocks. In case of ITC and BHEL, sentiments of investors are alike the SBI and Reliance.

Sudden exit of FIIs crashed the Nifty in the year 2008. To book the profit, and reduce the loss, domestic investors also followed the suit, which soiled the investment of an ordinary investor or retail investor. The shock was so big that, many investors preferred to stay away from the market. This kept Nifty trembling upto June 2009. Lack of clear cut agenda for market reforms, and unexpected come back of one party dominant government at the centre also affected the market.

Basically, bigger players in the market turned towards more lucrative markets like bullion and commodity, which reduced the stock market activity. As overall demand is reduced in the market, prices of stocks touched the lower limits, which were unthinkable before October 2008.

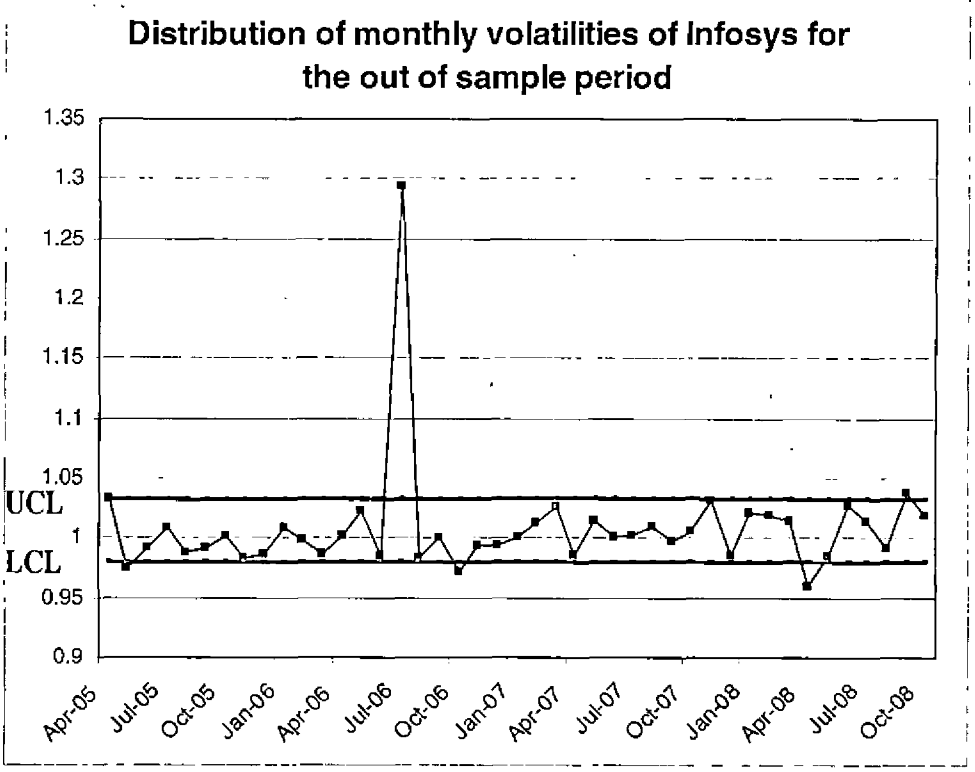
4.5.2 Confidence limits of volatility for the stock index and stocks

Based on the average monthly squared returns for the sample period for the stock index and the selected stocks, the confidence limits for each of them are calculated as Mean ± 1.96 S.E and is depicted in Table 4.13.

Table 4.13 Confidence limits of volatility for stock index and stocks

Stock/Index	**UCL** **Mean + 1.96 S.E**	**LCL** **Mean – 1.96 S.E**
Nifty	0.0003	0.0002
Reliance	0.0012	0.0005
Infosys	**1.0331**	**0.9802**
SBI	0.0007	0.0005
BHEL	0.0007	0.0005
ITC	0.0012	0.0008

Fig.4.70 Distribution of monthly volatilities of Infosys for the out of sample period



From Table 4.13 it can be observed that the average monthly squared returns of Infosys would not go below the limit 0.9802 and it can reach a peak of 1.0331under favourable market conditions. Knowledge about upper and lower confidence limits enables the investors to identify the signals of the market and decide about the timing to buy, hold or sell stocks in order to book profits. In the case of Infosys as it was evidenced from Table 4.3 and Figure 4.70, the distribution of monthly volatilities fall within the LCL and UCL except for a single outlier and thereby ensuring that the volatility of Infosys is predictable and under control.

Summary and Conclusion

CHAPTER 5

SUMMARY OF FINDINGS AND CONCLUSION

The growth of the equity market in India has been phenomenal in the present decade. Market witnessed increased interest for stock investment among the individual and institutional investors. As a result Indian stock market went through sky rocketing growth in past years. Increased penetration of market and its ever increasing global linkage brought a phenomenon of high risk and high reward into the Indian market. Indian stock market is today known as one of the most volatile markets in the world.

Volatility is the variability of asset price changes over a particular period of time. Volatility presents a strange paradox to market participants, as absence of volatility ensures meager returns, and very high volatility may cause heavy losses. The present study on 'forecasting volatility of the Indian stock market' has been conducted with the main objectives of examining the volatility behaviour of the Indian stock market, to forecast the sector- wise volatility of the Indian stock market and to identify the most efficient volatility forecasting model among the different models used.

For the study the biggest stock market in India in terms of total turnover and volume of transactions, ie, National Stock Exchange was selected. For analyzing the volatility behaviour of the Indian stock market as a whole, S&P CNX Nifty index was taken. Five companies representing five different sectors, namely, Reliance (diversified), Infosys (IT), SBI (banking), BHEL (engineering heavy) and ITC (FMCG) were selected for forecasting sector – wise volatility. The study used secondary data on daily close prices of individual stocks from November 1994 to October 2008, and for NIFTY, daily close values, from November 1995 to October 2008 from the website of National Stock Exchange, www.nseindia.com . The findings of the study are summarized in the ensuing section.

5.1 Summary of findings

Line graphs were used to depict the general movement of daily close values and daily close price of Nifty and the five companies respectively, which revealed an upward trend. Daily price returns showed lots of up and downs, showing the existence of high volatility. Since the existence of volatility was confirmed, to better understand the extent of volatility, average monthly squared price returns were calculated. When plotted, the monthly squared price returns revealed high peaks and troughs for the index and all sectors. The histogram drawn for the volatility of all samples showed that the distribution of volatility was not normal. There was positive skewness and all the distribution of volatility was leptokurtic. This proved the presence of high peak values (squared returns) in the sample data, exposing the evidence of volatility clustering and the possibility for prediction of future volatility.

The forecasting capabilities of five competing models, viz., random walk, historical mean, moving average, auto regression and exponential smoothing, was examined. As per the random walk model, the best forecast for this period's volatility is the last period's realized volatility. Random walk model was found suitable for the prediction of volatility of two sectors - IT (Infosys) and engineering heavy (BHEL) only. But the MAPE values were high.

Assuming the conditional expectation of the volatility constant, the historical mean model forecasts volatility as the historical average of the past observed volatilities. Historic mean model could not predict the volatility in the stock market with precision, for the index as well as for any of the five companies.

Moving-average method is a traditional time series technique in which the volatility is defined as equally weighted average of realized volatilities in the past 'm' months. Out of three, six, nine and twelve monthly moving averages taken for predicting the volatility three months moving average was found most suitable for all the samples.

In AR (1) method the familiar regression of actual volatilities on lagged values was fitted. In other words the first auto regression was performed on the first part of data which is meant for estimating the parameters and the estimates thus obtained were used for forecasting the volatility for the next month. For Reliance, Infosys and Nifty, the AR (1) model was very effective in prediction of volatility as compared to others. The actual and the predicted volatility graphs for these three samples moved without much variability in the same direction.

Exponential smoothing is an adaptive forecasting method that gives greater weight to more recent observations so that the finite memory of the market is represented. This method adjusts the forecasts based on past forecast errors and the forecast is calculated as a weighted average of the immediate past observed volatility. Reliance, Infosys and Nifty had good predictability of the volatility in the stock market by using the exponential smoothing model. By this method the errors of prediction were very less for almost all the samples under study, thereby showing the efficiency of the model in predicting volatility of stock markets.

The efficiency or the predictive capability of different models were compared using the statistics viz; Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and R . squared calculated for the data of sample period as well as, for the out of sample period. Based on the values of the above, different models were ranked according to their capability of prediction and with minimum information lost through error. The best identified model for forecasting the volatility of stock markets is the EWMA. Then comes AR (1) followed by MA (3), RWM and HMM. Thus it was concluded that out of the five models considered, superior models for predicting the volatility of stock markets are the Exponential weighted moving average model, followed by AR(1) and MA(3) models.

Once the best performing model, ie, EWMA was identified, using it, the volatility of the next six months i.e., July 2009 to December 2009, was predicted. Graphical representation of predicted volatility for all stocks indicated decreasing trend of volatility for the next six months, except for Infosys.

The confidence limits for the Nifty and the stocks of five companies based on volatility for the sample period were calculated and found that for Infosys the distribution of volatilities for the out of sample period are coming within the prefixed UCL and LCL and it ensures that the volatility is under control and predictable with high degree of precision.

5.2 Conclusion

The study revealed presence of strong volatility in the Indian stock market. While analysing sector -wise volatility, the diversified sector represented by Reliance Industries Limited showed the highest volatility compared to that of Nifty and the other sectors. In other words, Reliance is the most volatile stock among the samples selected for the study. Maximum weightage in index, strong growth prospectus, followed by huge market acceptance make the Reliance, reliable for high earnings for the investors. As company belongs to the diversified sector, the threat to the investors is comparatively less. This makes the stock more lucrative than other stocks. Reliance and Infosys had good predictability of volatility in the stock market. Out of the five models considered, superior models for predicting the volatility of stock markets are the Exponential weighted moving average model and AR(1) model followed by MA(3). Prediction of volatility using the efficient model identified indicated decreasing trend of volatility for the next six months, except for Infosys. The ever increasing market segments, advancement of technology, widening market reach and multi dimensions of stock market provide ample scope for further research in this area to the advantage of the investors and other market participants.

BIBLIOGRAPHY

Aggrawal,R., Inclan, C. and Leal,R. 2009. *Volatility in Emerging Stock Markets.* Available: http://faculty.msb.edu/aggarwal/volatility.PDF [22Feb.2009].

Ahoniemi,K. 2006. *Modeling and Forecasting Implied Volatility –an Econometric Analysis of the VIX Index.*[on line].Helsinki School of Econ. FDPE and HECER.DiscussionPap.No.129.ISSN17950562.Available:http://ethesis.helsinki.fi/julkaisut/eri/hecer/disc/129/modeling.pdf [19 Nov. 2008].

Al-Deehani,T. 2005. *Modelling Volatility Spillover in GCC Stock Markets using StructuralTimeSeriesAnalysis.*Available:http://www.kaiaedu.or.kr/kor/board/table/jaf/upload/3-Talla(2005).doc [22 Feb.2009].

Andersen,T.G., Bollerslevb,T., Dieboldc,F.X., and Labysd,P.1999. *Modelling and forecastingrealisedvolatility.*[online].Available:http://www.ssc.upenn.edu/~fdiebold/papers/paper43/abdl4.pdf [19 Nov. 2008].

Andersen, T.G., Bollersleve,T.,Dieboald,F.X., and Labys,P.2003. *Modelling and forecasting of realised volatility.*[on line].Econometrica 71 : 2,579-625. Available: http://www.jstor.org/pss/3082068 [19 Nov. 2008].

Anonymous. n.d. *Volatility forecasting of the S&P 500 index, an extreme value method vs the CARR model.*Available:https://editorialexpress.com/cgi-bin/conference/download.cgi?db_name=MMF2008&paper_id=101 [19 Nov. 2008].

Athanassakos, G. Kalimipalli,M.(2003) *Analyst Forecast Dispersion and Future Stock Return Volatility.* Available: http://info.wlu.ca/~wwwsbe/faculty/mkalimip/research/publishedpapers/Final_July%2022_03_dispersion_QJBE.pdf. [21 Nov.2008].

Badrinath, H.R. and Apate, P.G. 2005.*Volatility of spillovers across stock, call money and foreign exchange markets.* [online] National Stock Exchange, India. Available: http://www.nseindia.com/content/research/comppaper109.pdf [9 Dec.2007].

Banerjee,A. Sarkar,S.2006.*Modeling daily volatility of the Indian stock market using intra-day data.* Indian Inst. of Manage. Calcutta. WPS No. 588.Available: http://www.iimcal.ac.in/res/ upd%5CWPS%20588.pdf [19 Nov. 2008].

Bautista,C.C. 2004.*How volatile are East Asian stocks during high volatility periods?* Available:http://www.upd.edu.ph/~cba/bautista/papers/bautista_swarch1.pdf [22Feb.2009].

Bayar,A.and Faff,R.2004. *Forecasting stock market volatility: Further International Evidence.* Available: http://luxor.acadiau.ca/library/ ASAC/v25/articles/Balaban-Bayar-Faff.pdf [19 Nov. 2008].

Bluhma,H.H., and Yub,J. 2001. *Forecasting volatility: evidence from the German stockmarket.*Available:http://www.econometricsociety.org/meetings/am01/content/presented/papers/yu.pdf [19 Nov. 2008].

Brådford ,D. L..J. and Becht,M. 1992.*Excess volatility and the German stock market.18761990.*Available:http://econ161.berkeley.edu/pdf_files/German_Volatility.pdf.[19 Nov. 2008].

Busch,T. Christensen,B.J and Nielsen,M.O.2005. *Forecasting Exchange Rate Volatility in the Presence of Jumps.* [on line] Working Paper Series No. 217. Available:http://www.cls.dk/caf/wp/wp-217.pdf [19 Nov. 2008].

Campbell,S.D. 2005. *Stock market volatility and the great moderation.* Finance and economics discussion Series. Fed. Reserve Board, Washington, D.C. Available:http://www.federalreserve.gov/Pubs/feds/2005/200547/200547pap.pdf [19 Nov. 2008].

Carvalho,M.R.C.,Freire,M.C., Medeiros,M.C., and Souza,L.R. 2005. *Modeling and forecasting the volatility of Brazilian asset returns: a realized variance approach.*[on line]. No. 530.Available: http://www.econ.puc-rio.br/PDF/td530.pdf [19 Nov. 2008].

Chen,C.H.,Yu,W.C.,Zivot, E.(2008) *Predicting Stock Volatility Using After-Hours Information.* Available: http://course1.winona.edu/wyu/research/p10.pdf [19 Nov. 2008].

Chen,S.,Jeong,K.,and Hardel,W.2008. *Support vector regression based Garch model with application to forecasting volatility of financial returns.* [on line].Available:http://sfb649.wiwi.hu-berlin.de/papers/pdf/SFB649DP2008-014.pdf [19 Nov. 2008].

Chen,W.Y. and Lian,K.K.2005.*A Comparison of Forecasting Models for Asean Equity Markets.* Sunway Acad. J. 2, 1–12. Available:http://www.sunway.edu.my/others/vol2/wong1.pdf [22Feb.2009].

Choi,K., Yu,W.C., and Zivot,E.(n.d.). *Long memory versus structural breaks in modeling and forecasting realized volatility.*Available:http://faculty.washington.edu/ezivot/research/longMemoryStructuralBreaksRV.pdf [19 Nov. 2008].

Chou,H. Wang,D.2007. *Forecasting volatility on the U.K. stock market: A test of the conditional autoregressive range model.* Int.Res.J.Finance , Econ.10: 1450-2887 Available: http://www.eurojournals.com/irjfe%2010%20heng.pdf [19 Nov. 2008].

Christoffersen,P.F., Diebold,F.X., Cirano,N. 2005. *Financial asset returns, direction-of-change, forecasting, and volatility dynamics.* Available: http://web.management.mcgill.ca/peter.christoffersen/CHRISTOP/research/CD9_13Dec05.pdf [19 Nov. 2008].

Chowdhury,S.S., Mollik,A.T. and Akhter,S.2006.*Does Predicted Macroeconomic Volatility Influence Stock Market Volatility? Evidence from the Bangladesh Capital Market.*Available:http://www.unisa.edu.au/commerce/docs/Does%20Predicted%20Macroeconomic%20Volatility%20Influence%20Predicted%20Stock%20Market%20Volatility.pdf [22Feb.2009].

Claessen,H and Mittnik,S.*2004. Forecasting Stock Market Volatility and the Informational Efficiency of the DAX indexOptions Market.* CFS Working Paper No.2002/04. Available: http://www.ifk-cfs.de/papers/02_04.pdf [19 Nov. 2008].

De Long,J.B. and Grossman,R.S.1993. *Excess volatility on the London stock market, 1870-1990.*Available:http://www.j-bradfordelong.net/pdf_files/London_Volatility.pdf [19 Nov. 2008].

Diebold,F.X. Yılmaz,K.2007. *Macroeconomic Volatility and Stock Market Volatility World- wide.*[on line].Tusiad Koc University, Istanbul.Econ. Res.Forum.working paper.0711. Available: http://www.ku.edu.tr/ku/_images/EAF/erf_wp_0711.pdf [19 Nov. 2008].

Döpke, J.Hartmann, D. Pierdzioch,C. 2006. *Forecasting Stock Market Volatility with Macroeconomic Variables in Real Time*: Discussion Paper Series 2: Banking and Financial Studies No 01/2006 Available:http://www.bundesbank.de/download/bankenaufsicht/dkp/200601dkp_b.pdf [19 Nov. 2008].

Duarte,E.M.and Fonseca,J.A. 2002. *Volatility analysis of Portuguese stock market.* Available: http://www.stat.ucl.ac.be/Samos2002/proceedDuarte.pdf [19 Nov. 2008].

Engle,R.F. and Range,J.G.2008. *The Spline- Garch Model for Low Frequency Volatility and Its Global Macro economic Causes.* Available:http://pages.stern.nyu.edu/~rengle/SplineGarch.pdf [22Feb.2009].

Eriksson,A., Preve,D., and Yu,J.2007.*Forecasting Realised Volatility Using a Non negativeSemiperametricModel.*Available:http://www.mysmu.edu/faculty/yujun/Research/EPY-29-12-07.pdf [19 Nov. 2008].

Figlewski,S.2004.*ForecastingVolatility.*Available:http://pages.stern.nyu.edu/~sfiglews/Docs/Forecasting%20Volatility.pdf [19 Nov. 2008].

Flad,M. 2006.*Do macro factors help forecasting stock market volatility?* Johann WolfgangGoetheUniv.Frankfurt.Available:http://www.ecore.be/Papers/1177068383.pdf [19 Nov. 2008].

Fonseca,J.A. and Duarte,E.M. 2002. *Volatility analysis of Portuguese stock market.* Available: http://www.stat.ucl.ac.be/Samos2002/proceedDuarte.pdf [19 Nov. 2008].

Franses,P.H.and Dijk,D.V.*1996. Forecasting stock market volatility using(non-linear) GARCH Models. J. Forecasting. 15.229-235.*Erasmus University, Rotterdam, The Netherlands.Available:http://finance.martinsewell.com/stylizedfacts/volatility/FransesvanDijk1996.pdf [19 Nov. 2008].

Guo,H. and Savickas, R.2003. *Idiosyncratic Volatility, Stock Market Volatility, and Expected Stock Returns.*[on line].Working Paper 2003-028B Available: http://research.stlouisfed.org/wp/2003/2003-028.pdf [19 Nov. 2008].

Hassan,K.M., Al-Sultan,W.S. and Al-Saleem,J.A.2003.*Stock market efficiency in the Gulf cooperation council countries (GCC):The case of Kuwait stock exchange. ScientificJ.AdministrativeDevelopment*Vol.1No.1I.A.D.2003.Available:http://www.iad.gov.qa/arabic/images/stories/document/volume1/article1_2003.pdf [22Feb.2009].

Herath, H.S. and Kumar,P.2002.*The Jackknife Estimator for Estimating Volatility of Volatility of a Stock.* Available: http://web.unbc.ca/~kumarp/c5.pdf..[19 Nov. 2008

Hol,E., and Koopman,S.J.2000. *Forecasting the variability of stock index returns with stochastic volatility models and implied volatility.*[On line].TI 2000-104/4. TinbergenInst.DiscussionPaper.Available:http://www.tinbergen.nl/discussionpapers/00104.pdf[19.Nov.2008]

Hwang,S., Satchell,S.E. 2001.*GARCH Model with Cross-sectional Volatility;GARCHX Models.* Available: http://www2.warwick.ac.uk/fac/soc/wbs/research/wfri/wpaperseries/wp01-16.pdf. [19 Nov. 2008].

Janakiramanan, S. 2007. *Underpricing and long run performance of initial public offering in Indian stock market.*[online]. National Stock Exchange, India, Available: http://www.nseindia.com/content/research/comppaper184.pdf [12 Nov.2007]

Jiang,G.J.,Tian Y.S.(n.d.) *Model-Free Implied Volatility and Its Information Content.* Available: http://www.rotman.utoronto.ca/finance/seminars/030530_tian.pdf [19 Nov. 2008].

Kalev P.S.2006. *Intraday and interday time-zone volatility forecasting.* Dep. Accounting and Finance. Monash Univ.
Available:http://www.melbournecentre.com.au/ResearchGrants/4.Kalev_Discussion%20Paper.pdf [19 Nov. 2008].

Kalimipalli, M. and Ramachand, L (2002). *Changes in liquidity following exposure to foreign shareholders: The effect of foreign listing and issue of American Depository Receipts, by Indian firms.* [Online]. National Stock Exchange, India. Available: http://www.nseindia.com/content/research/Paper31.pdf [6 Dec.2007].

Karadag Ali, M. 2008. *Analysis of Turkish stock market with Markov regime switchingvolatilitymodels.*[online].Available:http://www3.iam.metu.edu.tr/iam/images/113/Mehmetlikaradagthesis.pdf [19 Nov. 2008].

Kasman,S.K.,and Kasman,A. 2002. *Volatility in the Turkish stock market: an industry level analysis.* Available:http://eab.ege.edu.tr/pdf/2_2/C2-S2-%20M3.pdf [19 Nov. 2008].

Khedhiri,E. and Muhammad,N.2008.*Empirical analysis of the UAE stock market volatility.* Int. Res. J. Finance and Econ.15:1450-2887 Available: http://www.eurojournals.com/irjfe%2015%20sami.pdf [22Feb.2009].

Kirankumar, K. and Mukhopadyay, C (2002.). *Equity market interlinkages transmission of volatility-A case study of U.S. and India.* [Online]. National Stock Exchange, India. Available: http://www.nseindia.com/content/research/Paper39.pdf [17 Dec.2007].

Kovacic,Z.J.2008. *Forecasting volatility: evidence from the Macedonianstock exchange.* Int.Res.J Finance, Econ.18: 1450-2887 Available: http://www.eurojournals.com/ irjfe_18_14_Zlatko.pdf [19 Nov. 2008].

Kumar and Rakesh 2007. *Economic Growth and Volatility in Indian Stock Market: A Critical Analysis. South Asian J. Mgmt.* Available: http://findarticles.com/p/articles/mi_qa5483/is_200704/ai_n21295047?tag=content;col1 [14Feb.2009].

Kumar,S.S. 2006. *Forecasting volatility – evidence from Indian stock and forex markets.*[online]IIMK/WPS/08/FIN/2006/06.Available:http://dspace.iimk.ac.in/bitstream/2259/289/1/ForecastingVolatility.pdf [19 Nov. 2008].

Lamba, A.S. 2004. *An analysis of the dynamic relationship between South Asian and developed equity markets.* [online]. National Stock Exchange, India. Available: http://www.nseindia.com/research /lat83.pdf [24 Jan.2008]

Laws,J. and Gidman,A.2000. *Forecasting stock market volatility and the application of volatility trading models.* Available:http://www.ljmu.ac.uk/AFE/AFE_docs/cibef1100b.PDF [19 Nov. 2008].

Levine,R. 1996. *Stock Markets: A Spur to Economic Growth.* Available:http://www.imf.org/external/pubs/ft/fandd/1996/03/pdf/levine.pdf [22Feb.2009].

Levine, R.1997.Stock *markets, economic development, and capital control liberalization.Investment* Company Institute. Perspective series of occasional papers. Vol. 3 / No. 5 Available: http://www.ici.org/pdf/per03-05.pdf [22Feb.2009].

Long.,V.T. 2008. *Empirical Analysis of Stock Return Volatility with Regime Change Using Garch Model: The Case of Vietnam Stock Market.* Available: http://www.vdf.org.vn/workingpapers/vdfwp084.pdf [22Feb.2009].

Longmore,R.and Robinson,W. 2004. *Modelling and forecasting exchange rate dynamics: an application of asymmetric volatility models.*[on line].WP2004/03.Res.Services Dep. Bank of Jamaica. Available:http://bankofjamaica.net/uploads/pdf/papers_pamphlets/papers_pamphlets_modelling_and_forecasting_exchange_rate_dynamics__an_application_of_aysmmetric_volatility_models.pdf [19 Nov. 2008].

Lux ,L.and Kaizoji,T.2004. *Forecasting Volatility and Volume in the Tokyo Stock Market: The Advantage of Long Memory Models.Econ.Working Paper No. 2004.* Available: http://opus.zbw-kiel.de/volltexte/2004/1936/pdf/EWP-2004-05.pdf [19 Nov. 2008].

Magnus,F.J.*2006. Modelling and Forecasting volatility of returns on the Ghana stock exchange using GARCH models.* Am. J. Appl. Sci. 3 (10): 2042-2048,1546-9239.Available: http://www.scipub.org/fulltext/ajas/ajas3102042-2048.pdf [19 Nov. 2008].

Maheu, J.M., Liu, C.2005.*Modelling and forecasting of realized volatility: the role of power variation.* Available: http://www.ccfr.org.cn/cicf2006/cicf2006paper/20060127131140.pdf [19 Nov. 2008].

Marcucci,J.2005. *Forecasting stock market volatility with Regime Switching GARCH models.*Dep. of econ ,Univ.of California ,San Diego. USA. Available: http://www.greta.it/jae/poster/10_2_Marcucci.pdf [19 Nov. 2008].

Martens,M. Chen Chang,Y. Taylor,S.J.2002. *A comparison of seasonal adjustment methods when forecasting intraday volatility.*[on line]. The J. Fianancial Res. Vol. XXV, No. 2 .Pages283–299.Available: http://people.few.eur.nl/ mmartens/jfr2002.pdf [19 Nov. 2008].

Mishra,A.K.,Swain,N. and malhotra,D.K.2007. *Volatility Spillover between Stock and Foriegn Exchange Markets: Indian Evidence. Int.j.Business.* Available: http://findarticles.com/p/articles/mi_qa5364/is_200707/ai_n21287733 [14Feb.2009]

Nathani,A.2007. *Forecasting NIFTY volatility true insights: informed decisions.*I-Peritus Solutions & Services Private Ltd. Available: http://www.iperitus.com/docs/I-Peritus_VolForecast_ver1.0.pdf [19 Nov. 2008].

Pan,H. and Zhang,Z.2006. *Forecasting financial volatility: Evidence from Chinese stock market.* Working paper in economics .and finance. No. 06/02, School of Economics, Finance and Business, Univ. of Durham UK. Available:http://www.dur.ac.uk/economics.wp/wp0602.pdf [19 Nov. 2008].

Perron P.,and Qu,Z.2008. *Long-memory and level shifts in the volatility of stock market return indices.* Available: http://people.bu.edu/qu/paper2/lm-shifts.pdf [19 Nov. 2008].

Patev, P.and Kanaryan, N.2005.*Modelling and Forecasting the Volatility of Thin Emerging Stock Markets. The case of Bulgaria.* Available: http://www.bnb.bg/bnb/home.nsf/vPages/Research_Conferences_2005_NK/$FILE/Patev-Kanaryan-BNB.pdf [22Feb.2009].

Qayyum,A. and Kemal A.R. 2006. *Volatility Spillover Between the Stock Market and the Foreign Exchange Market in Pakistan.*Available:http://mpra.ub.uni-muenchen.de/1715/1/MPRA_paper_1715.pdf [22Feb.2009].

Rao Ramana,S.V. and Tripathy, N.2008.*Volatility tests and effiicent stock markets: a study in India. J. Int. Business* and Econ.Available: http://findarticles.com/p/articles/mi_6775/is_2_8/ai_n31127149[14Feb.2009].

Selcuk, F.C.2005. Asymmetric Stochastic Volatility in Emerging Stock Markets. Available: http://www.bilkent.edu.tr/~faruk/fsAFE2005.pdf [22Feb.2009].

Shan,Y.2005. *Analysts forecast and future stock market volatility-a firm level analysis for NYSE firms.* Available: http://www.library.unsw.edu.au/~thesis/adt-NUN/uploads/approved/adt-NUN20070314.093025/public/02whole.pdf. [19 Nov. 2008].

Snehabagaraman, P. 2003. *Do futures and options trading increases stock market volatility*?[online].NationalStockExchange,India.Available:http://www.nseindia.com/content/research/Paper60.pdf [6 Dec. 2007]

Sucarrat,G. 2006. *What determines the volatility of weekly Norwegian exchange rates? A non-technical summary.*
*A*vailable:http://www.forskningsradet.no/servlet/Satellite?_charset_=iso-8859-1&c=Page&pagename=ForskningsradetEngelsk%2FHovedsidemal&cid=1179127750262&querystring=2006.+What+determines+the+volatility+of+weekly+Norwegian&spell=true&filters=langcodes%252Cen&isglobalsearch=true&configuration=nfrsearchersppublished [19 Nov. 2008].

Tang,Q.and Chen,J. n.d. *On Analysis of the Volatility of the Stock Markets in China.*
Available:http://www.china-review.org/news/manage/image/46153443.DOC
[22Feb.2009].

Yılmaz,K. 2008. *Global Financial Crisis and the Volatility Spillovers across Stock Markets.*Available: http://www.ku.edu.tr/ku/_images/EAF/erf_researchnote_0801.pdf
[22Feb.2009].

Yu, J. 2002. *Forecasting volatility in the New Zealand stock market.* Dep.of Econ. Univ. of Auckland, New Zealand. Available: http://www.mysmu.edu/faculty/yujun/Research/YuAFE.pdf [19 Nov. 2008].

FORECASTING VOLATILITY OF THE INDIAN STOCK MARKET

By

KHADILKAR GURUPRASAD HARI

ABSTRACT OF THE THESIS
Submitted in partial fulfillment of the requirement for the degree of

Master of Science in Co-operation & Banking
(Rural Banking & Finance Management)

Faculty of Agriculture

Kerala Agricultural University, Thrissur

Department of Rural Banking & Finance Management
COLLEGE OF CO-OPERATION, BANKING & MANAGEMENT
VELLANIKKARA, THRISSUR-680 656
KERALA, INDIA
2009

ABSTRACT

The present study on 'forecasting volatility of the Indian stock market' was conducted with the main objectives of examining the volatility behaviour of the Indian stock market, to forecast the sector- wise volatility of the Indian stock market and to identify the most efficient volatility forecasting model among the different models used.

For the study the biggest stock market in India in terms of total turnover and volume of transactions, ie, National Stock Exchange was selected. For analyzing the volatility behaviour of the Indian stock market as a whole, S&P CNX Nifty index was taken. Five companies representing five different sectors were selected for forecasting sector – wise volatility. The study used secondary data on daily close prices of individual stocks from November 1994 to October 2008, and for Nifty, daily close values, from November 1995 to October 2008 from the website of National Stock Exchange, www.nseindia.com.

The study revealed presence of strong volatility in the Indian stock market. The histogram drawn for the volatility of all samples showed that the distribution of volatility was not normal. There was positive skewness and all the distribution of volatility was leptokurtic. This proved the presence of high peak values (squared returns) in the sample data, exposing the evidence of volatility clustering and the possibility for prediction of future volatility.

While analysing sector -wise volatility, the diversified sector represented by Reliance Industries Limited showed the highest volatility compared to that of Nifty and the other sectors. In other words, Reliance is the most volatile stock among the samples selected for the study. Reliance and Infosys had good predictability of volatility in the stock market. The best identified model for forecasting the volatility of stock markets is the EWMA. Then comes AR (1) followed by MA (3), RWM and HMM. Random walk model was found suitable for the prediction of volatility of two sectors - IT (Infosys) and engineering heavy (BHEL) only. But the MAPE values of these were high. Historic mean model could not predict the volatility in the stock market with precision, for the index as well as for any of the five companies. Out of

three, six, nine and twelve monthly moving averages taken for predicting the volatility three months moving average was found most suitable for all the samples.

Prediction of volatility using the most efficient model of EWMA identified indicated decreasing trend of volatility for the next six months, except for Infosys. The confidence limits for the Nifty and the stocks of five companies based on volatility for the sample period found that for Infosys the distribution of volatilities for the out of sample period are coming within the prefixed UCL and LCL and it ensures that the volatility is under control and predictable with high degree of precision.

The ever increasing market segments, advancement of technology, widening market reach and multi dimensions of stock market provide ample scope for further research in this area to the advantage of the investors and other market participants.