AN ANALYSIS OF PRICE VOLATILITY, TRADING VOLUME AND MARKET DEPTH OF FUTURES MARKET IN INDIA

A Thesis submitted to the Pondicherry University in partial fulfilment of the requirements for the award of the degree of

DOCTOR OF PHILOSOPHY

In

COMMERCE

By

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This is to Certify that the Ph.D thesis entitled ***"An Analysis of Price Volatility, Trading Volume and Market Depth of Futures Market in India"*** *submitted for the award of the Degree of DOCTOR OF PHILSOPHY by K.SRINIVASAN is the bonafide research work done by him in the Department of Commerce (SOM), Pondicherry University, Pondicherry, and that the research has not previously formed the basis for the award of any Degree, Associateship, Fellowship or any other similar title and also, that it represents entirely an independent work carried out by the candidate under my supervision and guidance.*

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DECLARATION

I, **K. Srinivasan,** *here by declare that the thesis entitled,* ***"An Analysis of Price Volatility, Trading Volume and Market Depth of Futures Market in India",*** *submitted to the Pondicherry University for the award of Degree of Doctor of Philosophy in Commerce is my original work carried out by me and no part of the thesis has been submitted for the award of any Degree, Diploma, Associateship, Fellowship of other similar title to any University or Institution.*

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Success Needs Nothing except True Efforts

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Executive Summary

Many associate the financial market mostly with the equity market. The financial market is, of course, far broader, encompassing bonds, foreign exchange, real estate, commodities, and numerous other asset classes and financial instruments. A segment of the market has fast become its most important one: derivatives. The derivatives market has seen the highest growth of all financial market segments in recent years. It has become a central contributor to the stability of the financial system and an important factor in the functioning of the real economy.

Despite the importance of the derivatives market, few outsiders have a comprehensive perspective on its size, structure, role and segments and on how it works. The derivatives market has recently attracted more attention against the backdrop of the sub prime lending crisis, financial crisis, fraud cases and the near failure of some market participants. Although the financial crisis has primarily been caused by structured credit-linked securities that are not derivatives, policy makers and regulators have started to think about strengthening regulation to increase transparency and safety both for derivatives and other financial instruments.

The study is purely based on the secondary data for examining futures market in terms of relationship, modeling and forecasting volatility in India. The study period spanned from January 2003 to December 2008 with a sample of 25 stock futures contracts. For the purpose of evaluating stock futures, we used ARCH/GARCH family model to draw valid conclusion. Our findings suggest that, volatility is a part and parcel of capital market and have a major effect in derivative market fluctuations, it is due to the other key determining factors like inflow of foreign capital into the country like exchange rate, balance of payment, interest rate etc. Rise in market capitalization leads to rise in inflation rates, Industrial Production Index (IIP) and Gross Domestic Product (GDP). Overall, it is clearly desirable to preserve the environment that has contributed to the impressive development of the derivatives market and enhances the overall depth, increases market liquidity and compresses spot market volatility in the Indian economy. However, some aspects of the futures trading terminal can still be improved further. Safety and transparency, and operational efficiency could be enhanced along proven and successful models helping the Indian derivatives market to become even safer and more efficient.

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List of Abbreviations and Explanation

(SEBI)	*Securities Exchange Board of India*
(NSE)	*National Stock Exchange*
(MSE)	*Madras Stock Exchange*
(BSE)	*Bombay Stock Exchange*
(NSDL)	*National Securities Depository Limited*
(CDSL)	*Central Depository Services Limited*
(S&P CNX)	*Standard & Poor CRISIL NSE Index*
(SENSEX)	*Sensitivity Index*
(NSCCL)	*National Securities Clearing Corporation Limited*
(ECs)	*Executive Committees*
(CEO)	*Chief Executive Officers*
(CPs)	*Commercial Paper*
(CBOT)	*Chicago Board of Trade*
(CME)	*Chicago Mercantile Exchange*
(CDs)	*Certificate of Deposits*
(WMFs)	*Warrants Mutual Funds*
(ETFs)	*Exchange Traded Funds*
(WDM)	*Wholesale Debt Market*
(CM)	*Capital Market*
(F&O)	*Futures & Options*

(SCRA)	*Securities Contracts Regulation Act*
(JPC)	*Joint Parliamentary Committee*
(ALBM)	*Automated Lending and Borrowing Mechanism*
(BLESS)	*Borrowing and Lending of Securities Scheme*
(FII)	*Foreign Institutional Investors*
(IIP)	*Industrial Production Index*
(IMM)	*International Monetary Market*
(LIFFE)	*London International Financial Futures Market*
(CAPM)	*Capital Asset Pricing Model*
(FIA)	*Futures Industry Association*
(JSE)	*Johannesburg Stock Exchange*
(NEAT)	*National Exchange for Automated Trading*
(CMs)	*Clearing Members*
(TMs)	*Trading Members*
(CPs)	*Custodial Participants*
(NSEIL)	*National Stock Exchange of India*
(MTM)	*Mark-to-Market*
(PRISM)	*Parallel Risk Management System*
(SEQ)	*Sequential Information Arrival Hypothesis*
(MDH)	*Mixture of Distribution Hypothesis*
(SPAN)	*Standard Portfolio Analysis of Risk*
(GDP)	*Gross Domestic Product*

(GNMA)	*Government National Mortgage Association*
(IMM)	*International Monetary Market*
(NYSE)	*New York Stock Exchange*
(ECU)	*European Currency Unit*
(VAR)	*Vector Auto regression*
(OSE)	*Osaka Securities Exchange*
(ADEX)	*Athens Derivatives Exchange*
(FTSE)	*Financial Times-Stock Exchange*
(RW)	*Random Walk*
(OLS)	*Ordinary Least Square*
(AR)	*Autoregressive*
(MA)	*Moving Average*
(GMM)	*Generalized Method Moments*
(LB Test)	*Ljung-Box Test*
(ADF)	*Augmented Dickey Fuller*
(PP)	*Phillips-Perron*
(AIC)	*Akaike Information Criterion*
(SIC)	*Schwartz Bayesian Criterion*
(EWMA)	*Exponential Weighted Moving Average*
(SV)	*Stochastic Volatility*
(VIX)	*Implied volatility Index*
(ARMA)	*Autoregressive Moving Average*

(ARFIMA)	*Autoregressive Fractional Integration Moving Average*
(ARCH)	*Autoregressive Conditional Heteroskedasticity*
(GARCH)	*Generalized Autoregressive Conditional Heteroskedasticity*
(TGARCH)	*Threshold GARCH*
(EGARCH)	*Exponential GARCH*
(IGARCH)	*Integrated GARCH*
(PARCH)	Power *ARCH*
(CGARCH)	*Component GARCH*
(QGARCH)	*Quadratic GARCH*
(FIEGARCH)	*Family Integrated Exponential GARCH*
(RMSE)	*Root Mean Square Error*
(MAE)	*Mean Absolute Error*
(MAPE)	*Mean Absolute Percentage Error*
(TU)	*Theil's U*
(HASE)	*Heteroskedasticity-Adjusted Squared Error*
(VECM)	*Vector Error Correction Model*
(DSI)	*Databank Stock Index*
(ICSS)	*Iterated Cumulative Sums of Squares*
(LE)	*Logarithmic Error*

Abstract

Many associate the financial market mostly with the equity market. The financial market is, of course, far broader, encompassing bonds, foreign exchange, real estate, commodities, and numerous other asset classes and financial instruments. A segment of the market has fast become its most important one: derivatives. The derivatives market has seen the highest growth of all financial market segments in recent years. It has become a central contributor to the stability of the financial system and an important factor in the functioning of the real economy.

Despite the importance of the derivatives market, few outsiders have a comprehensive perspective on its size, structure, role and segments and on how it works. The derivatives market has recently attracted more attention against the backdrop of the sub prime lending crisis, financial crisis, fraud cases and the near failure of some market participants. Although the financial crisis has primarily been caused by structured credit-linked securities that are not derivatives, policy makers and regulators have started to think about strengthening regulation to increase transparency and safety both for derivatives and other financial instruments.

The study is purely based on the secondary data for examining futures market in terms of relationship, modeling and forecasting volatility in India. The study period spanned from January 2003 to December 2008 with a sample of 25 stock futures contracts. For the purpose of evaluating stock futures, we used ARCH/GARCH family model to draw valid conclusion. Our findings suggest that, volatility is a part and parcel of capital market and have a major effect in derivative market fluctuations, it is due to the other key determining factors like inflow of foreign capital into the country like exchange rate, balance of payment, interest rate etc. Rise in market capitalization leads to rise in inflation rates, Industrial Production Index (IIP) and Gross Domestic Product (GDP). Overall, it is clearly desirable to preserve the environment that has contributed to the impressive development of the derivatives market and enhances the overall depth, increases market liquidity and compresses spot market volatility in the Indian economy. However, some aspects of the futures trading terminal can still be improved further. Safety and transparency, and operational efficiency could be enhanced along proven and successful models helping the Indian derivatives market to become even safer and more efficient.

Keywords: Stock Futures Returns, Trading Volume, Open Interest, Volatility, Modeling, GARCH Family Models, Forecasting.

CHAPTER - I

INTRODUCTION AND RESEARCH DESIGN

Every modern economy is based on a sound financial system and acts as a monetary channel for productive purpose with effecting economic growth. It encourages saving habit by throwing open and plethora of instrument avenues suiting to the individuals requirements, mobilizing savings from households and other segments and allocating savings into productive usage such as trade, commerce, manufacture etc.

Thus a financial system can also be understood as institutional arrangements, through which financial surpluses are mobilized from the units generating surplus income and transferring them to the others in need of them. In nutshell, financial market, financial assets, financial services and financial institutions constitute the financial system. The activities include exchange and holding of financial assets or instruments of different kinds of financial institutions, banks and other intermediaries of the market.

Broadly, the organizational structure of financial system includes the following three components; e.g.

- Financial Markets,
- Financial Institutions and Intermediaries,
- Financial Products.

Financial markets provide channels for allocation of savings to investment and provide variety of assets to savers in various forms in which the investors can park their funds. At the same time, financial market is one that integral part of the financial system which makes significant contribution to the countries' economic development. It establishes a link between the demand and supply of long-term capital funds. The economic strength of a country depends squarely on the state of financial market, apart from the productive potential of the country. The efficient allocation of fund by the capital market depends on the state of capital market. All the countries therefore focus more on the functioning of the capital market. Indian financial market has faced many challenges in the process of effecting more efficient allocation and mobilization of capital. It has attained a remarkable degree of growth in the last decade and in continuing to achieve the same in current decade also. Opening up of the economy and adoption of the liberalized economic policies have driven our economy more towards the free market. Over the last few years, financial markets, more specifically the security market were experiencing a lot of structural and regulatory changes. The major constituents of financial market are money market and the capital market catering to the type of capital requirements.

The capital market is a market for financial investments that are direct or indirect claims to capital (Gart, 1988)[1]. It is wider than the securities

[1] Gart, A; Handbook of the Money and Capital Market, Quorum Books, New York, 1988.

market and embraces all forms of lending and borrowing, whether or not evidenced by the creation of a negotiable financial instrument (Drake, 1980)[2]. The capital market comprises the complex of institutions and mechanisms through which intermediate term funds and long term funds are pooled and made available to business, government and individuals. The capital market also encompasses the process by which securities already outstanding are transferred (Dougall, 1986)[3].

Money Market: The money market refers to the market where borrowers and lenders exchange short-term funds to solve their liquidity needs. Money market instruments are generally financial claims that have low default risk, maturities under one year and high marketability.

Capital Market: It is a wide term used to comprise all operations in the new issues and stock market. New issues made by the companies constitute the primary market, while trading in the existing securities relate to the secondary market. It is to be noted that we can only buy in the primary market and not sell, but we can buy and sell securities in the secondary market. All long-term borrowings and lending constitute the capital market.

The securities market, however, refers to the market for those financial instruments that are commonly and readily transferable by sale. The securities market has two inter-dependent and inseparable segments they are, new issues

[2] Drake, P.J; Money, Finance and Development, Martin Robertson, Oxford, 1980.
[3] Douglall, He and Jace E. Gaumnitz; Capital Markets and Institutions, Prentice Hall, New Jersey, 1986.

(primary) market and the stock (secondary) market. The primary market provides the channel for sale of new securities, while the secondary market deals in securities previously issued. The issuer of securities sells the securities in the primary market to raise funds for investment and to discharge some obligation. The secondary market enables those who hold securities to adjust their holdings in response to changes in their assessment and risk and return. They also sell securities for cash to meet their liquidity needs. The price signals, which subsume all information about the issuer and his business including, associated risk generated in the secondary market, help the primary market in allocation of funds. This secondary market has further two components.

1. The spot market where securities are traded for immediate delivery and payment, the other is futures market where the securities are traded for future delivery and payment.
2. Another variant is the options market where securities are traded for conditional future delivery. Generally, two types of options are traded in the options market. A put option permits the owner to sell a security to the writer of the option at a pre-determined price before a certain date, while a call option permits the buyer to purchase a security from the writer of the option at a particular price before a certain date.

The market for derivatives has grown rapidly during the past decade owing to the broad range of applications for these derivative products and their wide acceptance by financial and non-financial firms. Financial derivatives are contracts that derive their value from an underlying asset or index. They are broadly grouped into currency derivatives, equity derivatives, commodity derivatives and interest derivatives.

Nowadays all firms are facing numerous kinds of risk in their normal course of business activities. Along with this, the development of economic globalization has led the society to what is called as a 'risky environment' by unfavorable external and internal disequilibrium. Due to the increased effects of globalization, economies are invariably exposed to global market factors and are volatile and sensitive to rising level of complexity of risks and changing conditions. Hence risk has become universal. However, to word of the ill effect of wide fluctuation and risk various financial innovations have taken place at all times. Derivatives are the most important among them, off late the uses of derivatives have become very predominant because of increased globalization and financial integration causing unpredictable variables and fluctuations. To mitigate the effects of these fundamental risks, firms are using financial derivatives. Employing the right strategy is only half the battle won; companies need to constantly monitor and assess the effectiveness of the hedging tools employed and ensure from time to time that they are in synchronized with the exposed risk.

With continuous innovation of financial instruments, rapid expansion of financial assets, terrorist attacks, corporate and risk management failures, risk management is a forefront topic in management today. Cutting across all functional areas, they occupy the top of the priority list of the management. The recent financial crises has proved this fact, and proved that the deterioration in the financial system has the potential to plunge the overall economy into a crisis despite the solid macroeconomic base of an economy. Financial risk is negligible and create excessive financial losses that are either endogenous which is under management's control or exogenous over which there is little or no control.

Financial risk management deals with financial risks arising from either macro economic factors like a catastrophe or terrorist attack etc., or from micro economic factors like exchange rate, interest rate, stock prices, commodity prices etc. Though derivative instruments provide benefits they come with certain risks as well. The specific risks arising out of usage of a particular derivative transaction largely depends on the terms of the transaction, financial condition, time frame of the contract, adversities in the macro and micro environment, and circumstances of the parties involved in the transaction.

Need of the Study

Derivative market as a counterpart of security market has been accepted worldwide. Even the developing countries have realized the importance of derivatives market. Despite the growing importance of derivative market over the past decades in depth study in derivative market are very few which can throw light on various relationship and on its inherent characteristics etc. Though studies are plenty in stock market, very few studies have been done on derivatives at national and international level. Even within the available researchers at the international level also the studies are mostly confined to U.S and Australia, and there is very little evidence of the existing literature in South Asia. Those few studies also do not throw much light on the in depth understanding of the derivative market characteristics as the results of consensus.

The impact of derivative market on the spot market in terms of market volatility, price changes etc also need careful and consorted analysis. Financial sector reforms, impact of technology, liberalization policy of the government, trend of globalization, etc., are the contributors to the development of derivative markets. Derivatives markets have been outstandingly successful due to reduction of funding costs by borrowers, enhancing the yield on assets, modifying the payment structure of assets. However, the policymakers, practitioners and regulators in these markets are concerned about the impact of derivatives market. One of the reasons for this concern is the belief that derivative trading may attract speculators who then destabilize spot prices. In the flipside, the presence of derivative market helps the speculators to take advantage of booking profit by entering in both the markets and their active presence may also bring a destabilizing effect in the stock market. It is believed that the speculators take advantage of earning profit when the volatility of share increases and as the volatility decreases the investors start investing in the stock market to make profit. The above diversified theoretical arguments create phenomenon of stock return and trading volume an important field for study.

The structural changes on the capital market more specifically stock market kindled by the financial reforms has brought the derivative market to a comparable global standard. The introduction of derivative market also was another step in furthering the capital market's development at par with developed market. In the present scenario, there is a need for in depth study of derivatives market and its link with the underlying security market and the price discovery process and forecasting the market volatility. The relationship between the settlement prices, trading volume, open interest and volatility etc, modeling and forecasting volatility for stock futures contract still remains the muddy water in the context of changing scenario and the behaviour of market players etc.

Statement of Problem

The fluctuations in futures markets has its root with the underlying spot market volatility, trading activity etc which are not only explained by publicly available information but also by non information like trade due to certain events, short selling and insider trading etc. These factors are considered to be the important information which influences both future prices and price fluctuations in futures market. Price movements, trading volumes and open interest can be jointly considered as aggregate market information and the volatility measures derived from high-frequency data may prove to be more information, and may help in better forecast. Since, most existing studies have focused on the relationship between market returns and trading activity variables, and only limited studies are available in the U.S and Australian futures markets in terms of examining open interest, this study tries to bring all the three variables together to study the inherent character of derivative market in India.

To understand market dynamics an accurate forecast is important to both practitioners and academicians. Modelling and forecasting volatility in stock futures contracts is one of the important areas in the finance literature. But existing literature reveals that most studies have focused on stock index futures and petroleum futures in the U.S markets. In India, no attempt has been made towards forecasting the volatility and its dynamics for stock futures contracts. Against this backdrop, it is worthwhile to study the relationship between the multivariate series and to identify the suitable model to forecast volatility for select stock futures contracts in India. The complexities of relationship between the variables, and difficulty in forecasting the volatility are still grey in derivatives market study. Hence the research has been made by the researcher to make an in-depth study.

Objectives of the Study

1. To study the conceptual framework of derivatives and development of derivatives market in India.
2. To assess the dynamic relationship between price volatility, trading volume and market depth for select stock futures contracts in India.
3. To identify the suitable model to forecast volatility for stock futures contracts in India.
4. Finally, to summarize the findings and provide suggestions for the policy makers, academicians and research community.

Hypothesis

In an attempt to study the price volatility, trading volume and market depth in Indian futures market and to identify a suitable model for forecasting volatility the following hypothesis are set;

1. Information arrival is simultaneous for all investors.

2. There is a positive contemporaneous relationship between futures returns and trading volume.

3. Volatility of stock futures contracts can be forecasted by linear models.

4. A non linear forecasting model can better forecast the volatility.

Research gap in the existing Studies

The study has been developed on the background of earlier studies attempted in this area. In empirical finance literature, there are many empirical papers that provide indirect evidence on the relationship between trading volume and stock returns. Clark (1973) examined Mixture of Distributions Hypothesis which plays a prominent role in the empirical finance arena. As suggested by Morgan (1976) volume is regarded as a major risk factor contributing to the volatility of returns, particularly in less liquid and thin markets including emerging markets. In the mixture model of Epps and Epps (1976), trading volume is used to measure disagreement among traders, as investors revise their reservation prices based on the arrival of new information to the market. Similarly, positive contemporaneous relationship between variance of price change and trading volume was linked by Ragalski (1978), Figlewski and Cornell (1981) who studied the basic relationship between the variables. Tauchen and Pitts (1983), and Lastrapes and Lamoureux (1990) alleges that the conditional heteroskedasticity in stock returns can be explained by a serially correlated mixing variable that measures the rate at which information is transmitted to the market. These authors have shown that the information arrivals stemming from the existence of exogenous variables which can be identified by the mixture of distributions, and these variables exhibit time-varying ARCH effect.

There is quite a strong body of literature advocating the use of the GARCH family of models to test the relationship between these variables. Lamoureux and Lastrapes (1990) examined the presence of ARCH/GARCH based on the hypothesis that daily returns are generated by a mixture of distributions, using trading volume as a proxy for the rate of daily information arrival. They found that volatility persistence vanishes under the presence of trading volume series in the conditional variance equation. Brailsford (1996) found that the direction in price change was significant across three measures of daily trading volume for the aggregate market and was significant for individual stocks. An overwhelming number of studies have examined both theoretical and empirical relationship between future return, trading volume and open interest. Bessembinder and Seguin (1993) investigated the relations between volume, volatility, and market depth in eight physical and financial futures markets and suggested that unexpected volume shocks have a larger effect on volatility, the role of open interest provides information to mitigate volatility and he suggested that the volatility-volume relation in financial markets depends on the type of trader. A large number of studies have been conducted at international level to test the relationship between futures return, trading volume and open interest contacts, whereas in India the empirical works are quite limited. Pati & Kumar (2006) tested the maturity, volume effects and volatility dynamics for Indian futures market and suggested that time-to-maturity is not a strong determinant for futures price volatility, but rate of information arrival proxies by volume and open interest are the important sources of volatility. Finally, they concluded that Samuelson Hypothesis does not provide support for Indian futures market so the investors should not base their investment decision on time-to-maturity. Hence, the current study attempts to shed light on the existing literature and to examine the relationship between future return, trading volume and market depth for stock futures contracts in India.

As far as modelling and forecasting is concerned, there exist a strand of literature focusing on the modelling and forecasting of equity markets by Akgiray (1989), Dimson and Marsh (1990), Pagan and Schwert (1990), Bollerslev et.al (1992), Francis and Van Dijk (1996), Brailsford and Faff (1996), McMillan, Speight and Gwilym (2000) and Brooks and Persand (2002). The observations of these studies are; First, large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility clustering is observed in financial returns data. Secondly, financial time series data often exhibit leptokurtosis, which indicate that the return distribution is fat-tailed as observed by Mandelbrot (1963), Fama (1965), Laurent and Peters (2002). Finally, changes in stock prices tend to be negatively related to changes in stock volatility which is identified to be “leverage effect” Black (1976), Christie (1982), Nelson (1991), Koutmas and Saidi (1995).

In light of the importance of volatility in financial markets, a seminal contribution to the study of stock market volatility was of Schwert (1989). He sought to establish which economic variables are highly correlated with volatility in returns, and found little evidence that volatility in economic fundamentals had a discernible influence on stock market returns. Another study by Lamoureux and Lastrapes (1990) assumed that volatility was influenced both by past forecast errors (GARCH) and by the volume of trading, where volume was interpreted as measuring the arrival of new information. He conjectured that, in general, GARCH effects in earlier studies were really measuring the persistence in the arrival of new information. To capture the above uniqueness, ARCH class of models were introduced by Engle (1982) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) by Bollerslev (1986) and Taylor (1986). Financial economists have long known that the daily range of the log price series contains extra information about the course of volatility over the day. Despite the elegant theory and the support of simulation results, the price range as a proxy of volatility has performed poorly in empirical studies. Therefore, the GARCH type of models are the most-adopted ones for modeling the time-varying conditional volatility, as they considers time varying variance as a function of lagged squared residuals and lagged conditional variance.

There exists quite a number of research work done on modelling and forecasting volatility at international level, however only a limited attempt has been made the Indian stock market in this direction. Varma (1999) examined the volatility estimation models comparing GARCH and EWMA models in the risk management setting. Pandey (2002) analyzed the extreme value estimators and found the performance with Parkinson estimator for forecasting volatility over these horizons. Karmakar (2005) has estimated that the movement in stock returns volatility is not explained by the fundamental economic factors, but reported the presence of 'fade' due to the actions of noise traders, liberalizing policies and procedures of the government. Kumar (2006) examined the comparative performance of volatility forecasting models in Indian markets and the results were found contrary to Brailsford and Faff (1996). Still, further research is needed to forecast the volatility of futures market for an in-depth understanding about the behavioural characteristics of Indian capital markets, and to fill the gap in the existing literature.

Data and Model Specification adopted for the Study

The study is purely based on the secondary data drawn from the website of NSE, India. The sample of data used in this exercise, spanned over the period from January 2003 to December 2008. During the sample period, the futures securities trade from 9:55 A.M to 3:30 P.M. All the required information for the stock futures contracts trade on the National Stock Exchange (NSE) and contract specifications and trading details were retrieved from their website (www.nseindia.com). Usually three types of contracts are traded simultaneously in the futures markets (i.e.) near month, middle month and far month futures contracts. Near month futures contracts are considered for the analysis, because most trading activities take place in the near month contracts than on the other two types of contracts. The data were analyzed by using the econometric software package Eviews. The purpose of the study is broken into two major sections;

1. First, to measure the dynamic relationship between price volatility, trading volume and market depth. For such measurement and analysis daily settlement prices, trading volume and open interest series were used by adopting the base model by Bessembinder and Seguin (1993) with modification of Mahmood and Salleh (2006). An adjusted continuously compounded return was calculated as $R_t = \ln(P_t/P_{t-1})$ where P_t and P_{t-1} are natural logarithms of adjusted return on day t and t-1 respectively. The logarithm of the price relative was used to calculate the price change. It is understood that the use of logarithmic price changes prevents non-stationarity of the price level of the data being affected by the future price variability.

2. Second, modeling and forecasting stock futures market volatility was attempted by using various statistical and econometrical models, for this methodology developed by Najand (2002) and Sadorsky (2006) was adopted in the futures market return series. The daily volatility of stock futures returns were estimated by the model developed by Schwert (1990) and Schwert and Seguin (1990).

Sampling Design of the Study

To examine the dynamic relationship between price changes, trading volume and market depth process and to attempt modeling and forecasting volatility of stock futures returns, 237 stock futures contract was process till 31st December 2008. Out of 237 stock futures, 25 stock futures contracts were selected. The dataset drawn over the period from January 2003 to December 2008 were considered for analysis. In this process, the study Sequential sampling method and in the process following companies become the representative sample for detailed analysis.

	Company Name	**Symbols**
1.	Associated Cement Co. Limited	ACC
2.	Bharat Electronics Limited	BEL
3.	Bharat Heavy Electricals Limited	BHEL
4.	Bharat Petroleum Corporation Limited	BPCL

5.	Cipla Limited	CIPLA
6.	Dr. Reddy's Laboratoires Limited	DRREDDY
7.	Grasim Industries Limited	GRASIM
8.	HCL Technologies Limited	HCLTECH
9.	Housing Development Finance Corporation Ltd.	HDFC
10.	Hero Honda Motors Limited	HEROHONDA
11.	Hindustan Petroleum Corporation Limited	HINDPETRO
12.	ICICI Bank Limited	ICICIBANK
13.	Infosys Technologies Limited	INFOSYSTCH
14.	ITC Limited	ITC
15.	Mahindra & Mahindra Limited	M&M
16.	Mahanagar Telephone Nigam Limited	MTNL
17.	National Aluminium Co. Ltd	NATIONALUM
18.	Oil & Natural Gas Corp. Limited	ONGC
19.	Polaris Software Lab Limited	POLARIS
20.	Ranbaxy Laboratoires	RANBAXY
21.	Reliance Industries Limited	RELIANCE
22.	State Bank of India	SBIN
23.	Tata Power Co. Limited	TATAPOWER
24.	Tata Tea Limited	TATATEA
25.	Wipro Limited	WIPRO

Limitation of the Study

Since this study is based upon the secondary data, all the limitations inherent to the secondary data are applicable to this study. In this research work, our special focus was to examine the relationship, modelling and forecasting volatility for select stock futures contracts in India. The overall structural patterns, volatility behaviour and persistence of information for stock futures contracts are alone considered for the period. The other key determining factors like Inflation Rates, Industrial Production Index (IIP), Gross Domestic Product (GDP), Exchange Rate etc. were not taken into account. The micro structure aspects of stock futures contracts returns have not been attempted. The thesis work is limited to the period from January 2003 to December 2008 and is based on daily data. In spite of these limitations, it is hoped that the findings will be instrumental to identify the state and representation of the derivative market in India.

Organization of Study

The study is divided into six chapters. Chapter - 1 presents the chronicle introduction of derivative markets, importance of study, Data and Methodology of the study, Need for the study, Statement of the problem, and Limitation to the study. Brief review of antecedent literature is presented in Chapter - 2. Chapter - 3 discusses the conceptual framework of derivatives and the development of derivatives market. Mechanisms of futures trading include its structure, types of products, functions, memberships, economic and social roles of futures markets and most fundamental factors that influence stock indexes. Chapter - 4 incorporates the dynamic relationship between price volatility, trading volume and market depth. Chapter - 5 examines strength of modelling and forecasting volatility for stock futures contracts through Linear and Non-linear models. Finally, summary, concluding remarks and recommendations for future studies are presented in Chapter - 6.

CHAPTER - II

REVIEW OF LITERATURE

Out of many liberalization policies and structural changes implemented by the government of India one of the most noteworthy was introduction of derivatives in Indian securities markets. Derivatives are believed to be very important to the stock market as well as for the economy of a country in terms of its risk management capability. The arrival of this new financial product in the securities markets has treated renewed interest in the academicians, researchers and practitioners to learn more about derivatives and derivatives markets, its operations and implications. Thus the empirical works on derivatives market has grown manifold in recent years at national and international level.

This empirical research work adds to the growing literature on existing research by examining the relationship between price volatility, trading volume and market depth for futures markets, and forecasting the symmetric and asymmetric behaviour of futures market. As a prelude the literatures that considered the characteristics of return and volume relationship without specific reference to the open interest as proxy variables for calculating market depth are reviewed. While the reference of open interest is often mentioned briefly in most futures textbooks, relatively little research has considered this specific relationship between price volatility, trading volume and market depth for futures markets. The present research focused on relationship and modeling volatility is expected to be helpful to test the market efficiency, market setting, anomalies in investor behavior and its applicability for the futures markets. An exhaustive literature review has been carried to identify the gap. For the sake of clarity and simplicity all the studies reviewed have been categorized the relationship studies and forecasting and modeling studies.

1. *Relationship between Futures Returns, Trading Volume and Market Depth Variables:*

Thomas Epps and Mary Lee Epps (1976)[1] have investigated the financial markets based upon two-parameter portfolio model to identify the stochastic dependence between transaction volume and changes in security price from one transaction to next. The change price can be viewed as mixture of distributions with transaction volume as the mixing variable. In common stocks, these distributions appear to be pronounced in the excess of frequency near the mean and a deficiency in outliers, relative to the normal. Finally, the findings are consistent with the hypothesis that stock price changes over fixed intervals of time follow mixtures of finite variance distributions.

Richard Rogalski (1978)[2] examined whether security prices and volume are causally related. The existing models that attempt to analyze the interdependence of price and volume in speculative markets are dependent. Significant cross correlations were observed at zero lag using a 5% significance level. The results suggest that the knowledge of behavior of volume may marginally improve conditional price forecasts over price forecasts based on past prices alone. A shortcoming of the methodology is that one cannot distinguish between contemporaneous feedback and unidirectional causality for which there is no lag effect. In other words, sample cross correlations that are non-zero primarily at lag zero are consistent with three types of causality: volume causes price change, price change causes volume, and feedback between price change and volume. All three cases are indicative of dependence as revealed by this study. Finally, the results of this study have not established that speculative markets are operating inefficiently. This would require correlation between current price change and lagged volume. No such dependence has been found in this study. Thus, even if volume series could be predicted from past volume values by an appropriate ARMA model, such predictions would contain no information relevant to the expected value of price change. Such predictions would be useful, however, in forecasting the variance of price change.

Figlewski (1981)[3] has analyzed the impact of futures trading in Government National Mortgage Association (GNMA) on price volatility in the cash market. The objective of this study was to examine price volatility, the standard deviation of day to day price changes. The empirical evidence showed that price volatility in the GNMA cash market was related to several factors like increased volatility, measured by GNMA's outstanding and proxies for the volume of cash market activity, and lower average prices tended to stabilize the market, while futures market activity increased the volatility of prices. Several possible reasons for this result were discussed; however there were no evidence of insufficient speculative activity in futures relating to hedging, and price manipulation because of the extensive safeguards against it. The futures prices are believed to be determined largely by the actions of inexperienced new class of traders who were likely to have less information than the GNMA securities and set prices in the cash market. When the additional "noise" in futures prices is transmitted to the cash market, price volatility increases. Finally, the effect is expected to diminish as they become more seasoned and broaden the population of GNMA.

Tauchen George and Pitts Mark (1983)[4] studied the relationship between the variability of daily price change and the daily volume of trading on speculative markets for the period from 6th January to 30th June 1979. The work extends the theory of speculative markets in two ways. First, the joint probability distribution of the price change was derived along with trading volume over any interval of time within the trading day. And secondly, the paper tried to determine how joint distribution changes as more traders enter (or exit from) the market. The results of the estimation found reconciling the conflict between the price variability-volume relationship for the market and the relationship obtained by previous investigators for other speculative markets.

Grammatikos and Saunders (1986)[5] examined the contemporaneous and sequential relation between price variability and trading volume in futures markets using disaggregated data and improved measures of price variability. The sample consisted of daily observations for five different foreign currency futures traded on the International Monetary Market (IMM): the German mark, the Swiss franc, the British pound, the Canadian dollar, and the Japanese yen over the period March 1978-March 1983. They employed both classical and Garman-Klass estimators of price volatility, to test whether there exist positive contemporaneous correlations between trading volume and price volatility. The results appeared to be consistent with the MDH and inferences were drawn as maturity is not a suitable surrogate for the common directing variable. Specifically, while maturity has a strong effect on volume, no such relation is found for price variability. Finally, consistent with previous work with stock market data it was found that, in majority of the cases price variability and trading volume were contemporaneously correlated, there were a significant number of cases in which a sequential relation between price variability and volume appeared to be present.

Karpoff Jonathan (1987)[6] attempted an empirical and theoretical research into the price-volume relation for 18 financial markets including equities, futures, currencies and Treasury Bills. The theoretical justifications for studying price volume relationship, that were put forth are, the returns or trading volume relation provides insight into the structure of financial markets. Second, the return or trading volume relation is important for event studies that use a combination of stock returns and trading volume data to draw inferences. Third, the returns or trading volume relation is critical to the debate over the empirical distribution of speculative prices. The main conclusion has been the positive correlation between price and volumes exists and is mainly conspicuous with larger volumes.

Bessembinder & Seguin (1992)[7] have examined whether greater futures trading activity is associated with greater equity market volatility for S&P 500 index from January 1978 to September 1989. He evaluated with the help of Pearson Correlation Coefficients, Regression of S&P 500 return standard deviation for spot and future trading using dummy variables. Their findings were consistent with the theories predicting that active futures markets enhance the liquidity and depth of equity markets. They provide additional evidence suggesting that active futures markets are associated with decreased rather than increased volatility. However, the evidence reported here, that equity volatility declines with predictable futures-trading activity, is consistent with the reasoning that the low cost of futures trading attracts additional informed traders, and the equity volatility is reduced in future market.

Douglas Foster and Viswanathan (1993)[8] examined the empirical behavior of stock market trading volume, trading costs, and price change for New York Stock Exchange data from 1988, with the help of Ordinary Least Square Method. The Intraday test results indicate that, for actively traded firms trading volume, adverse selection costs, and return volatility are higher in the first half-hour of the day. This evidence is inconsistent with the Admati and Pfleiderer (1988) model which predicts that trading costs are low when volume and return volatility are high. Intraday test results showed that, for actively traded firms, trading volume is low and adverse selection costs are high on Monday, which is consistent with the predictions of the Foster and Viswanathan (1990) model. The result indicates that existing theoretical models based on the adverse selection faced by the market maker are broadly consistent with observed patterns in the volume-volatility relation. That is, intraday trading volume is high when returns are most volatile.

Bessembinder & Seguin (1993)[9] has examined the relations between volume, volatility, and market depth in eight physical and financial futures markets, employing econometric methods that accommodate volatility persistence, asymmetries in the volume-volatility relation and interactions of conditional return means and conditional return volatilities over the period from May 1982 to March 1990. The evidences suggest that linking volatility to total volume does not extract all information. When volume is partitioned into expected and unexpected components, the paper finds that unexpected volume shocks have a larger effect on volatility. Further, the relation is asymmetric; the impact of positive unexpected volume shocks on volatility is larger than the impact of negative shocks.

Hiemstra and Jones (1994)[10] examined the dynamic relation between daily Dow Jones stock returns, percentage changes in New York Stock Exchange (NYSE) and trading volume by using both linear and nonlinear Granger causality tests. By applying the tests to check daily Dow Jones stock returns and percentage changes in NYSE trading volume over the period from 1915 to 1946 and 1947 to 1990. The modified Baek and Brock test provides evidence of significant bidirectional nonlinear causality between stock returns and trading volume in both sample periods. It also examined whether the nonlinear causality from volume to stock returns detected by the modified Baek and Brock test could be due to volume serving as a proxy for daily information flow in the stochastic process generating stock return variance. After controlling for simple volatility effects, the modified Baek and Brock test continued to provide evidence of significant nonlinear Granger causality from trading volume to stock returns. However, nonlinear theoretical mechanisms and empirical regularities could have been considered when devising and evaluating models for the joint dynamics of stock prices and trading volume.

Brailsford Timothy (1994)[11] has empirically analyzed the relationship between trading volume and stock return volatility in the Australian market with the period from 24th April 1989 to 31st December 1993. Trading volume was then examined in the context of conditional volatility using a GARCH framework. He tested both the asymmetric model and the mixture of distributions hypothesis in relation to the Australian market. The results indicate strong support for the asymmetric model. Furthermore, the results were also found consistent with Lamoureux and Lastrapes [1990] and showed that ARCH effects are diminished and persistence in variance is reduced when trading volume is incorporated as an explanatory variable in the general ARCH model. These results have implications for inferring return behaviour from trading volume data. Hence, there is evidence that if trading volume proxies for the rate of information arrival, then ARCH effects and much of the persistence in variance can be explained.

Andersen (1996)[12] demonstrated the return volatility-trading volume relationship by integrating the market microstructure framework in which informational asymmetries and liquidity needs motivate trade in response to information arrivals. A continuously compounded daily return series, corrected for dividends and stock splits, is constructed from closing prices on IBM common stock over January 1, 1973 to December 31, 1991 with a sample of 4693 observations. The resulting system modified the so-called "Mixture of Distribution Hypothesis" (MDH). The dynamic features were governed by the information flow, modeled as a stochastic volatility process, and generalize standard ARCH specifications. Specification tests support the modified MDH representation and show that it vastly outperforms the standard MDH. Finally, our findings suggest model may be useful for analysis of the economic factors behind the observed volatility clustering in returns.

Ragunathan & Peker (1997)[14] investigated the nature of the relationship between volume, price variability and market depth for four futures contracts traded on the Sydney Futures Exchange and is based on the methodology developed by Bessembinder and Seguin (1992, 1993) between January 1992 to December 1994. He tested the asymmetries in volume and open interest shocks by separating volume and open interest into expected and unexpected variables, this study envisaged the asymmetric relationship between volume, open interest and volatility, and tried to investigate whether unexpected volume and open interest had a positive or negative shock. The results lead to the conclusion that positive volume shocks have a greater impact on volatility than negative shocks. The same conclusion is arrived at when open interest shocks are analyzed, that is, a positive open interest shock is more likely to have an impact on volatility than a negative shock. Therefore, it can be concluded that market depth does have an effect on volatility.

Galloway and Miller (1997)[15] explored the relation between index futures trading and volatility in equity market using the S&P MidCap 400 stock index and MidCap 400 index futures. Daily return and trading volume data were obtained for 398 stocks from the CRSP database for three separate periods. The first i.e. pre-index period includes 250 trading days before June 5, 1991. This period precedes both the existence of MidCap index and the trading of MidCap futures. The second, or interim, period includes 175 trading days after June 5, 1991 till February 13, 1992. The study documents a significant decrease in return volatility and systematic risk, and a significant increase in trading volume for the MidCap 400 stocks after the introduction of MidCap index. A control sample of medium-capitalization stocks, however, exhibits similar contemporaneous changes in these measures. The MidCap stocks and control stocks also experienced a significant decrease in volatility and an increase in volume after the introduction of MidCap 400 index futures. Consequently, the study confirms that there is no significant relationship between futures trading and volatility in the stock market. Finally, a new puzzle emerged concerning why there are market-wide changes in risk and liquidity. Prior studies document that aggregate stock market volatility varies over time and the variation is related to a variety of economic variables.

Jacobs and Onochie (1998)[16] revealed that there is a positive relationship between trading volume and price volatility, by measuring the price changes in conditional heteroskedasticity in international financial futures markets by applying bivariate GARCH(1,1). The underlying products are interest rate assets representing investments in various international money and bond markets of Sterling, Eurodollar, U.S. Treasury bond, German Government bond (Bund), 3-month European Currency Unit (ECU), and the Euromark. The result suggest that there is a strong evidence of second-order dependence in the joint return and trading volume process for various international financial futures markets and the level of trading volume positively influences the conditional variance of futures price change. It also inferred that the issue of time varying volatility is of importance to option pricing. The implication of these findings that futures price changes and volume are not only jointly distributed, but also influences price volatility, can guide theorists and practitioners alike in rethinking the pricing relationships for financial futures.

Gong-meng Chen, Michael Firth and Oliver Rui (2001)[17] examined the dynamic relationship between returns, volume, and volatility for major nine national stock indexes for the period from 1973 to 2000. They evaluated with the help of quadratic time trend method, Augmented Dickey Fuller test, Regression the daily trading volume on stock returns and absolute returns, Vector Auto regression (VAR) and EGARCH techniques were used to examine the returns, trading volume, conditional volatility relation. The results show a positive correlation between trading volume and absolute value of stock price change. Granger Causality tests demonstrated that for some countries, returns cause volume and volume causes returns. The findings indicate that trading volume contributes some information to the returns process and more can be learned about the stock market through studying the joint dynamics of stock prices and trading volume than by focusing only on the univariate dynamics of stock prices. The results of the study were found robust across all nine major stock markets, implying that there are similar returns, trading volume, and volatility patterns across all markets under study.

Toshiaki Watanabe (2001)[18] examined the relation between price volatility, trading volume and open interest for Nikkei 225 stock index futures traded on the Osaka Securities Exchange (OSE) by employing the method developed by Bessembinder and Seguin (1993) for the sample period extended from 24th August 1990 to 30th December 1997. The reason for investigating the Nikkei 225 futures traded on the OSE was that the OSE changed regulation such as margin requirements, price range and time interval in updating quotation several times. The authors felt interesting to examine whether changes in regulation may influence the effects of volume on volatility. Therefore, the samples prior to and beginning 14 February 1994 were analyzed separately. However, no relation between price volatility, volume and open interest was found for the period prior to 14 February 1994, when the regulation increased gradually. This result provides evidence that the relation between price volatility, volume and open interest may vary with the regulation.

Bhanupant (2001)[19] investigated the dynamic relationship between stock index returns and trading volume using the Augmented Dickey-Fuller (ADF), Linear and Non-Linear Granger Causality hypothesis test on the National Stock Exchange (NSE) data 1 January 1996 to 6 August 2002 with a total of 1649 data points. Linear Granger Causality test was used to investigate the linear relationship while the Non-Linear Granger causality was investigated using modified Baek and Brock test proposed by Hiemstra and Jones (1994) for the daily returns on S&P CNX Nifty and the total trading volume at NSE. Bidirectional linear Granger causality between index returns and volume change was observed for the period when rolling settlement was either not introduced or partially introduced. The period, when rolling settlement was introduced, there found no evidence of linear causality in either direction. The shift in linear causal relationship indicates that efficiency at NSE has improved with introduction of rolling settlement mechanism. Nonlinear Granger causality between the returns and volume change was not evident in either direction.

Otavio Medeiros & Bernardus Van Doornik (2006)[20] investigated the empirical relationship between stock returns, return volatility and trading volume for Brazilian stock market covering a period 1st March 2000 to 29th December

2005. The empirical methods used include cross-correlation analysis, unit-root tests, bivariate simultaneous equations regression analysis, GARCH modeling, VAR modeling, and Granger causality tests. Their evidence suggests that there was a significant relationship between stock returns and trading volume, which is detected in the cross-correlation analysis. Additionally, by applying Granger-causality, the results showed no signs of causality between trading volume and stock returns. However, a simultaneous equation analysis showed that stock returns depend on trading volume, but it does not apply the other way. This result contributes to the understanding of the microstructure of emerging stock markets.

Pati & Kumar (2006)[21] attempted to examine the maturity and volume effects on the volatility dynamics for futures price in Indian Futures Market for the period from January 1, 2002 to December 29, 2005 for near month contract with 1009 sample data points. For empirical analysis they used ARMA-GARCH, ARMA-EGARCH models. The empirical evidence suggests that there is time-varying volatility, volatility clustering and leverage effect in Indian futures market. With respect to volume-volatility relationship, the results suppressed the Mixtures of Distribution Hypothesis. This study concluded that time-to-maturity is not a strong determinant of futures price volatility, but rate of information arrival proxied by volume and open interest are the important sources of volatility. This relationship has important implications for the new futures contracts. This study does not provide support for the Samuelson Hypothesis in

Indian futures market, which is found to be informational efficient. The finding of this study had a message for investors, market regulator-market surveillance that risk management practices should be further strengthened to take care of greater market volatility associated with an increased volume of trading. Finally, the result suggests maturity effect does not hold in Indian futures markets, the investors should not base their investment decision on time-to-maturity.

Mahmood & Salleh (2006)[22] examined the relationship between return, trading volume and market depth for two futures contracts, namely Stock Index Futures and Crude Oil Futures traded at the Kaula Lumpur Option and Financial Futures and Commodity and Monetary Exchange for the period from 15th December 1995 to 19th January 2001. They tested with the two famous hypothesis one, whether the sequential arrival of new information to the market move both the trading volume as well as price. The second one is about the mixture of distribution hypothesis where information may be considered as mixing variable. They used the diagnostic tests like Unit root Test, Ljung-Box Test and ARIMA (10,1 ,0) and evaluated with the help of GARCH (1,1). The effects of volume as well as open interest, proxy of market depth, on volatility and vice versa were also studied. Since both volume and open interest were found highly serially correlated, these variables were divided into expected and unexpected components. Finally, the results showed a positive expected and unexpected volume and market depth effect on volatility.

Eric Girard & Rita Biswas (2007)[23] surveyed the relationship between volatility and volume in 22 developed markets by using 27 emerging markets for the period from January 1985 to June 2005. In this study the empirical analysis were carried out by applying TGARCH model specification for explaining the daily time dependence with the rate of information arrival to the market for all stocks traded in frontier market exchange. Thus, using volume as a proxy for the flow of information, TARCH was found to be an appropriate model to mimic the conditionality of second moments. Compared to developed markets, emerging markets showed a greater response to large information shocks and exhibited greater sensitivity to unexpected volume. Both of these findings evidenced the presence of noise trading and speculative bubbles in emerging markets. Their results suggest that negative relation was found between expected volume and volatility in several emerging markets, which can be attributed to the speculative trading activity which drives bid-ask spreads higher, and diminishes the relative inefficiency in those markets. The findings showed that official price reporting mechanisms and insider trading laws are also relatively weaker in these countries; a change in local policies to design better systems is warranted if foreign investors are to be attracted to these markets.

Christos Floros & Dimitrios Vougas (2007)[24] examined the contemporaneous relationship between trading volumes and returns in Greek stock index futures contracts in the Athens Derivatives Exchange (ADEX) for the period September 1999 to August 2001. They utilized the tools like Generalized Method Moments (GMM), Unit root test and GARCH effect. The study suggested that GARCH effects were explained by trading volume under both GARCH and GMM. For FTSE/ASE-20, trading volume contributes significantly in explaining GARCH effects. However, the estimated results of GMM suggested that there is a significant relationship between lagged volume and absolute returns, while a positive contemporaneous relationship does not hold good. Their findings indicate that market participants use volume as indicators of prices, but for FTSE/ASE Mid 40, the empirical results give different conclusions. Both GARCH and GMM methods confirm that there is no evidence of positive relationship between trading volume and returns.

Malabika & Srinivasan (2008)[25] analyzed the empirical relationship between stock return, trading volume and volatility for select Asia-Pacific Stock Market by applying preliminary test, Granger Causality test and EGARCH (1,1) model. The data set comprises of seven national stock markets for the period spanning from 1st January 2004 to 31st March 2008. The results evidenced a significant relationship between trading volume and the absolute value of price changes. Granger Causality test was used to explore, whether return causes volume or volume causes return. The results suggested that the returns were influenced by volume and volume also was influenced by returns for most of the markets.

Therefore, trading volume contributes some information to the return and volatility for determining contemporaneous and lagged volume effect after incorporation. The empirical results were found robust across the national markets during the study period.

Mahajan and Singh (2008)[26] suggested the pattern of information flow between trading volume and return volatility using daily data for Nifty index during the period from July 2001 to March 2006. The methods used included Correlation analysis, Unit root tests, VAR modeling, Granger causality test, GARCH (1,1) and EGARCH model. The study provided evidence of low but significant positive contemporaneous relationship between volume and return volatility that was indicative of both mixture of distribution and sequential arrival hypothesis. The differential cost of taking long and short positions were examined by applying asymmetric EGARCH (1,1) model to check the relationship between the variables. The study further confirmed a weak unidirectional causality from volume to return volatility, which also indicates the mild support for sequential information flow directed from volume to price change. The study contributes to the enhance understanding of researchers, regulators, speculators, and other participants in market on market efficiency and information processing.

2. Modelling and Forecasting Futures Market Volatility:

Franses and Van Dijk (1996)[27] compared the volatility forecasting performance of GARCH model, Quadratic GARCH model and Threshold GARCH models against Random Walk model using weekly dataset for German, Dutch, Italian, Spanish and Swedish stock index returns over the period from 1986 to 1994. They report that the random walk model performs particularly well when the crash of 1987 was included in the estimated sample, while the QGARCH model can significantly improved the linear GARCH model and found no significant change in forecasting.

McMillan, Speight and Apgwilym (2000)[28] analyzed and compared the volatility forecasting performance by using GARCH models, asymmetric TGARCH and exponential GARCH models for the Financial Times-Stock Exchange (FTSE 100) index and Financial Times Actuaries All Share index at the London Stock Exchange. The dataset are partitioned into in-sample and out-sample estimation periods from 2 January 1984 to 31 July 1996 for the FTSE100 index and 1 January 1969 to 31 July 1996 for the FTA All Share index data, the out-of-sample forecast periods covering the remaining period from 1995 to 1996 for both data sources. A total of ten volatility forecasting models are considered, including the historical mean, moving average, random walk, exponential smoothing, exponentially weighted moving average, simple regression, GARCH, TGARCH, EGARCH, and CGARCH models. The forecasting performed for monthly, weekly and daily data frequencies under symmetric and asymmetric loss functions. The results suggest that the random walk model provides superior monthly volatility forecasts, while random walk, moving average, and recursive smoothing models provide moderately superior weekly volatility forecasts, and GARCH, moving average and exponential smoothing models provide marginally superior daily volatility forecasts. If attention is restricted to one forecasting method for all frequencies, the most consistent forecasting performance is provided by moving average and GARCH models. More generally, their results suggested that GARCH class models provide relatively poor volatility forecasts.

Najand Mohammad (2002)[29] examined the relative ability of various models to forecast daily stock index futures volatility for S&P 500 futures index between January 1983 and December 1996 with a continuous sequence of 3561 observations are gathered over fourteen year period. He estimated the models using 3500 and 3380 observations and saving the last 60 and 180 observations for out-of-sample forecasting comparisons between models. The linear and non linear models employed for the study are Random Walk, AR model, MA model, Single Exponential Smoothing models, Double (Holt) Exponential Smoothing models, GARCH - M, EGARCH and ESTAR models. Their findings suggest autoregressive (AR) model is a more appropriate model under RMSE and MAPE criteria. In non linear model, GARCH and ESTAR model fitting were more appropriate than linear models by using RMSE and MAPE error statistics. Finally, EGARCH appeard to be the best model for forecasting stock index futures price volatility.

Yu Jun (2002)[30] explored the volatility forecasting performance for New Zealand Stock Exchange 40 index for the sample period consists of 4741 daily returns over the period from 1 January 1980 to 31 December 1998. The competing modes contain both simple models such as the Random Walk, Historical average, Moving Average, Simple Regression, Exponential smoothing, Exponentially-weighted moving average (EWMA) and complex models such as ARCH, GARCH, SV model. Four different measures were used to evaluate the forecasting accuracy, namely, the root mean square error (RMSE), the mean absolute error (MAE), the Theil-U statistic and the LINEX loss function. The main results are the following: (1) the stochastic volatility model provides the best performance among all the models; (2) ARCH-type models can perform well or badly depending on the dataset chosen for the study. (3) The regression and exponentially weighted moving average models do not perform well according to any assessment measure, in contrast to the results found in various markets. Moreover, all the models examined in this paper belong to the univariate time series family and multivariate models should be kept into consideration to forecast volatility. However, he finds that the added information cannot improve the out-of sample forecasting performance and there are some other variables that are useful to forecast volatility, such as inflation rates or numbers of listed companies.

Pandey Ajay (2002)[31] reported the empirical performance of various unconditional volatility estimators and conditional volatility models by using S&P CNX Nifty, India. The dataset on S&P CNX Nifty for the period 1st January 1996 to 31st December 2001 were considered by using different class of models. In order to test the ability of models estimated to forecast volatility, he compared the unconditional estimators with the realized volatility measure. For conditional volatility models, the forecasts for the same periods are obtained by estimating models from the time-series prior to the forecast period. The results indicate, that the conditional volatility models provide less biased estimates, extreme-value estimators are more efficient estimators of realized volatility. As far as forecasting ability of models is concerned, conditional volatility models fare extremely poorly in forecasting five-day (weekly) or monthly realized volatility. In contrast, extreme value estimators, other than the Parkinson estimator, perform relatively well in forecasting volatility over these horizons.

Caiado Jorge (2004)[32] investigated the volatility forecast for daily and weekly data for Portuguese Stock Index (PSI-20) by using simple GARCH, GARCH -M, Exponential GARCH and Threshold ARCH models from the period January 2, 1995 to November 23, 2001 for a total of 1708 and 359 observations respectively. The out-of sample forecast error statistics Root Mean Square Prediction Error, Mean Absolute Prediction Error and Mean Absolute Percentage Prediction Error for each model obtained by sequences of both 100 one day ahead and 20 one week ahead forecasts for PSI - 20 indexes. The findings suggested that, there are significant asymmetric shocks to volatility in daily stock returns and declined by 24.42 per cent, but the same was not evidenced in the weekly stock returns, indicating that the Portuguese stock market becomes more nervous when negative shocks take place. Finally, the EGARCH models were found to provide better daily forecasts, while the GARCH model with the variance equation provided superior weekly forecasts. Therefore, he concluded that reduction of the sample period for estimation improves the accuracy of predicting future observations of the PSI-20 index and stock returns.

Sarno Lucio and Valente Giorgio (2005)[33] have investigated the dynamic relationship between spot and futures prices in stock index futures markets using data since 1989 at weekly frequency for three major stock market indices - the S&P 500, the Nikkei 225 and the FTSE 100 indices by using a conventional cost of carry model to show that futures and stock prices must be Cointegrated and, therefore, linked by a VECM that can be used both to explain and forecast stock returns. The data set comprises weekly time series on prices of futures contracts written on the S&P 500, the Nikkei 225 and the FTSE 100 indices. The sample period examined spans from January 1989 to December 2002. The empirical work was carried out during the period January 1989-December 1998, reserving the last four years of data for out-of-sample forecasting tests. The empirical results provided evidence in favor of the existence of international spillovers across these stock markets and a well-defined long-run equilibrium relationship between spot and futures prices which was consistent with mean reversion in the futures basis. Using the estimated models in an out-of-sample forecasting exercise it was found that both nonlinearity and international spillovers are important in forecasting stock returns. Overall, their empirical evidence suggests that the statistical performance of the linear and nonlinear models examined, differs little in terms of conditional mean, regardless of whether allowance is made for international spillovers across the stock indices. In particular, they focused on the information provided by the futures market for forecasting stock returns.

Karmakar (2005)[34] estimated the conditional volatility models in an effort to capture the stock market volatility in India by employing GARCH (1,1) models by suing three sets of data. The first 2 sets comprised of S & P CNX Nifty and BSE Sensex for the period from 2nd January, 1991 to 10th June 2003. The third set comprised of daily closing prices of 50 underlying individual companies from June 1994 to October 2002. To evaluate the models in terms of out-of-sample forecast accuracy by Mean Error, Mean Absolute Error, Mean Absolute Percentage Error and Root Mean Square error are investigated whether there is any leverage effect in Indian companies. It is observed that the GARCH (1,1) model provides reasonably good forecasts of market volatility. The findings suggest, the movement in stock market return volatility is not explained by the fundamental economic factors, but also the presence of 'fade' due to the actions of noise traders in the market might be associated with these immeasurable elements of stock price volatility. However, the initial boost up of share prices and the resultant fluctuation were believed to be due to fundamental economic factors of the period which were supplemented by a number of liberalization policies and procedures of the government. Finally, the real cause of excessive movement was attributed to the irrational behaviour of the market speculators and frenzy investors who drove the price away from fundamental level resulting in fads or bubble as the natural outcome of the price formation process.

Gospodinov, Gavala and Jiang (2006)[35] investigated several parametric and nonparametric volatility measures, such as implied, realized and model-based volatility for S&P 100 index and the forecasting performance of different volatility models were evaluated among ARFIMA models, Near-integrated AR model, EGARCH, FIEGARCH and Stochastic volatility models. The daily dataset were used for the exercise for the S&P 100 index and the implied volatility index VIX for the period June 1, 1988 to May 17, 2002. To obtain measures of realized and historical volatility S&P 100 returns were used as proxies of the latent integrated volatility process. The result suggested that implied volatility provides valuable information about future movements of volatility and the information content of option prices were considered as more efficient methods for modeling and forecasting the volatility process. Furthermore, their findings suggest that combined information from different volatility models tends to improve the performance of volatility forecasts, especially at long forecasting horizons. Finally, their paper considered only forecasts from univariate models by using simultaneously information from stock returns and option prices by including the implied volatility in a GARCH-type model or adding exogenous variable that contain some incremental information about volatility such as trade volume, that lead to increased forecast accuracy.

Jaesun Noh and Tae-Hwan Kim (2006)[36] analyzed both implied volatility and high frequency historical volatility for different financial time series by using two time series, the S&P 500 and FTSE 100 futures, to measure the predictive power of implied volatility and historical volatility using both daily and high frequency returns over a non-overlapping monthly sample period of January 4, 1994 through June 30, 1999 by using Augmented Dickey-Fuller test, Phillips-Perron (1988) test, Johansen's co-integration test, Wald test for the coefficient restrictions and GMM estimation. For both futures, was selected the next closest maturity month with 1385 daily observations for S&P 500 futures and for the FTSE 100 futures there are 1386 daily observations. Their findings suggest that implied, realized and historical volatilities are co-integrated over a non-overlapping monthly sample. The results showed that both implied volatility and historical volatility using high-frequency returns could outperform each other in forecasting future volatility. Implied volatility has more incremental forecasting information than historical volatility for the S&P 500 futures. However, they found that implied volatility outperforms historical volatility in forecasting future volatility for the S&P 500 futures. The results also indicated that historical volatility using high frequency returns could be an unbiased forecast for the FTSE 100 futures.

Sadorsky Perry (2006)[37] used several different univariate and multivariate statistical models to estimate forecasts of daily volatility in petroleum futures price returns. The univariate models used were Random Walk, Historical Mean, Moving Average, Exponentially Smoothing (ES), Linear Regression model (LS), Autoregressive Models (AR), GARCH (1,1), Threshold GARCH, MGARCH and State Space model (SS). Two multivariate models, Vector Autoregression (VAR) and Bivariate GARCH were also used. The data for this study consisted of daily closing observations for futures price returns on crude oil, heating oil 2, unleaded gasoline, and natural gas. The data set for crude oil, heating oil 2 and unleaded gasoline covers the period February 5, 1988 to January 31, 2003 for a total of 3911 observations. The natural gas data set covers the period April 3, 1990 to January 31, 2003 with 3349 observations. The out-of-sample forecast summary statistics included well known measures like mean squared error (MSE), mean absolute deviation (MAD) and the Theil U statistic. The out-of-sample forecasts were evaluated using forecast accuracy tests and market timing tests. The TGARCH model fits well for heating oil and natural gas volatility and the GARCH model fits well for crude oil and unleaded gasoline volatility. Simple moving average models seem to fit well in some cases provided the correct order is chosen. Despite the increased complexity, models like State Space, Vector Autoregression and Bivariate GARCH did not perform as well as the single equation GARCH model. Most of the models out perform a random walk and there is evidence of market timing.

Magnus and Fosu (2006)[38] have modeled and forecasted volatility of returns on the Ghana Stock Exchange using a linear random walk (RW) model to test the market efficiency, a symmetric GARCH (1,1) models and two asymmetric EGARCH(1,1), and TGARCH(1,1) models to capture the main characteristics of financial time series such as fat-tails, volatility clustering and the leverage effect. The sample of data used in this exercise is the daily closing prices of the Ghana Stock Exchange Databank Stock Index (DSI) over the period extending from 15 June 1994 to 28 April 2004 making total observations of 1508 excluding public holidays. In order to make forecasts, the full sample was divided into two parts comprising 1342 in-sample observations and 166 out of sample observations from 31 March 2003 to 28 April 2004. They found that the DSI exhibited the stylized characteristics such as volatility clustering, leptokurtosis and asymmetry effects associated with stock returns on more advanced stock markets. The random walk hypothesis is also rejected for the GSE DSI returns. The parameter estimates of the GARCH models (α and β) suggest a high degree persistence in the conditional volatility of stock returns on the Ghana Stock Exchange. The evidence of high volatility persistence and long memory in the GARCH models suggests that an integrated GARCH model may be more adequate to describe the DSI series. By and large, the GARCH (1,1) model able to model and forecast the conditional volatility of the DSI better than the other competing models.

Covarrubias. et.al (2006)[39] empirically modeled the volatility of daily changes in 10-year US Treasury rate by utilizing the iterated cumulative sums of squares (ICSS) algorithm to detect regime shifts in the volatility of the interest rate changes. Daily data from Global Financial covering the period from April 4, 1994 through November 13, 2001 were taken for estimating the two competing GARCH models using 1927 observations and saving the last 60 observations for out-of-sample forecasting comparisons. The analysis utilized, Augmented Dickey-Fuller statistic to test the null hypothesis of the series and GARCH (1,1) framework which has been shown to be a parsimonious representation of conditional variance that adequately fits many economic time series. To assess the forecasting performance of the volatility models, they calculate asymmetric error statistics for the 60 one-step-ahead forecasts by mean mixed error statistics that give different weights to under- and over-predictions of volatility of similar magnitude. The results indicated that the information about regime shifts was used in conjunction with a GARCH model to determine the effects of shocks on volatility persistence. Consistent with previous research findings, volatility persistence was found significantly reduced by incorporating regime shifts. Moreover, the regimes generally correspond with major economic events and announcements in the direction that one might expect.

Hongyu Pan and Zhichao Zhang (2006)[40] explored a number of linear and GARCH-type models for predicting the daily volatility of Shanghai and Shenzhen equity indices in the Chinese stock market. The initial data set used for estimating both the indices were from 4 January 2000 to 31 December 2004 with 1200 daily observations. Out-of-sample forecasts were constructed for daily data from 5 January 2000 to 15 March 2004 by applying the following methodology Random walk model, Historical mean model, Moving average model, Exponentially smoothing model, GARCH, GJR-GARCH, EGARCH and APARCH models. The paper consisted of three volatility forecasting techniques, one asymmetric (Standard loss functions) and two values at risk (VAR) criteria i.e. mean absolute error, and mean squared error. The models were estimated under three distributions. First, for the Shenzhen stock market, the traditional method seems superior, and the moving average model was favored for forecasting daily volatility, but for Shanghai index the GARCH, APARCH-N and moving average models was favoured under different criteria. Second, in the

Shenzhen stock market the GJR and EGARCH model performed better than other GARCH-type models and found with no evidence of asymmetric effect. However, they could not find any single model that performs best under all the criteria. But, it appeared that the random walk model was a poor performer, irrespective of both the series on which it was estimated and the loss function used to evaluate the forecast.

Kumar (2006)[41] attempted to examine the efficacy of competing volatility models in forecasting the context of Indian stock and Forex markets. A total of ten different competing models were evaluated on the basis of two categories of evaluation measures like symmetric and asymmetric error statistics. In this study they considered S & P CNX Nifty index and Indian rupee/US dollar exchange rate data were collected from Jun 3 1990 till Dec 31 2005 and Jan 3 1994 till Dec 31 2005 respectively. Out of the total monthly observations 126 for Nifty and 85 Forex market were used for estimating the model parameters and the remaining observations were used for out of sample forecasting. The forecasting performance of each model were estimated using Mean absolute error (MAE), Root Mean Square Error (RMSE), Theil's U (TU) and Mean Absolute Percentage Error (MAPE). Based on an out of the sample forecasts and a majority of evaluation measures they found that GARCH (4, 1) and EWMA methods lead to better volatility forecasts in the Indian stock market and the GARCH (5, 1) will achieve the same in the Forex market. The same models performed better on the basis of asymmetric error statistics also. Moreover, the findings are contrary to the findings of Brailsford and Faff (1996) who found no single method as superior.

Banerjee & Sarkar (2006)[42] attempted to model the daily volatility, using high frequency intraday data, in the stock index return of a very popular stock market in India, using high frequency intra-day data covering a period from June 01, 2000 through December 16, 2003, is used to model volatility using various established volatility models like Random walk, Historical Average, EWMA, GARCH, EGARCH, TGARCH and PGARCH models. The remaining data set, from December 17, 2003 through 30 January, 2004, was used to test the efficacy of various models using RMSE, MAE and Theil-U statistic. Their findings suggest that the Indian stock market experiences with volatility clustering and found GARCH-type models could predict the market volatility better than simple volatility models, like historical average, moving average etc. It was also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect. Finally, their results showed that the change in trading volume in the market directly affects the volatility of asset returns and volatility clusters are not very persistent in India, but it is contrary to experienced countries. Further, the presence of FII in the Indian stock market does not appear to increase the overall market volatility. These findings have profound implications for the market regulator.

Hourvouliades (2007)[43] examined the existence and nature of volatility clustering phenomena in the Athens FTSE 20 index futures contract. The purpose of this analysis was to offer an in-depth analysis of volatility clustering, with negative shocks being more persistent than positive ones, in the domestic derivatives market of Greek. They employed the various methodologies like Simple regression, Single exponential smoothing, Holt-Winter's multiplicative smoothing, GARCH (1,1) and EGARCH (1,1) models in order to compare their forecasting power on volatility for the period from January 2002 to November 2006 with a total sample of 1223 observation. The study used a set of forecasting indicators in order to compare the power of the various forecasting techniques such as MAE, RMSE, MAPE and Theil's U statistics. The result showed that volatility clustering was found, with returns following a normal distribution and exponential smoothing seemed to offer superior forecast efficiency, despite the more sophisticated GARCH models have similar results, showing the persistence of volatility and that decay its serial correlation slowly. However, the single exponential smoothing method is offering a better explanation than the seasonal HWM method, showing that the market has no seasonal trends and the EGARCH model was not able to show its superiority in forecasting non-symmetric effects. Finally, the explanation of the market's behaviour it is proved that negative shocks seems in general to be more powerful and persistence.

Zlatko J. Kovacic (2008)[44] estimated the behavior of Macedonian Stock Exchange and focusing on the relationship between returns and conditional volatility. The data used in the paper wee the daily closing market index MBI-10 from January 4, 2005 to September 21, 2007, with 632 observations. However, 605 observations were effectively used to calculate returns summary statistics and for estimation. The last 27 observations were left for examination of the out-of-sample forecasting accuracy for conditional mean a GARCH-M model, and for the conditional variance one symmetric (GARCH) and four asymmetric GARCH types of models (EGARCH, GJR, TARCH and PGARCH) were tested. The forecasting performance of each model were evaluated both in-sample and out-of-sample by using three symmetric and two asymmetric measures. Three standard symmetric measures were used to evaluate in-sample and out-of-sample forecasting accuracy they are the root mean square error (RMSE), the mean absolute error (MAE) and the Theil inequality coefficient (TIC). They suggested the innovations in the conditional variance which was highly persistent indicating that large changes in returns tend to be followed by large changes and small changes tend were followed by small changes, which meant that volatility clustering is observed in the Macedonian financial returns series. Moreover, the conditional variance in the mean equation measuring the risk premium effect was statistically significant across all models. However, the sign of the risk premium parameter is negative. The implication is that increase in volatility would decrease returns, which is an unexpected result, but could be theoretically justified. Finally the two unusual results related to risk premium and leverage effects, i.e. anomalies in stock market behavior could be expected in the early period of emerging stock markets.

Rashid and Ahmad (2008)[45] evaluated the relative performance of linear versus nonlinear models to forecast stock index volatility by using daily data for the period January 2001 to November 2007 for Karachi Stock Exchange. The purpose of this study was to predict the daily stock price index by employing linear and non linear models like: random walk, autoregressive model, moving average, exponential smoothing, Holt exponential smoothing models, GARCH, EGARCH and PARCHES models, to assess the forecasting performance of the models by considering Root Mean Square Error (RMSE). It was found that, among linear models of stock price index volatility, the exponential smoothing models ranked first using the RMSE criterion. They also found that within the nonlinear models, the GARCH model was superior as compared to the EGARCH and the PGARCH models. Finally, the study concluded based on the RMSE that the nonlinear ARCH-class models clearly dominate the linear models in out-of-sample forecasting exercise for stock price index volatility.

Angelidis and Degiannakis (2008)[46] argumented in their paper that the intra-day model generates the most accurate forecasts in three European equity markets under the framework of two financial applications, i.e., VaR forecasting and prediction of option prices, plus a volatility forecasting exercise. The intra-day dataset was obtained from Olsen and associates and comprises three European stock indices: the CAC (from January 3, 1995 to September 8, 2003), the DAX30 (from July 3, 1995 to December 29, 2003) and the FTSE100 (from January 2, 1998 to December 30, 2003) indices by using a simple inter-day model TARCH, a complex inter-day model FIAPARCH and an intra-day model ARFIMAX. To measure the accuracy of the models in forecasting the one-day-ahead conditional variance via three loss functions: (i) the MSE, (ii) the Heteroskedasticity-Adjusted Squared Error (HASE), and (iii) the Logarithmic Error (LE). The results indicated that there was no one unique model for all cases that can be deemed an adequate one, and therefore investors must be extremely careful when they use one model in all cases. Nevertheless, despite this general conclusion, a researcher must use an inter-day model for inter-day based financial applications and intra-day datasets for intra-day volatility forecasting.

McMillan and Garcia (2009)[47] have examined the forecasting performance of competing models for intra-day volatility in IBEX-35 index futures market during the period from 17 January 2000 up to 31 December 2003, which implies 991 trading days. For this period, they have extracted the data on prices for the IBEX-35 index future and generated a 5-minute returns series. In each and every minute more than one trade can occur, so it is possible that different prices exist for the IBEX-35 index futures at every minute. The dataset was aggregated in two ways. First, to examine the volatility forecasts at different frequencies the 5-

minute returns data were aggregated to 10, 15, 20, 30, 60, 120 and 240 minutes. Second, to construct the realized volatility as an aid to forecast evaluation they aggregated the squared 5-minute returns over the same frequencies. The intra-day volatility for futures market was tested using GARCH, PARCH, CGARCH, IGARCH, FIGARCH, FIEGARCH, HYGARCH models. The results presented here suggest that the HYGARCH and FIEGARCH model provides the best forecast for intra-day volatility and very high-frequency forecasts. Moreover, the IGARCH and FIGARCH models were performed better at frequencies of 1 hour and lower. Finally, the CGARCH model appears to provide consistent performance across all frequencies and the FIEGARCH model performs particularly well when weighting under predictions of volatility higher than over predictions.

Conclusion

This chapter has provided as a platform for the empirical work carried out in examining the relationship between price volatility, trading volume and market depth for futures markets, and forecasting the symmetric and asymmetric behaviour of futures market. Numerous studies have attempted at international level for testing the futures market variables, whereas in India studies on futures markets on testing the relationship and modeling volatility behaviour were quite limited. Bhanupant (2001) investigated the dynamic relationship between stock return and trading volume using linear and non-linear Granger causality and evidenced the relationship have improved after rolling settlement mechanism. Mahajan and Singh (2008) examined the dynamic relationship between trading volume and return for NSE. They found that volatility dynamics was weak and evidenced unidirectional causality running from volume to return and indicated mild support for sequential information hypothesis. Malabika, Srinivasan and Devanadhen (2008) have tested the relationship between return and trading volume series for select Asia-Pacific stock market and envisage bidirectional causality exist between most of the stock exchanges.

Studies relating to modeling and forecasting futures market volatility were examined by Varma (1999) for volatility estimation by using GARCH model and EWMA models in the risk management setting. Pandey (2002) analyzed the extreme value estimators and found the performance with Parkinson estimator for forecasting volatility over these horizons. Karmakar (2005) estimated the movement in stock returns volatility which was found not well explained by the fundamental economic factors, but the presence of 'fade' actions taken by the noise traders, liberalizing policies and procedures of the government were found contrary. Kumar (2006) examined the comparative performance of volatility forecasting models in Indian markets and found the results were contrary to Brailsford and Faff (1996). Hence, the current study attempts to shed light on the relationship and modeling volatility behaviour for selected stock futures market in India, to fill the gap in the existing literature.

CHAPTER - III

THEORETICAL OVERVIEW OF FUTURE AND OPTIONS MARKET

Many associate the financial market with the equity market. The financial market is, of course, far broader, encompassing bonds, foreign exchange, real estate, commodities, classification of other asset and financial instruments. Of late segment of the market that has fast become its most important one is the derivatives market. The derivatives market has seen the highest growth among all financial market segments in recent years. It has become a central contributor to the vibrant state of the financial system and has emerged as an important factor in the functioning of the real economy. Despite the importance of the derivatives market, many a sections of society want to have a comprehensive perspective on its size, structure, role etc and on how it works.

Last decade was one of the most eventful decades in the International financial markets, more specifically derivatives market. On one side, just few derivatives disaster stories were enough to bring entire business of derivatives under the limelight, make every one worry about unknown risks associated with derivatives, and elevate derivatives into mysterious “something”; while on the other side, there were people who started understanding the derivatives and used the derivatives for hedging and mitigating risks while adding liquidity to the markets.

The derivatives market has recently attracted more attention against the backdrop of the financial crisis, fraud cases and the near failure of some market participants. Although the financial crisis has primarily been caused by structured credit-linked securities that are not derivatives, policy makers and regulators have started to think about strengthening regulation to increase transparency and safety both for derivatives and other financial instruments. Before discussing the prerequisites for a well functioning derivatives market, it is useful to consider the fundamentals and characteristics of this market along with the mechanics of trading, its economic and social functions and the dynamics of derivative market functioning with special reference to futures market.

Derivatives

Derivatives are financial instruments that are mainly used to protect against or to manage risks, and very often also serve arbitrage or investment purposes, providing various advantages compared to securities. Derivatives come in many varieties and can be differentiated by how they are traded, the underlying they refer to, and the product type.

A derivative instrument, broadly, is financial contracts whose payoff structure is determined by the value of an underlying commodity, security, interest rate, share price index, exchange rate, and oil price alike. Thus, a derivative instrument derives its value from some underlying variable. A derivative instrument by itself does not constitute ownership. It is, instead, a promise to convey ownership. All derivatives are based on some “cash” products. The underlying basis of a derivative instrument may be any product including

1. Commodities like grain, coffee beans, orange juice etc.
2. Precious metals like gold and silver
3. Foreign exchange rate.
4. Bonds of different types, including medium and to long-term negotiable debt securities issued by governments, companies, etc.
5. Short-term debt securities such as T-bills

Derivatives are specialized contracts which are employed for a variety of purpose including reduction of funding costs by borrowers, enhancing the yield on assets, modifying the payment structure of assets to correspond to the investor’s market view. In the organized derivatives market where derivative products are traded, future market plays a defining role. Futures contracts are traded on exchanges, and they are standardized according to the rules and regulations of the exchange. The exchange determines the exact quality and quantity of the goods to be delivered per contract, when the contract terminates and the location of the delivery. This standardization facilitates secondary market trading and enhances the liquidity of the market. The parties involved need not concern themselves with the creditworthiness of other players because the exchange itself guarantees the performance of all parties. The seller of a futures contract is said to be in the 'short' position and the buyer is said to be in the 'long' position. The date at which the parties must complete the transaction is the settlement or delivery date. The price agreed to by two parties is known as the futures price.

Types of Derivatives

The most commonly used derivatives contracts are forwards, futures, options. Here we take a brief look at various derivatives contracts that have come to be used.

Forward Contracts

A forward contract is an agreement between two parties to buy and sell of a commodity or financial asset at certain future time for a certain price. Historically, the forward markets are forerunners of futures markets. A forward contract is a simple derivative that can be contrasted with a spot contract, which is an agreement to buy or sell an asset today where as the forward contract at a future period. A forward contract is traded in the over-the-counter market usually between two financial institutions or between a financial institution and one of its clients.

One of the parties to a forward contract assumes a long position and agrees to buy the underlying asset on a certain specified future date for a certain specified price. The other party assumes a short position and agrees to sell the asset on the same date for the same price. Forward contracts on foreign exchange are very popular. Most large banks have a "forward desk" within their foreign exchange trading room that is devoted to the trading of forward contracts.

Futures Contracts

Like a forward contract, a futures contract is an agreement between two parties to buy or sell an asset at a certain time in the future for a certain price. Unlike forward contracts, futures contracts are normally traded on an exchange. To make trading possible, the exchange specifies certain standardized features of the contract. As the two parties to the contract do not necessarily know each other, the exchange provides a mechanism that gives the two parties a guarantee that the contract will be honored.

The largest exchanges on which futures contracts are traded are the Chicago Board of Trade (CBOT) and the Chicago Mercantile Exchange (CME). On these and other exchanges throughout the world, a very wide range of commodities and financial assets form the underlying assets in the various contracts. The commodity includes even pork bellies, live cattle, sugar, wool, lumber, copper, aluminum, gold, and tin. The financial assets include stock indices, currencies, and Treasury bonds.

One way in which a futures contract is different from a forward contract is that an exact delivery date is usually not specified. The contract is referred to by its delivery month, and the exchange specifies the period during the month when delivery must be made. For commodities, the delivery period is often the entire month. The holder of the short position has the right to choose the time during the delivery period when it will make delivery. Usually, contracts with several different delivery months are traded at any one time. The exchange specifies the amount of the asset to be delivered for one contract and how the futures price is to be quoted. In the case of a commodity, the exchange also specifies the product quality and the delivery location.

Options Contracts

Options are traded both on exchanges and in the over-the-counter market. There are two basic types of options. A call option gives the holder the right to buy the underlying asset by a certain date for a certain price. A put option gives the holder the right to sell the underlying asset by a certain date for a certain price. The price in the contract is known as the exercise price or strike price; the date in the contract is known as the expiration date or maturity date. American options can be exercised at any time up to the expiration date. European options can be exercised only on the expiration date. Most of the options that are traded on exchanges are American. In the exchange-traded equity options market, one contract is usually an agreement to buy or sell 100 shares. European options are generally easier to analyze than American options, and some of the properties of an American option are frequently deduced from those of its European counterpart.

It should be emphasized that an option gives the holder the right to do something. The holders not necessarily have to exercise this right. This is what distinguishes options from forwards and futures, where the holder is obligated to buy or sell the underlying asset. It need to be noted that it costs nothing to enter into a forward or futures contract, where as there is a cost for acquiring an option.

Emergence of Financial Derivatives

Derivative products initially emerged as hedging devices against fluctuations in common prices, and commodity-linked derivatives remained the sole form of such products for almost three hundred years. Financial derivatives came into limelight in the post-1970s due to growing instability in the financial markets. However, since their emergence, financial derivatives products have become very popular and in 1990's, overtaking the commodity derivatives they accounted for about two-thirds of total transaction in derivative market. In recent years, the market for financial derivatives has grown tremendously in terms of variety of instruments available, their complexity and also in terms of turnover. In the class of equity derivatives world over, futures and options on stock indices have gained more popularity than on individual stocks, especially among institutional investors, who are the major users of index-linked derivatives. Even small investors find the usefulness of derivatives became of the existence of a high correlation between the popular indexes with various portfolios. The lower costs associated with index derivatives than derivative products based on individual securities is another reason for their growing use.

Players in Derivative Markets

Derivatives markets have been outstandingly successful. The main reason is that they have attracted many different types of traders and have a great deal of liquidity. When an investor wants to take one side of a contract, there is usually no problem in finding someone who is prepared to take the other side.

Three broad categories of traders can be identified among the players in the market they are: hedgers, speculators, and arbitrageurs. Hedgers use futures, forwards, and options to reduce the risk that they face from potential future movements in a market variable. Speculators use them to bet on the future direction of a market variable. Arbitrageurs take offsetting positions in two or more instruments to lock in a profit.

Hedgers

Hedging is the prime reason which has led to the emergence of derivatives. The availability of derivatives allows one to undertake many activities at a considerably lower risk. Hedgers, therefore, are important components of the derivatives markets. Hedgers are the traders who wish to eliminate the risk associated with price of an asset and they may take a long position or short position on a commodity to lock in existing profits. The main purpose is to reduce the volatility of a portfolio, by reducing the risk. Nevertheless, while a forward contract requires no payment, an option contract involves an initial cost. In the event of call is not exercised, the premium paid for it becomes a net loss while if it is exercised, the profit resulting from the call exercise compensates the cost.

Speculators

Hedgers are the people who wish to avoid the price risk; while speculators are those who are willing to take such risk. These are the people who take positions in the market and assume risks, to profit from fluctuations in prices. In fact, the speculators consume information, make forecasts about the prices and put their money in these forecasts. In this process, they feed information into prices and hence contribute to market efficiency. By taking positions, they are betting that a price would go up or they are betting that it would go down. Depending on their perceptions, they may take long or short positions on futures or options or may hold spread positions. Derivatives make speculation easy with least investment. In the absence of the derivatives, speculative activity would become very difficult as it might require huge funds to be invested.

Speculators in the derivatives market may be categorized as scalpers, day traders and position traders. Scalpers attempt to profit from small changes in the contract price. Day traders speculate on the price movements during single trading day, thus open and close positions many times a day but do not carry any positions at the end of the day. Obviously, they monitor the prices continuously and generally attempt to make profit from just a few ticks per trade. On the other hand, the position traders attempt to gain from price fluctuations by keeping their positions open for longer durations - may be for a few days, weeks or even months. They use fundamental analysis, technical analysis and other information available to them to form their opinions on the likely price movements Vohra and Bagri (2008).

Arbitrageurs

Arbitrageurs attempt to earn risk-free profits by exploiting market imperfections. An arbitrageur profits by trading a given commodity or other items that sells for different prices in different markets. Thus, arbitrage involves making risk-less profit by simultaneously entering into transactions in two or more markets. If a certain share is quoted at a lower rate on the NSE and at a higher rate on the BSE, an arbitrageur would make profit by buying the share at NSE and simultaneously selling it at BSE, this type of arbitrage is “arbitrage over space”. If an arbitrageurs feels that the futures are being quoted at a high level considering the cost of carry, the arbitrageurs would buy securities underlying today and sell the future in market maturing in a month or two hence. Similarly, since futures and options with various expiration dates are traded in the market, there are likely to be several arbitrage opportunities in trading. Thus, if a trader believes that the price differential between the futures contracts on the same underlying asset with differing maturities is more or less than what the arbitrageur perceives them to be, then appropriate positions in them may be taken to make profits.

It may be noted that the existence of well-functioning derivatives markets alters the flow of information into the prices. This is because, in a purely cash market, speculators feed information into the spot prices. In contrast, the presence of a derivatives market ensures that a major part of the transformation of information into prices, due to lower transactions costs involved in derivative a market, and then it gets transmitted to the spot markets. It is here that the arbitrageurs provide a link between the derivatives market and the cash market by synchronizing the prices in the two markets. Thus, through their actions, the arbitrageurs provide a critical link between the cash and derivatives markets.

Significance of Derivative Market

The derivatives market performs a number of economic functions; they are

1. **Price Discovery:** Prices in an organized derivatives market reflect the perception of market participants about the future and lead the prices of underlying to the perceived future level. The prices of derivatives converge with the prices of the underlying at the expiration of the derivative contracts. Thus derivatives help in discovery of future as well as current prices.

2. **Risk Transfer:** Due to the inherent link of derivatives market with the underlying cash market, witnesses higher trading volumes because of participations by more players who would not have otherwise participated for lack of an arrangement to transfer risk.

3. **Controlled Speculative Trading:** Speculative trades shift to a more controlled environment due to the existence of derivatives market. In the

absence of an organized derivatives market, speculators trade in the underlying cash markets and margining, monitoring and surveillance of the activities of various participants become extremely difficult in derivative markets.

4. **Financial Architecture:** An important incidental benefit that flows from derivatives trading is that it acts as a catalyst for new entrepreneurial activity. The derivative has a history of attracting many bright, creative, well-educated people with an entrepreneurial attitude. They often energize others to create new business, new products and new employment opportunities, the benefit of which is immense.

5. **Enhances Volume of Activity:** Derivatives market help to increase savings and investment in the long run and transfer of risk enables the market participants to expand their volume of activity.

Models of Futures Price

The relationship between spot and futures prices can be explained by two models, they are Cost of Carry model and Expectations model. According to this view, futures prices depend on the cash price of the asset and the cost of storing the underlying asset from the present to the delivery date of the futures contract. Second, according to the expectations model, the futures price today equals to the cash price that traders expects to prevail for the underlying asset on the delivery date the futures contract.

Cost of Carry Model

The relationship between futures prices and spot prices can be summarized in terms of the cost of carry. This measures the storage cost plus the interest that is paid to finance the asset less the income earned on the asset. For a non-dividend-paying stock, the cost of carry is r, because there are no storage costs and no income is earned; for a stock index, it is r - q, because income is earned at rate q on the asset. For a currency, it is r - r_f for a commodity with storage costs that are a proportion u of the price, it is r + u; and so on.

For an investment asset, the futures price is

$$F_0 = S_0 e^{cT}$$

For a consumption asset, it is

$$F_0 = S_0 e \{c \_ y\}^T$$

Where,

F_0 is the Futures Price at time t.

S_0 is the Spot Price at time t.

c stands for Holding or Carry Cost

T stands for Time till Expiration.

y is the convenience yield.

If $F > Se^{rT}$ or $F < Se^{rT}$, then arbitrage opportunities exist between the futures and spot markets. Arbitrageurs can then simultaneously take positions in the underlying market and futures market, and hence lock in a secure pay off.

Expectations Model

The price relationship between two markets can be obtained by considering the relationship between risk and expected return. According to the Capital asset Pricing Model (CAPM), the two types of risks are; systematic and unsystematic. Unsystematic risk does not matter much to the investor, as it can be eliminated by holding a well-diversified portfolio. However, systematic risk cannot be diversified away, because it arises from a correlation between returns from the investment in stock market as whole. Hypothetically, a speculator who takes a long futures position in the hope that the spot price of the asset will be above the futures price at maturity and puts the present value of the futures price into a risk-free investment while simultaneously taking a long futures position. The proceeds of the risk-free investment are used to buy the asset on the delivery date. The asset is then immediately sold for its market price. The cash flows to the speculator are;

Time 0: $- F_0e^{-rT}$

Time T: $+ S_T$

Where, S_T is the price of the asset at time T. The present value of this investment is;

$$- F_0e^{-rT} + E\ (S_T)e^{-kT} = 0 \qquad \text{or } F_0 = E\ (S_T)e^{(r-k)T}$$

The value of k depends on the systematic risk of the investment. If S_T is uncorrelated with the level of the stock market, the investment has zero systematic risk. In this case K = r, and $F_0 = E\ (S_T)$. If S_T is positively correlated with the stock market as whole, the investment has positive systematic risk, $F_0 < E\ (S_T)$. Finally, if S_T is negatively correlated with the stock market, the investment has negative systematic risk, in such case $k < r$, and shows that $F_0 > E\ (S_T)$ Hull (2004).

International Derivatives Markets

A comparison of the derivatives markets, over the last few years, among various countries gives rise to an interesting pattern. The exchanges of the developed markets have shown robust growth and maintained their leadership position over last five years; at the same time, emerging market exchanges have gained a position of eminence with strong growth trends. It is evident from the data presented in Table 3.1 to 3.4 given below that Indian market has emerged fourth along with markets in Korea, Spain and Israel, but only in case of single stock option contracts traded Indian market stood at 16^{th} position.

Table: 3.1 Top Five Exchanges (Number of Stock Index Futures Contracts traded)

Exchange	Number of Contracts traded in 2008*	Number of Contracts traded in 2003	Percentage Changes
EUREX	371,504,525	155,988,661	138.16 %
NSE, India	141,261,516	10,557,024	1238.08 %
Osaka SE	90,965,674	13,231,287	587.50 %
Euronext Liffe	76,525,955	56,898,050	34.50 %
Singapore Exchange	45,256,382	8,609,973	425.63 %

Source: World Federation of Exchanges, * January to October 2008.

Table: 3.2 Top Five Exchanges (Number of Stock Index Option Contracts traded)

Exchange	Number of Contracts traded in 2008*	Number of Contracts traded in 2003	Percentage Changes
Korea Exchange	2,011,059,741	3	#
Chicago Board Option Exchange	435,860,762	110,822,096	293.30 %
EUREX	371,155,699	108,504,304	242.07 %
NSE, India	89,099,694	1,332,417	6587.07 %
TAIFEX	77,154,336	21,720,084	255.22 %

Source: World Federation of Exchanges, * January to October 2008, #Very large figure due to small base

Table: 3.3 Top Five Exchanges (Number of Single Stock Futures traded)

Exchange	Number of Contracts traded in 2008*	Number of Contracts traded in 2003	Percentage Changes
JSE	307,836,600	4,585,919	6.612.65 %
NSE, India	165,706,741	25,572,505	547.99 %
EUREX	121,656,741	7,004,235	1,636.90 %
Euronext Liffe	94,223,989	N.A	N. A
BME, Spanish	35,301,142	12,492,568	182.58 %

Source: World Federation of Exchanges, * January to October 2008, N.A refers to the 2003 data pertains to that of Euronext

Table: 3.4 Top Five Exchanges (Number of Single Stock Options traded)

Exchange	Number of Contracts traded in 2008*	Number of Contracts traded in 2003	Percentage Changes
ISE	767,805,138	220,988,837	247.44 %
Chicago Board Option Exchange	463,710,159	,173,033,695	167.99 %
Philadelphia SE	409,010,094	89,458,901	357.20 %
EUREX	276,165,919	188,239,823	46.71 %
Sao Paulo SE	260,696,612	175,622,679	48.44 %
NSE, India	8,009,365	5,607,990	42.82 %

Source: World Federation of Exchanges, * January to October 2008.

Derivatives Market in India

The derivatives market is a new market design of the Indian equity market, which play a vital role in disseminating information and offsetting undesirable price risks. It ensures the cheapest trading facilities to the investors and shareholders. The development of markets for derivatives was initially not possible in view of prohibition in the Securities Contracts (Regulation) Act, 1956 (SCRA). The preamble to Act itself spoke of prohibiting options trading. Section 20 of the Act explicitly prohibited all options in securities. Under this Act, by a notification in 1969, Government prohibited all forward trading in securities in order to curb unhealthy practices and to prevent undesirable transactions. The introduction of trading in derivatives required withdrawal of these prohibitions Narain (2003).

The first step towards introduction of derivatives trading in the Indian financial markets was the promulgation of the Securities Laws (Amendment) Ordinance, 1995, which withdrew the prohibition on options in securities. The market for derivatives, however, did not take off, as there was no regulatory framework to govern trading of derivatives. SEBI set up a 24 member committee under the chairmanship of Dr. L.C.Gupta on November 18, 1996 to develop appropriate regulatory framework for derivatives trading in India. The committee submitted its report on March 17, 1998 prescribing necessary pre-conditions for introduction of derivatives trading in India. The committee recommended that derivatives should be declared as "securities" so that regulatory framework applicable to trading of "securities" could also govern trading of securities. SEBI also set up a group in June 1998 under the Chairmanship of Prof. J. R. Varma, to recommend measures for risk containment in derivatives market in India. The report, which was submitted in October 1998, worked out the operational details of margining system, methodology for charging initial margins, broker net worth, deposit requirement and real - time monitoring requirements.

In December 1999, amendment to Securities Contracts (Regulation) Act, was notified, making way for derivatives trading in India. In June 2000, Futures contracts on Nifty and Sensex were launched, followed by Options contracts on Nifty and Sensex (European style). The Options contracts on stocks (American style) and Futures contracts on stocks in June, July and November 2001, respectively. The number of underlying stocks and indexes has increased over the years and presented in Table: 3.5 showing exponential increase of options futures traded.

In the Indian market, the Index option contracts are cash settled European style options. Stock options are also cash settled American style contracts. Interest rate derivatives are based on notional 10-years bonds and 91-days T-bill. All exchange-traded equity derivatives contracts are cash settled contracts.

Table: 3.5 Futures and Options Traded on NSE & BSE

Financial Year	NSE - Stocks	NSE - Index	BSE - Stocks	BSE - Index
2001 - 2002	31	1	31	1
2002 - 2003	41	1	38	1
2003 - 2004	53	2	42	1
2004 - 2005	52	2	46	1
2005 - 2006	117	3	76	7
2006 - 2007	155	3	89	7
2007 - 2008	265	7	126	7

Source: BSE, NSE.

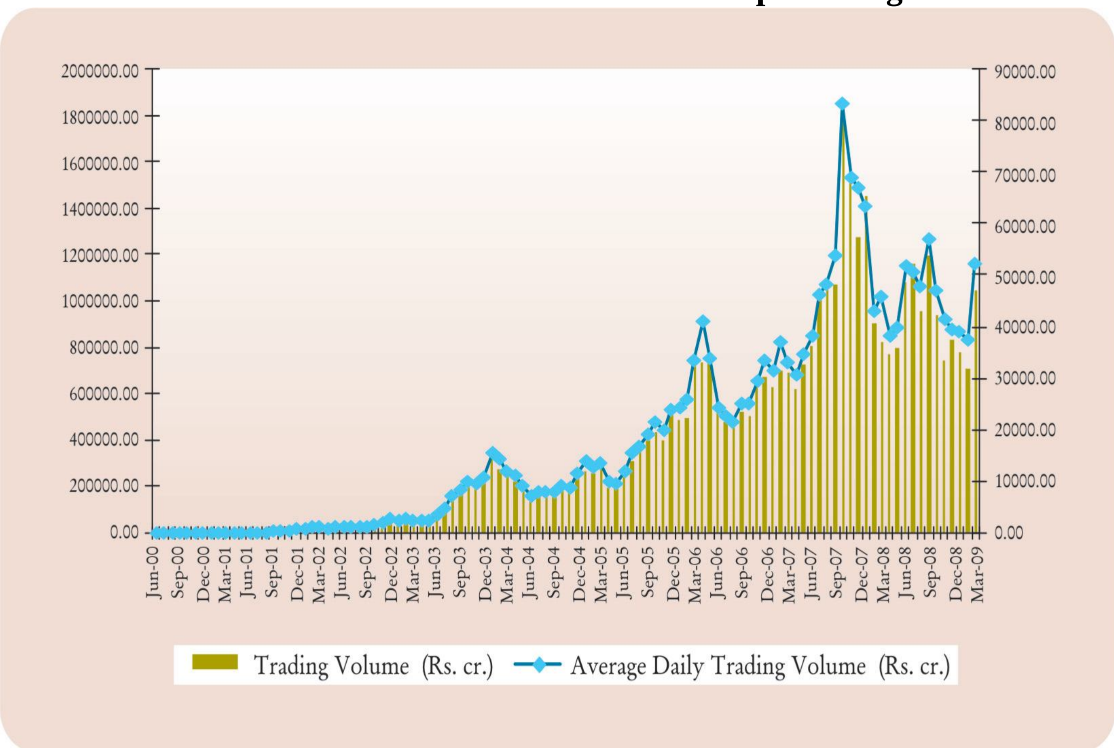
Table: 3.6 Total Derivatives turnover since inception (in Rs. Crore)#

Period	NSE	BSE	Total
2001 - 2002	101,925	1,917	103,842
2002 - 2003	439,865	2,475	442,340
2003 - 2004	2,130,447	12,074	2,142,521
2004 - 2005	2,547,053	16,112	2,563,165
2005 - 2006	4,824,245	9	4,824,254
2006 - 2007	7,356,271	59,007	7,415,278
2007 – 2008	13,090,478	242,308	13,332,786
2008 to Dec 2008	5,963,894	11,491	5,975,385

Source: BSE, NSE. # Excluding Currency Derivatives

Turnover in the derivatives segment, since inception, is presented in Table: 3. 6 and Chart 3.1. During 2001 - 02, turnover on NSE was Rs. 101,925 Crore and during 2007 - 2008 it was Rs 13,090,478 Crore. Likewise, during 2001 - 2002, turnover on BSE was Rs. 1,917 Crore and during 2007 - 2008 it was Rs. 242. 308 Crore. Turnover on BSE increased till 2004 - 2005 but during 2005 - 2006 there was a noticeable decrease in turnover. The turnover on BSE has started increasing since 2006 - 2007. During the financial year 2008 to 31st December 2008, the total turnover in NSE and BSE were observed with Rs. 59, 63,894 Crore and Rs. 11,491 Crore, respectively.

Chart: 3.1 Business Growth of Futures & Options Segment



Source: www.nseindia.com

India's Experience in Future & Options

India's experience with the launch of equity derivatives market has been extremely positive with the global derivatives market. The derivatives turnover on the NSE has surpassed the equity market turnover. The turnover of derivatives on the NSE increased from Rs. 23,654 million in 2000 - 01 to Rs. 130,904,779 million in 2007- 08. India is one of the most successful developing countries in terms of a vibrant market for exchange-traded derivatives. This reiterates the strengths of the recent developments of India's securities markets, which are based on nationwide market access, anonymous electronic trading, and a predominantly retail market. There is an increasing belief that the equity derivatives market is playing a major role in shaping price discovery.

As per Indian Securities Market Review (ISMR) 2009, NSE ranked as the eighth largest derivatives exchange in the world, the second largest exchange in terms of number of contracts traded in single stock futures and the third largest in terms number of contracts traded in the index futures category. The derivatives trading at NSE commenced on June 12, 2000 with futures trading on S&P CNX Nifty Index. Subsequently, the product base has been increased to include trading in options on S&P CNX Nifty Index, futures and options on CNX IT Index, Bank Nifty Index, CNX Nifty Junior, CNX 100, Nifty Midcap 50 Indices, S&P CNX Defty and 234 single stocks were observed in Table: 3.7 as of March 2009.

The various products on the derivative segment of NSE and their date of launch is shown in the table below.

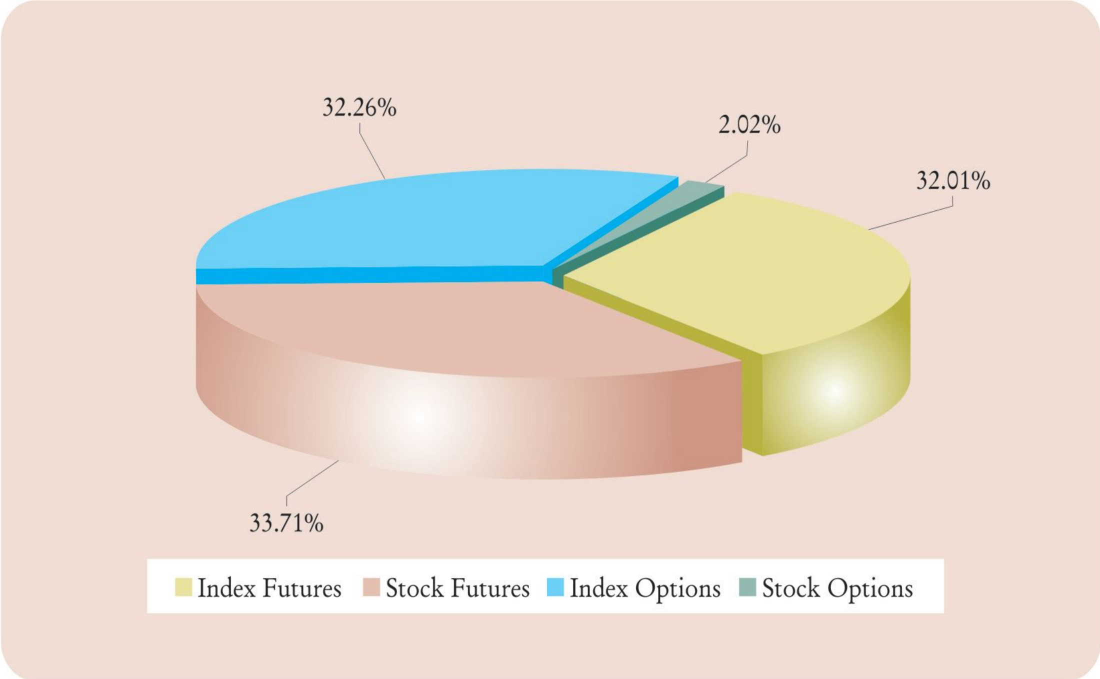
Table: 3.7 Products available for trading on Derivatives Segment

Products on Derivative Segment	Date of Launch
S&P CNX Nifty Futures	June 12, 2000
S&P CNX Nifty Options	June 4, 2001
Single Stock Options	July 2, 2001
Single Stock Futures	November 9, 2001
Interest Rate Futures	June 24, 2003
CNX IT Futures & Options	August 29, 2003
Bank Nifty Futures & Options	June 13, 2005
CNX Nifty Junior Futures & Options	June 1, 2007
CNX 100 Futures & Options	June 1, 2007
Nifty Midcap 50 Futures & Options	October 5, 2007
Mini Nifty Futures & Options on S&P CNX Nifty	January 1, 2008
Long term Options on S&P CNX Nifty	March 3, 2008
S&P CNX Defty Futures and Options	December 10, 2008

Source: www.nseindia.com

As per Indian Securities Market Review (ISMR) 2009, the total number of contract traded increased by 54.68% to 66 crore contracts during 2008-09. Out of the total contracts traded, 33.71% of the contracts were traded on Stock futures followed by index options on which 32.26% of the contracts were traded. Number of contracts traded on Index futures was 32.01% while 2.02% of the total contracts were traded on stock options are envisaged in Chart 3.2.

Chart: 3.2 Product Wise Numbers of Contracts Traded during 2008-09



Source: www.nseindia.com

Mechanics of Futures Trading:

Trading Mechanism

The derivatives trading system at National Stock Exchange is called National Exchange for Automated Trading (NEAT) - Futures and Options (F&O) trading system. It provides a fully automated screen-based trading for all kind of derivative products available on NSE on a nationwide basis. It practices an anonymous order driven market, which operates on a strict price/time priority. It provides tremendous flexibility to users in terms of kinds of orders that can be placed on the system. Various time and price related conditions like Immediate or Cancel, Limit/Market Price, Stop Loss, etc. can be built into an order. Trading in derivatives is essentially similar to that of trading of securities in the Clearing Member (CM) segment.

The NEAT-F&O trading system distinctly identifies two groups of users. The trading user more popularly known as trading member has access to functions such as, order entry, order matching and order & trade management. The clearing user uses the trader workstation for the purpose of monitoring the trading members for whom he clears the trades. Additionally, he can enter and set limits on positions, which a trading member can take.

Contract Specification

The index futures and index options contracts traded on NSE are based on S&P CNX Nifty Index, CNX IT Index, Bank Nifty, CNX Nifty Junior, CNX 100, Nifty Midcap 50 and S&P CNX Defty while stock futures and options are based on individual securities. Mini futures and options contracts and long term options contracts are also available on S&P CNX Nifty. Stock futures and options were available on 234 securities as of March 2009.

As regard to expiration, at any point of time there are only three contract months available for trading, with 1 month, 2 months and 3 months to expiry. These contracts expire on last Thursday of the expiry month and have a maximum of 3-month expiration cycle. If the last Thursday is a trading holiday, the contracts expire on the previous trading day. A new contract is introduced on the next trading day following the expiry of the near month contract. All the derivatives contracts are presently cash settled.

Charges:

Brokerage Charges

The maximum brokerage chargeable by a trading member in relation to trades affected in the contracts admitted to dealing on the F&O segment of NSE is fixed at 2.5% of the contract value in case of index futures and stock futures. In case of index options and stock options it is 2.5% of notional value of the contract [(Strike Price + Premium) × Quantity)], exclusive of statutory levies.

Transaction Charges

The transaction charges payable to the exchange by the trading member for the trades executed by him on the F&O segment are fixed at the rate of Rs. 2 per lakh of turnover (0.002%) subject to a minimum of Rs. 1, 00,000 per year. However, for the transactions in the options sub-segment the transaction charges is levied on the premium value at the rate of 0.05% (each side) instead of on the strike price as levied earlier. For a trading member participating in trading S&P CNX Nifty at any time during the year till September 30, 2009 there would be no transaction charges. The trading member would be required to make a lump sum contribution of Rs.500/- for the whole year as a contribution to Investor Protection Fund.

Clearing and Settlement:

NSCCL undertakes clearing and settlement of all trades executed on the F&O Segment of the Exchange. It also acts as legal counterparty to all trades on this segment and guarantees their financial settlement. The Clearing and Settlement process comprises of three main activities, viz., Clearing, Settlement and Risk Management.

Clearing Mechanism

The first step in clearing process is to work out open positions and obligations of clearing members (CMs). The open positions of a CM is arrived at by aggregating the open positions of all the Trading Members (TMs) and all Custodial Participants (CPs) clearing though him, in the contracts which they have traded. The open position of a TM is arrived at by summing up his proprietary open position and clients' open positions, in the contracts which they have traded. While entering orders on the trading system, TMs identify orders as either proprietary or client. Proprietary positions are calculated on net basis for each contract and that of clients are arrived at by summing together net positions of each individual client. A TM's open position is the sum of proprietary open position, client open long position and client open short position.

Settlement Mechanism

All futures and options contracts are cash settled i.e. through exchange of cash. The underlying for index futures/options cannot be delivered. The settlement amount for a CM is netted across all their TMs/clients, across various settlements. For the purpose of settlement, all CMs are required to open a separate account with National Securities Clearing Corporation Limited (NSCCL) designated clearing banks for F&O segment.

Settlement of Futures Contracts on Index or Individual Securities

Futures contracts have two types of settlements, the Mark-to-Market (MTM) settlement which happens on a continuous basis at the end of each day, and the final settlement which happens on the last trading day of the futures contract.

1. **MTM Settlement for Futures:** The positions in futures contracts for each member are marked-to-market to the daily settlement price of the relevant futures contract at the end of each day. The CMs who have suffered a loss are required to pay the mark-to-market (MTM) loss amount in cash which is in turn passed on to the CMs who have made a MTM profit. This is known as daily mark-to-market settlement. CMs are responsible to collect and settle the daily MTM profits/losses resulted by the TMs and their clients clearing and settling through them. Similarly, TMs are responsible

to collect/pay losses/ profits from/to their clients by the next day. The pay-in and pay-out of the mark-to-market settlement are effected on the day following the trade day (T+1).After completion of daily settlement computation, all the open positions are reset to the daily settlement price. Such positions become the open positions for the next day.

2. **Final Settlement for Futures:** On the expiry day of the futures contracts, after the close of trading hours, NSCCL marks all positions of a CM to the final settlement price and the resulting profit or loss is settled in cash. Final settlement of profit or loss amount is debited or credited to the relevant CM's clearing bank account on the day following expiry day of the contract.

3. **Settlement Prices for Futures:** Daily settlement price on a trading day is the closing price of the respective futures contracts on such day. The closing price for a futures contract is currently calculated as the last half an hour weighted average price of the contract in the F&O Segment of NSE. Final settlement price is the closing price of the relevant underlying index/security in the Capital Market segment of NSE, on the last trading day of the Contract.

Risk Management System

NSCCL has developed a comprehensive risk containment mechanism for the F&O segment. The salient features of risk containment measures on the F&O segment are:

1. The financial soundness of the members is the key to risk management. Therefore, the requirements for membership in terms of capital adequacy (Net Worth, Security Deposits) are quite stringent.

2. NSCCL charges an upfront initial margin for all the open positions of a Clearing Member (CM). It specifies the initial margin requirements for each futures/options contract on a daily basis. It follows VaR-based margin computed through SPAN (Standard Portfolio Analysis of Risk). The CM in turn collects the initial margin from the trading members (TMs) and their respective clients.

3. The open positions of the members are marked to market based on contract settlement price for each contract at the end of the day. The difference is settled in cash on a T+1 basis.

4. NSCCL's on-line position monitoring system monitors a CM's open position on a real-time basis. Limits are set for each CM based on his effective deposits. The on-line position monitoring system generates alert

messages whenever a CM reaches 70 %, 80 %, 90 % and a disablement message at 100 % of the limit. NSCCL monitors the CMs for Initial Margin violation, Exposure margin violation, while TMs are monitored for Initial Margin violation and position limit violation.

5. CMs are provided a trading terminal for the purpose of monitoring the open positions of all the TMs clearing and settling through him. A CM may set limits for a TM clearing and settling through him. NSCCL assists the CM to monitor the intra-day limits set up by a CM and whenever a TM exceeds the limits, it stops that particular TM from further trading.

6. A member is alerted of his position to enable him to adjust his exposure or bring in additional capital. Margin violations result in disablement of trading facility for all TMs of a CM in case of a violation by the CM.

7. A separate Settlement Guarantee Fund for this segment has been created out of deposits of members.

The most critical component of risk containment mechanism for F&O segment is the margining system and on-line position monitoring. The actual position monitoring and margining is carried out on-line through Parallel Risk Management System (PRISM) using Standard Portfolio Analysis of Risk (SPAN) system for the purpose of computation of on-line margins, based on the parameters defined by SEBI.

Economic and Social Functions of Futures Markets

Future markets are of critical importance for any financial markets in particular and global market in general. Instability of interest rates, currency values, and stock index prices represent great headaches for financial planners and forecasters. Futures trading serves as a tool that helps minimize the risk of this market disturbance. Financial managers use futures as risk management tools, which are generally successful in significantly reducing the potential for drastic losses in cash positions. In addition, the degree of leverage provided by futures is not available with any other financial instruments, which underlines their singular importance. With futures, speculators are able to creatively develop portfolios for which the level of risk is minimized Robert T. Daigler (1993).

The central purpose of futures trading is to support healthy competition, capital formation, and new product development. By reducing barriers to competition, futures help to safeguard and improve the general competitiveness of the economy. Futures exchanges are institutions that represent great equality of opportunity through access to improved forms of information flow which characterizes highly efficient markets. Futures trading enhance investment levels and savings flow. Finally, by creating a wide collection of new saving instruments, futures markets encourage the mobilization of savings and provide a rich variety of risk repackaging services, increasing the flow of funds between savers and investors, and simulating the growth of financial inter-mediation services Powers & Castelino (1991). Nevertheless, the central economic functions performed by futures are still in the fields of competitive price discovery and the hedging of price risks.

Futures markets provide information about the prices of underlying markets and serve as an accurate reflection of market expectations. The role of price discovery has been assigned to futures markets. Futures prices are established through open and competitive trading on the floor of the exchange. Prices reflect what is estimated to be the underlying supply and demand of an asset at some specific future date. These prices are public or global information. This process makes prices visible and available to everyone and establishes equilibrium between current and anticipated cash prices.

Another important function of futures markets is the shifting of risk through hedging. Futures markets separate price risk from other business risks and allow for transferring the price risk from traders who wish to transfer it to speculators who are willing to assume it. Thus, futures help traders to reduce or control risk exposure, the results of adverse price fluctuations Edwards & Cindy W. Ma (1992). There have been some important criticisms; however, lodged against futures markets. The critics claim that futures markets don’t provide sufficient benefits to the economy and society at large. Some critics argue that futures cause many economic problems such as higher interest rates, greater volatility of prices and rates, scarcity of resources; some go so far as to paint that the futures market are the high-tech form of legalized gambling-moral suspicion of dishonest gain Siems (1997). These criticisms may be based on pervasive perceptions-or misperceptions-of the role of speculators in futures markets. There is a widespread perception that futures markets are accurately characterized as entailing high leverage and great risk Edwards & Cindy W. Ma (1992). Despite these criticisms, however, the contribution of futures markets to the maintenance of a smoothly operating financial economy is undeniable.

It is often claimed that futures increase price volatility, leading to higher risk premiums and less efficient pricing. In one study of the volatility of futures prices, cash prices, and the magnitude of speculation was measured in sixteen futures exchanges; it was claimed that increased speculation increased premium risks in the futures market by increasing price volatility. The results of this study are at odds with the widespread assumption that speculation reduces the size of the risk premium. As mentioned above, another very frequently cited criticism of the futures market has to do with the charge of gambling. Unlike gambling, however, the risks from futures are not artificially created: rather, they arise naturally from the price fluctuations of the underlying spot market. Hence, futures markets do not create new risks; they simply let the hedger shift the risk of price changes to a person who is willing to assume them. Another important difference between gambling and futures markets are the way in which legal regulations and governmental regulatory agencies oversee futures markets to prevent unfair practices or manipulations Robert T. Daigler (1993).

In short, there are many advantages of futures markets to the economy and traders in particular. Futures increase market efficiency by providing information to decision-makers and planners. Commissions-bid-ask spreads and short-sell costs are less than they are on the cash market, so hedgers are able to hedge their position at a lower cost. There are also built in safeguards against credit risks as a result of clearing associations' guarantees. Finally, it is easy to enter this market became of relatively low capital requirements, increasing access to accommodate smaller players.

Fundamental Factors Affecting Stock Indexes Futures Markets

There are several factors that influence the development of stock market indexes. The relative importance of individual factors is likely to vary over time in significant ways. Over a long term, improvements in corporate earnings drive the secular trend of the stock market. This secular trend is based on earnings. The computation of the net present value of the future stream of earning depends on three variables: earnings, interest rates, and time. The effects of changes in the estimates of futures interest rates and earnings are compounded over time. This is a major reason for stock price volatility. The factors that effect stock market indexes are generally the same factors that influence earnings. These factors include interest rates, monetary policy, exchange rates, business cycles, inflation, and the state of the economy in general Smith Courtney (1992).

Trends in earnings over the long term are basic determinants of a market's future direction. Changes in the growth rates of earnings will have a significant impact on the direction of the stock market. The prices of the entire stock market will be determined by earnings over the long term. People tend to buy stocks when the stock market is undervalued and sell stocks when the market is overvalued. Therefore, it is necessary to monitor the extent to which the market is undervalued, overvalued, or accurately priced.

The monetary policies of a nation's Central Bank exert a powerful influence on capital market. Money generated by a Central Bank can ultimately be spent in many areas of the economy, including the stock market. Increased liquidity in an economy means that there is more money that can be invested in the stock market. Moreover, a Central Bank exerts a powerful influence on short-term interest rates too by controlling bank reserves and setting discount rates and interest rates which have an enormous impact on stock markets. Long-term interest rates also have a powerful impact on stock markets especially so far as bonds represent one of the major competitors of the stock market for attracting investments. Public sector borrowing requirements are often financed by the issue of gilt edged stock. If the government needs to borrow large amounts of money, interest rates are likely to increase, which is undesirable for the stock market John Millers (1992).

In addition, the general state of the economy also has a profound influence on the stock market. Expectations of future economic strength can cause people to think that future earnings will rise as well, so that stock prices will go up. It is generally believed that a strong economy corresponds with increasing stock prices. One especially important indicator of economic growth is the Gross Domestic Product (GDP). The GDP represents the total output of goods and services of the economy as a whole. When the GDP is high, share prices reflect capital growth. If GDP figures show stable growth, share prices generally rise or remain stable. When GDP shows a decline in the rate of growth, prices start to fall and people tend to sell their equities. Another fundamental indicator of the state of a stock market is consumer spending, which is a more rapid signal of change than the GDP; it can be classified according to sectors which indicate which sections of the economy are working well.

Exchange rates are another important factor that influences stock market prices. A strong national currency is especially important for companies that import goods and raw materials. The equities of the companies involved reflect the potential change in earnings; the profits of importers go down as the currency weakens. A weakening currency means higher interest rates and, therefore, a bad situation for the equity market. Inflation has a major impact on stock market indices. Inflation has an impact on the value of financial assets, as well such as stocks and bonds, and depreciates the earnings of the company. As the rate of inflation rises, people tend to purchase more consumer goods as they are concerned that prices will continue to increase. This attitude tends to shift the direction of financial resources away from investment and towards consumption. Finally, psychological factors also have a great influence on the equity market. Psychological trends and the depth of the sentiment involved can have a powerful effect on the stock market.

Conclusion

The study concludes that the derivatives market and its instruments are very dynamic and have quickly emerged as the most important segment of financial market. Futures contracts are a type of forward contract traded on organized exchanges featuring highly standardized contracts terms. The market has a complex operational environment with brokers, exchanges, and industry organization and a federal agency all playing their respective roles. Finally, the regulatory bodies govern the activities of a variety of like arbitragers, speculators etc. and thus facilitate future market effectively fulfill its economic functions of price efficiency and risk allocation. The imperatives for a well-functioning market are efficiency, price discovery and safety. Overall, it is clearly desirable to preserve the environment that has contributed to the impressive development of the derivatives market which performs various important economic functions.

However, it is imperative for policy makers to put efforts such that safety, transparency and operational efficiency could be enhanced along proven and successful models helping the global derivatives market to become even safer and more efficient.

CHAPTER - IV

THE EMPIRICAL RELATIONSHIP BETWEEN PRICE VOLATILITY, TRADING VOLUME AND MARKET DEPTH OF STOCK FUTURES

4.1 Introduction

Financial media regularly reports daily trading activities to the stock markets. The information content of this data in terms of volatilities of price, trading volume and market depth has long attracted the attention of many researchers, policy makers and investors, to examine if there is any relationship between these variables and the types of relationship that exist between these variables. Trading volume offers useful information for practitioners and investors in investment decisions, as well as for researchers and policy makers in testing the theories of financial economics. The contemporaneous relation between price movements, trading volume and open interest on financial markets keeps attracting the attention of many financial economists. Karpoffs (1987) seminal paper summarizes the importance of this research area by presenting the following argument. First, the returns or trading volume relation provides insight into the structure of financial markets. Second, the returns or trading volume relation is important for event studies that use a combination of stock returns and trading volume data to draw inferences. Third, the returns or trading volume relation is critical to the debate over the empirical distribution of speculative prices. As far as relationship between volume and price changes relative is concerned, a positive relationship was documented first by Ying (1966).

Later, empirical research of Granger and Morgenstern (1963) also focused only on positive contemporaneous relationship between asset price volatility and trading volume. This dissertation adds to the growing literature by examining the relationship between stock returns and trading volume data, with two different dimensions. First, on the prices changes and trading volume, if moves together with the market, which is called Sequential Information Arrival hypothesis (SEQ). Second, the dimensions from the information may be considered as mixing variables under the Mixture of Distribution hypothesis (MDH). It is really intricate; to test the informational content of futures market by using futures market returns series. There is an old Wall Street adage that “It takes trading volume to make prices move”. Hence, the basic logic in using trading activity variable is due to the explanatory power in predicting future price changes.

The primary aim of this dissertation is to empirically examine the relationship between price volatility, trading volume and market depth for select stock futures contracts. The underlying argument for price-volume relationship relies on the rate of information arrival in the financial market. More precisely it is relevant to know whether the information arrival is Sequential or a Mixture of Distribution. One of the main observations of the earlier analyses on the stock return and trading volume relationship is that they are all performed on stock markets. However, the results from stock futures contracts can be interesting for several reasons. First, price movements can only capture the impact of that 'news' on the average change in investor's expectations. Second, trading volume has the specificity of reflecting the cumulative response of investors. Finally, open interest can prove useful towards the end of the major market moves. Many studies reported a contemporaneous correlation between stock returns and trading volume variables, but the investigation on causal relationship between these variables in global markets are quite limited and still it remains like muddy water.

The sample used in this study includes daily closing prices, trading volume and open interest for select 25 stock futures contracts traded on the National Stock Exchange (NSE). The study uses return series of the contracts from January 2003 to December 2008. For each security, three types of contracts are usually traded simultaneously. The first is the expiring contract that is in the delivery month. The second is the nearby contract that has the next nearest delivery dates. The third kind is the more distant contracts. Price changes in all three kinds of contract are highly correlated.

Since most trading activities take place in the near-month contract, only near-month contract are examined. This also controls the maturity effect on future prices. Due to monthly maturity effect, futures market will roll or switch over to the next closest five days prior to maturity for calculating returns. An adjusted return is calculated as $R_t = \log (P_t/P_{t-1})$ where P_t and P_{t-1} are natural logarithms on day t and t-1 respectively. The logarithm of futures market return is used to prevent non-stationarity and eliminate future price variability. As far the trading volume and open interest, the study applies logarithmic procedure on other variables, also to account for the non - stationarity in the series.

4.2. Econometric Methodology

4.2.1. Unit Root Test:

The study first tests the stationarity of the time series for price changes, trading volume and open interest. Engle and Granger (1982) have shown that many time series variables are non-stationary or different order of integration *i.e.* I(1) series. Since most of time series have unit roots and are non stationary as indicated, by Nelson and Plosser (1982), and as proved by Stock and Watson (1988), that conventional regression techniques on non-stationary time series may produce spurious regression. Hence, the Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test are employed to infer the stationarity of the series.

4.2.1.1. Augmented Dickey Fuller (ADF) test:

Augmented Dickey Fuller (1979) implicitly assumes that the estimated errors are statistically independent and homoscedastic. Heteroskedasticity does not affect a wide range of unit root test statistics. However, a problem will occur if the estimated residual ε_t is not free from autocorrelation since, this invalidates the test. The well-known example of unit root non-stationary is the random walk model. There might be three possibilites for any time sereis. The time series might be a random walk, a random walk with drift, or random walk with drift and time trend. The three possible forms of the ADF test are given by the following equation;

$$\Delta Y_t = \gamma_1 y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + \varepsilon_t$$
$$\Delta Y_t = \alpha_0 + \gamma_1 y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + \varepsilon_t$$
$$\Delta Y_t = \alpha_0 + \gamma_1 y_{t-1} + \alpha_2 t + \sum_{i=1}^{p} \beta_i \Delta y_{t-1} + \varepsilon_t$$

Where, ε_t is white noise. The additional lagged difference terms are being determined by minimum number of residuals free from autocorrelation. This could be tested for in the standard way such as Akaike Information Criterion (AIC) or Schwartz Bayesian Criterion (SIC), or more usefully by the lag length criteria of the white noise series. The tests are based on the null hypothesis (H_0): Y_t is not I (0). If the calculated ADF test statistics are less than their critical values from table, then the null hypothesis (H_0) is accepted and the series are non-stationary or integrated to zero order.

4.2.1.2. Phillips-Peron (PP) test:

The distribution theory supporting the Dickey-fuller tests is based on the assumption that the error terms are statistically independent and have a constant variance. Thus, while using the ADF methodology one has to make sure that the error terms are uncorrelated and that they really have a constant variance. Phillips and Perron (1988) developed a generalization of the ADF test procedure that allows for fairly mild assumptions concerning the distribution of errors. The PP regression equations are as follows;

$$\Delta Y_{t-1} = \alpha_0 + \gamma_{yt-1} + \varepsilon_t$$

where, the ADF test corrects for higher order serial correlation by adding lagged differenced terms on the right-hand side, the PP test makes a correction to the t statistic of the coefficient γ from AR (1) regression to account for the serial correlation in ε_t. The statistics are all used to test hypothesis $\gamma = 0$, i.e., there exists a unit root. So, the PP statistics are just modifications of the ADF t statistics that take into account the less restrictive nature of the error process.

4.2.2. Generalized Autoregressive Conditional Heteroskedasticity Model

The Engle (1982) autoregressive conditional heteroskedasticity (ARCH) model is the most extensively used time-series models in the finance literature. The ARCH model suggests that the variance of residuals at time *t* depends on the squared error terms from past periods. The residual term ε_{it} is conditionally normally distributed and serially uncorrelated. The strength of the ARCH technique is that it uses the established and well specified models for economic variables; the conditional mean and conditional variance are the only two main specifications.

A useful generalization of this model is the GARCH parameterization. Bollerslev (1986) extended Engle's ARCH model to the GARCH model and it is based on the assumption that forecasts of time varying variance depend on the lagged variance of the asset. The GARCH model specification is found to be more appropriate than the standard statistical models, because it is consistent with return distribution, which is leptokurtic and it allows long-run memory in the variance of the conditional return distributions. As a result, the unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period. The GARCH (1,1) model works well in most applied situations Najand and Yung (1991) and Bollerslev (1992). The basic and most widespread model GARCH (1,1) can be expressed as;

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$\varepsilon_t \mid I_{t-1} \; N(0, h_t), \; h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2$$

Where, R_t denotes the realized return, h_{it} is the conditional variance, which is proxies by R_{t-1}, α, β and λ are the coefficients to be estimated. The sizes of the parameters β and λ measure the short-run dynamics of the resulting volatility time series. The λ scaling parameter h_t now depends both on past values of the information, which is captured by the lagged squared residual terms, and on past values of itself, which are captured by lagged h_t terms. The β parameter refers to the last periods forecast variance, the larger coefficients value of GARCH term characterizes the informational effects to conditional variance that take a long time to die out. In GARCH model, the coefficients of variance equation β and λ should be less than 1 (i.e.) GARCH is weekly stationery if the $\Sigma\beta_i + \Sigma\lambda_j < 1$, the latter two quantifying the persistence of shocks to volatility Nelson (1992).

4.2.3. Augmented GARCH Model:

The types of persistence in conditional variance can be picked up by estimating a GARCH model. The Augmented GARCH model was developed by Duan (1997) tests most of the popular univariate parameterization and allows us to add explanatory variables in the GARCH specification of the conditional variance equation. Engle (1982) and Bollerslev (1986) emphasized the inclusion of exogenous variables in the conditional variance. Volume and open interest series are included to evaluate their incremental significance in return prediction. The Augmented GARCH model may be expressed as;

$$\begin{aligned} R_t &= a + bR_{t-1} + \varepsilon_t \\ \varepsilon_t \mid I_{t-1} &\; N(0, h_t), \\ h_{it} &= \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{k=1}^{m} \psi_k X_k \end{aligned}$$

Where, R_t is the realized return, h_{it} is the conditional variance, λ is the lag of squared residuals from the mean equation and provides news about volatility clustering, β is the last period's forecast variance and ψ is a set of explanatory variables that might help to explain the variance of the equation.

4.2.3.1. Expected Components of Trading Volume and Open Interest:

The trading activity and open interest variables are introduced in the conditional variance equation to investigate their effects on volatility. Specifically, to evaluate their incremental significance in return prediction on volume, volume prediction on return, return prediction on open interest and open interest prediction on return volatility estimation are given below by utilizing Augmented GARCH model in the following equation;

Return Prediction on Trading Volume:

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{k=1}^{m} \psi_k V_k$$

Returns Prediction on Open Interest:

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{k=1}^{m} \psi_k O_k$$

Where, R_k, V_k and O_k represent the future returns, trading volume and open interest for the stock futures contracts. Engle (1982) and Bollerslev (1986) emphasized that inclusion of exogenous variables in the conditional variance will facilitate to explain the incremental significance in the equation.

4.2.3.2. Unexpected Components of Trading Volume and Open Interest:

Initially, the univariate Box-Jenkins methods were employed to partition trading volume and open interest series into expected and unexpected components Bessembinder and Seguin (1993). Partitioning the series into expected and unexpected components separates out information shocks that might otherwise enter the market. An ARIMA model was estimated for trading volume and open interest series to decompose futures trading volume into expected and unexpected components. The uncorrelated residuals of the conditional mean equation were the unexpected innovations of trading volume and open interest, which were then squared and included in the Augmented GARCH conditional variance specification. Bessembinder and Seguin (1992) provide evidence consistent with the reasoning that expected and unexpected trading volume conveys different information to market participants.

The unexpected trading activity and unexpected open interest variables were then introduced in the conditional variance equation to investigate their effects on volatility. Specifically, to evaluate their incremental significance of return prediction on unexpected trading volume, unexpected trading volume prediction on return, return prediction on unexpected open interest and unexpected open interest prediction on return the volatility estimation are given below by utilizing Augmented GARCH model in the following equation;

Return Prediction on Unexpected Trading Volume:

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{k=1}^{m} \psi_k UV_k$$

Returns Prediction on Unexpected Open Interest:

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{k=1}^{m} \psi_k UO_k$$

Where, UV_k and UO_k are the trading volume and open interest for the stock future contracts. Engle (1982) and Bollerslev (1986) emphasized inclusion of exogenous variables in the conditional variance which will facilitate the explanation the incremental significance in the equation.

4.3. Results and Discussion:

To assess the distributional properties of the daily stock futures returns, trading volume and open interest, various descriptive statistics are summarized in Table 1 in terms of Mean, Standard deviation, Skewness, Kurtosis, Jarque-Bera test and Ljung-Box (LB) Q statistics for 5 and 15 lags corrected for heteroskedasticity following Diebold (1988), for select 25 stock future contracts for the period from April 1, 2003 to December 31, 2008. The descriptive statistics for return, trading volume and open interest are presented in Panel A, B and C, respectively of the Table: 1.

Table: 1. Summary Statistics for Return, Trading Volume & Open Interest

Panel: A. Descriptive Statistics for Return

Sl. No:	Company	Mean	S.D	Skewness	Kurtosis	J-B	Probability	LB-Q (5)	LB-Q (15)
1	ACC	.00140	0.0235	-0.7379	7.9437	1391.948	0.000	246.97*	253.08*
2	BEL	.00140	0.0256	0.0613	8.8152	1769.12	0.000	291.7*	297.02*
3	BHEL	.00177	0.0320	-8.3726	179.829	1651072	0.000	249.87*	253.89*
4	BPCL	.00047	0.0254	0.1704	7.0518	865.279	0.000	279.45*	321.61*
5	CIPLA	-.00093	0.0563	-21.4828	562.627	1648650	0.000	316.7*	320.8*
6	Dr. REDDY	-.00034	0.0292	-11.0610	266.459	3658105	0.000	309.73*	323.69*
7	GRASIM	.00162	0.0225	0.0863	6.3275	581.032	0.000	288.63*	309.24*
8	HCLTECH	.00040	0.0334	-6.7007	135.691	93083.9	0.000	328.4*	351.15*
9	HDFC	.00156	0.0232	0.2390	8.4396	1560.49	0.000	263.09*	283.29*
10	HEROHONDA	.00104	0.0215	-0.0694	5.0023	210.8428	0.000	242.15*	260.95*
11	HINDPETRO	-.00010	0.0267	-0.1936	7.5925	1111.639	0.000	294.15*	327.52*
12	ICICIBANK	.00139	0.0243	-0.1538	6.3215	582.338	0.000	232.82*	243.71*
13	INFOSYSTCH	-.00077	0.0489	-19.9953	523.457	1424803	0.000	317.91*	320.11*
14	ITC	-.00088	0.0771	-32.0364	1098.06	6297103	0.000	300.39*	300.91*
15	M & M	.00155	0.0307	-9.5150	215.756	2385946	0.000	269.05*	279.26*
16	MTNL	-1.8300	0.0275	-0.5489	8.6644	1742.265	0.000	232.89*	249.59*
17	NATIONALUM	.00144	0.0305	-0.2754	7.6379	1141.624	0.000	282.66*	296.61*
18	ONGC	.00080	0.0263	-2.9181	42.1801	82118.69	0.000	269.58*	278.01*
19	POLARIS	-.00036	0.0367	-0.4949	14.1692	6579.907	0.000	286.99*	298.89*
20	RANBAXY	-.00029	0.0289	-12.3636	309.469	4943384	0.000	316.69*	318.84*
21	RELIANCE	.00167	0.0224	-2.2919	29.9043	38856.68	0.000	329.05*	347.07*
22	SBIN	.00139	0.0239	-0.6830	7.6814	1244.598	0.000	250.17*	261.18*
23	TATAPOWER	.00184	0.0282	-0.6337	12.7361	5044.873	0.000	218.38*	247.62*
24	TATATEA	.00116	0.0234	-0.2056	8.4711	1575.345	0.000	218.84*	233.19*
25	WIPRO	-.00084	0.0447	-14.5317	327.1354	5542542	0.000	352.94*	354.92*

Note: * Significance at 0.01 per cent level respectively.

The statistics reported in Panel: A, shows that the mean return for CIPLA, Dr. REDDY, HINDPETRO, INFOSYSTCH, ITC, MTNL, POLARIS, RANBAXY and WIPRO were observed with negative sign. The standard deviation of the futures returns series were higher for ITC and CIPLA respectively. The statistics shows that returns are negatively skewed, except for BEL, BPCL, GRASIM and HDFC. The negative skewness implies that the return distribution of the stock futures returns have a heavier tail of large values and hence a higher probability of earning negative returns. The value of kurtosis exceeds 3, which is indicates that the unconditional return distributions are not normal. The Jarque-Bera (JB) test confirms that normality is rejected at a p-value of almost 1. The LB Q statistics for return series at 5 and 15 lags shows that the null hypothesis of no serial correlation cannot be rejected.

Panel: B. Descriptive Statistics for Trading Volume

Sl. No:	Company	Mean	S.D	Skewness	Kurtosis	J-B	Probability	LB-Q (5)	LB-Q (15)
1	ACC	8.1259	0.8471	-0.6021	4.3386	169.5411	0.000	121.11*	139.99*
2	BEL	6.0616	1.2647	-0.0959	3.0908	2.357889	0.000	109.05*	114.12*
3	BHEL	7.5937	0.9705	-0.4919	4.5593	177.9199	0.000	118.68*	126.27*
4	BPCL	6.8417	0.7176	-0.1432	3.4764	16.17457	0.000	123.86*	140.8*
5	CIPLA	6.7501	1.0977	-0.4682	3.8512	83.8236	0.000	108.5*	115.85*
6	Dr. REDDY	6.8551	0.8864	-0.3597	4.0198	81.52842	0.000	111.83*	123.12*
7	GRASIM	7.1496	0.8728	-1.0935	5.8592	678.1407	0.000	167.14*	196.05*
8	HCLTECH	6.8767	0.6899	-0.7970	6.2662	691.3029	0.000	144.92*	184.95*
9	HDFC	6.3100	1.2847	-0.5950	3.3942	82.24779	0.000	107.01*	119.34*
10	HEROHONDA	6.7471	0.7220	-0.3454	4.5420	149.4247	0.000	109.26*	122.95*
11	HINDPETRO	7.4072	0.7801	-0.2401	3.7968	45.30653	0.000	124.45*	141.82*
12	ICICIBANK	7.9373	1.1948	-0.0078	2.7106	4.394083	0.000	135.37*	151.95*
13	INFOSYSTCH	8.9255	0.7079	-0.8850	6.3885	764.2606	0.000	114.08*	132.11*
14	ITC	7.6402	0.9868	-0.5514	3.3490	70.03666	0.000	158.31*	166.99*
15	M & M	7.6075	0.7571	-0.8294	4.7573	305.397	0.000	116.47*	131.62*
16	MTNL	7.7294	0.9194	-0.1903	3.9334	53.18206	0.000	139.72*	156.39*
17	NATIONALUM	6.7858	0.8181	-1.0229	6.3169	794.8074	0.000	140.44*	153.5*
18	ONGC	8.3988	1.0499	-3.0380	16.799	11897.9	0.000	119.34*	132.72*
19	POLARIS	7.1467	0.8450	-0.2007	3.6591	31.17936	0.000	96.36*	104.34*
20	RANBAXY	7.6267	0.8500	-0.4318	3.7212	66.20618	0.000	146.34*	162.33*
21	RELIANCE	9.8220	0.8135	-0.2686	4.1467	83.65667	0.000	124.55*	155.73*
22	SBIN	9.2320	0.7040	-0.9386	5.7545	581.5259	0.000	128.6*	132.03*
23	TATAPOWER	7.3456	0.9844	-0.5812	4.1999	146.0724	0.000	109.31*	132.48*
24	TATATEA	6.4377	0.9419	-0.2514	3.2395	16.24212	0.000	124.36*	128.96*
25	WIPRO	7.7849	0.5748	-1.2147	8.6938	2005.549	0.000	144.51*	160.50*

Note: * Significance at 0.01 per cent level respectively.

Panel: B of the Table 1 presents some basic characteristics of the trading volume. The mean and standard deviation of the trading volume series were observed with positive and the fluctuations in BEL, HDFC and ICICIBANK were quite abnormal. The value of skewness and kurtosis for trading volume displayed some interesting characteristics. For normally distributed random variables skewness is zero and kurtosis is three. Each of the series is skewed towards the left and distribution of tails that are much fatter than a normal distribution, except ICICIBANK which was found Platykurtic. The unpredictability of the trading volume behaviour can be seen by looking at the Ljung-Box Q statistics for 5 and 15lags for the trading volume series.

Panel: C. Descriptive Statistics for Open Interest

Sl. No:	Company	Mean	S.D	Skewness	Kurtosis	J-B	Probability	LB-Q (5)	LB-Q (15)
1	ACC	14.9810	0.6143	-0.4465	3.75644	71.62784	0.000	69.88*	71.46*
2	BEL	12.8577	0.9251	-0.9904	5.44543	517.9149	0.000	82.58*	84.06*
3	BHEL	13.8963	0.6122	-1.0735	5.60375	596.0349	0.000	68.66*	71.92*
4	BPCL	14.1318	0.6249	-1.2813	6.34752	930.1225	0.000	71.57*	73.67*
5	CIPLA	14.1452	1.5739	-0.5405	2.50519	73.98873	0.000	60.49*	64.11*
6	Dr. REDDY	13.5951	0.9107	-0.5042	3.46568	64.57255	0.000	68.59*	69.94*
7	GRASIM	13.5134	0.5162	-0.7398	4.82057	288.0435	0.000	70.89*	72.84*
8	HCLTECH	14.2268	0.7193	-0.5886	3.98729	123.5422	0.000	69.14*	71.42*
9	HDFC	12.9157	0.9721	-1.2245	5.07387	539.0013	0.000	39.73*	43.28*
10	HEROHONDA	13.6453	0.6228	-1.1676	5.65626	654.6582	0.000	68.75*	70.91*
11	HINDPETRO	14.9953	0.5826	-0.9813	5.44249	513.8032	0.000	76.92*	80.02*
12	ICICIBANK	15.2000	0.7062	-0.8678	4.38715	258.3479	0.000	52.21*	55.29*
13	INFOSYSTCH	14.0810	1.0172	-0.7283	2.99035	110.9601	0.000	51.16*	55.91*
14	ITC	14.8021	1.7488	-0.2164	1.70398	97.70521	0.000	58.63*	60.28*
15	M & M	14.3972	0.5446	-1.1327	5.48584	591.534	0.000	68.09*	70.44*
16	MTNL	16.0489	0.8985	-1.0495	4.48742	346.3857	0.000	67.15*	69.63*
17	NATIONALUM	14.8775	0.6166	-1.7041	6.84562	1381.884	0.000	59.49*	62.05*
18	ONGC	14.9190	0.8842	-2.4521	13.5369	7069.152	0.000	63.97*	66.31*
19	POLARIS	15.2797	0.6978	-1.2172	4.65529	453.5802	0.000	80.16*	82.18*
20	RANBAXY	14.7485	0.9345	-0.6366	2.64082	91.53306	0.000	75.01*	78.21*
21	RELIANCE	16.0235	0.6189	-0.7596	3.93874	166.3952	0.000	62.24*	64.27*
22	SBIN	15.5673	0.4589	-1.6900	7.69788	1752.883	0.000	76.81*	78.51*
23	TATAPOWER	14.3935	0.6756	-0.2171	3.61484	29.65072	0.000	60.22*	65.38*
24	TATATEA	13.6914	0.7510	-0.9350	4.66039	327.2922	0.000	77.56*	78.95*
25	WIPRO	14.4131	1.0825	-0.7665	2.79123	125.2973	0.000	60.29*	63.15*

Note: * Significance at 0.01 per cent level respectively.

Panel: C also presents the basic statistics relating to the open interest series, the mean of open interest which was found to be large for RELIANCE and MTNL. The most volatile market was found to be ITC with 1.7488 and the least volatile open interest contract being SBIN with 0.4589 per day. Despite the skewness found to be relatively small with a negative magnitude, kurtosis value was observed with leptokurtic and platykurtic effect except INFOSYSTCH with mesokurtic. Here, the JB statistics was higher and statistically significant and hence null hypothesis of non normality of the series was rejected. The Ljung-Box Q statistics for the open interest series envisaged that the stock futures displayed of ARCH effects which is evidenced from the significant autocorrelations coefficients.

Table: 2. Unit Root Test

Panel: A. Augmented Dickey Fuller Test

Sl. No:	Company	Returns			Trading Volume			Open Interest		
		Intercept	Trend	Both	Intercept	Trend	Both	Intercept	Trend	Both
1	ACC	-14.5751	-14.5694	-14.5807	-12.1226	-12.1685	-12.1153	-11.3690	-11.3990	-11.3729
2	BEL	-17.2147	-17.2076	-17.2186	-14.6093	-14.6072	-14.6155	-12.3213	-12.3753	-12.3043
3	BHEL	-12.9756	-12.9687	-12.9809	-12.2293	-12.2241	-12.1910	-12.3859	-12.3807	-12.3905
4	BPCL	-12.3827	-12.3767	-12.3873	-12.0700	-12.0764	-12.0744	-13.2811	-13.2999	-13.2817
5	CIPLA	-12.9863	-12.9809	-12.9914	-14.0598	-14.0712	-14.0571	-10.8379	-10.9428	-10.7838
6	Dr. REDDY	-14.0531	-14.0473	-14.0587	-13.9943	-14.0476	-13.9948	-11.2703	-11.3333	-11.2483
7	GRASIM	-12.3440	-12.3401	-12.3482	-12.5051	-12.5286	-12.4940	-11.2745	-11.3026	-11.2772
8	HCLTECH	-13.3619	-13.3588	-13.3674	-13.1290	-13.1238	-13.1345	-12.1315	-12.1264	-12.1341
9	HDFC	-14.2634	-14.2592	-14.2692	-14.1318	-14.1381	-14.0530	-12.3254	-12.4406	-12.3277
10	HEROHONDA	-14.2638	-14.2567	-14.2685	-12.8293	-12.8404	-12.8345	-12.9070	-12.9207	-12.9124
11	HINDPETRO	-12.4051	-12.3991	-12.4098	-11.0282	-11.0297	-11.0273	-12.9759	-12.9749	-12.9813
12	ICICIBANK	-13.5267	-13.5357	-13.5310	-14.2539	-14.2485	-14.1936	-11.4849	-11.5066	-11.4554
13	INFOSYSTCH	-12.9829	-12.9746	-12.9881	-13.4755	-13.4739	-13.4810	-12.0945	-12.0967	-12.0593
14	ITC	-12.6651	-12.6600	-12.6704	-12.9868	-13.0001	-12.9703	-10.0176	-10.0514	-09.9731
15	M & M	-12.5518	-12.5473	-12.5569	-15.1355	-15.2107	-15.1370	-12.5416	-12.5651	-12.5370
16	MTNL	-12.4344	-12.4280	-12.4387	-09.8970	-09.9154	-09.8935	-11.8313	-11.9481	-11.7355
17	NATIONALUM	-13.2924	-13.2869	-13.2978	-11.4561	-11.5094	-11.4332	-11.8695	-12.0216	-11.8502
18	ONGC	-12.5414	-12.5362	-12.5467	-09.4355	-13.1752	-09.3451	-11.2937	-10.8899	-11.2094
19	POLARIS	-12.8900	-12.8832	-12.8948	-11.1129	-11.1198	-11.1113	-14.6103	-14.8337	-14.5940
20	RANBAXY	-14.3314	-14.3255	-14.3372	-10.9882	-11.0442	-11.4346	-10.1860	-10.2850	-10.3946
21	RELIANCE	-12.9320	-12.9312	-12.9374	-13.1497	-13.1446	-13.0947	-12.8732	-12.9264	-12.8716
22	SBIN	-12.7943	-12.7967	-12.7981	-11.9296	-11.9702	-11.8888	-12.8746	-12.9806	-12.8795
23	TATAPOWER	-13.0569	-13.0517	-13.0625	-11.0451	-11.1004	-11.0061	-12.0023	-12.0383	-12.0008
24	TATATEA	-14.0267	-14.0209	-14.0324	-12.6725	-12.7349	-12.6758	-11.0059	-11.1548	-11.0103
25	WIPRO	-13.8970	-13.8891	-13.9023	-13.9547	-13.9485	-13.9605	-13.4948	-13.5174	-13.4049

Note: The significant value at 1 % for ADF test for intercept, trend and with both are – 2.5665, -3.4357 and -3.9667 respectively.

Panel: B. Phillips – Perron Test

Sl. No:	Company	Returns			Trading Volume			Open Interest		
		Intercept	**Trend**	**Both**	**Intercept**	**Trend**	**Both**	**Intercept**	**Trend**	**Both**
1	ACC	-566.122	-567.155	-565.666	-173.945	-196.850	-170.438	-94.572	-98.324	-94.611
2	BEL	-388.461	-388.484	-386.527	-113.012	-113.562	-113.261	-93.619	-96.251	-93.362
3	BHEL	-451.414	-451.171	-451.555	-185.987	-186.563	-179.841	-98.758	-98.868	-98.888
4	BPCL	-265.564	-265.386	-265.651	-144.028	-143.896	-144.134	-104.857	-104.789	-104.912
5	CIPLA	-474.173	-474.685	-474.432	-112.780	-116.563	-111.145	-57.601	-59.410	-56.985
6	Dr. REDDY	-479.750	-479.737	-479.963	-129.898	-136.802	-129.467	-86.828	-89.285	-85.501
7	GRASIM	-409.733	-410.151	-406.843	-139.015	-181.745	-118.540	-96.812	-98.083	-96.727
8	HCLTECH	-462.595	-462.512	-461.251	-161.511	-161.416	-161.579	-86.706	-86.556	-86.350
9	HDFC	-416.942	-417.165	-416.336	-89.504	-91.299	-89.149	-39.073	-39.295	-39.146
10	HEROHONDA	-393.359	-393.518	-393.014	-252.517	-261.489	-252.318	-91.114	-91.181	-91.235
11	HINDPETRO	-316.558	-316.383	-316.609	-162.876	-159.909	-161.965	-100.135	-102.048	-100.271
12	ICICIBANK	-272.350	-273.803	-271.896	-145.185	-144.731	-133.927	-76.210	-75.189	-75.407
13	INFOSYSTCH	-445.289	-445.092	445.519	-234.896	-234.678	-234.740	-78.841	-78.883	-77.840
14	ITC	-1034.70	-1041.81	-1035.28	-253.980	-278.534	-221.480	-65.814	-66.182	-64.937
15	M & M	-544.698	-549.367	-544.046	-166.923	-185.979	-166.196	-92.282	-92.629	-92.079
16	MTNL	-554.107	-554.146	-545.530	-116.514	-118.030	-115.968	-72.803	-74.160	-71.197
17	NATIONALUM	-352.546	-353.390	-352.385	-116.842	-119.195	-116.536	-76.444	-78.537	-76.042
18	ONGC	-417.230	-417.719	-413.701	-88.824	-92.237	-87.549	-66.383	-69.709	-65.383
19	POLARIS	-341.825	-341.929	-341.818	-118.305	-118.758	-118.173	-133.673	-165.267	-129.051
20	RANBAXY	-443.284	-443.273	-443.498	-202.504	-437.829	-181.313	-82.814	-85.920	-80.599
21	RELIANCE	-399.246	-399.413	-398.942	-536.838	-542.334	-194.945	-106.144	-110.005	-105.087
22	SBIN	-313.232	-313.673	-312.599	-196.414	-196.448	-183.671	-106.093	-108.223	-106.153
23	TATAPOWER	-499.383	-497.616	-498.130	-96.856	-97.868	-96.226	-81.827	-82.191	-81.834
24	TATATEA	-429.072	-429.026	-429.129	-208.459	-268.429	-209.194	-88.542	-93.746	-88.621
25	WIPRO	-500.368	-500.225	-492.883	-207.410	-207.963	-207.528	-95.245	-96.340	-93.462

Note: The significant value at 1 % for Phillips-Perron test for intercept, trend and with both are – 2.5665, -3.4357 and -3.9667 respectively.

To set the stage for the distributional properties of price volatility, trading volume and open interest, the order of integration of the variables were initially determined and presented in Table 2. One of the main concerns of the time series is to investigate whether the multivariate series contain unit root. In order to check the stationarity of the series, both Augmented Dickey Fuller (ADF) test and Phillip-Perron test were conducted and their results are presented in Panel A and Panel B. The results allow us to reject the hypothesis that price volatility, trading volume and open interest have unit root in favour of hypothesis of stationarity even at 1 per cent level at Mac Kinnon critical value.

Table: 3

Autoregressive Model for Trading Volume and Open Interest

Sl. No:	Company Name	Futures Volume			Futures Open Interest		
		AR (p)	**LB (6)**	**LB (12)**	**AR (p)**	**LB (6)**	**LB (12)**
1	ACC	2	7.1196	12.732	4	7.8134	25.629
2	BEL	3	17.528	19.605	4	6.6811	24.237
3	BHEL	2	11.818	15.796	4	6.2433	21.677
4	BPCL	4	11.500	20.380	4	5.6881	20.995
5	CIPLA	3	16.615	18.656	6	5.4269	19.125
6	Dr. REDDY	3	8.2167	12.139	4	6.5115	21.000
7	GRASIM	5	11.783	13.585	5	6.1721	19.827
8	HCLTECH	6	10.922	13.077	6	4.4944	15.888
9	HDFC	2	5.2807	5.5198	2	0.6352	1.4745
10	HEROHONDA	4	8.9459	14.300	4	4.11441	15.552
11	HINDPETRO	4	16.621	21.287	4	6.4349	23.634
12	ICICIBANK	3	9.1215	12.403	4	6.5978	19.023
13	INFOSYSTCH	2	5.6295	8.9912	3	8.6683	20.798
14	ITC	2	14.929	20.376	2	12.340	25.762
15	M & M	2	10.509	16.339	5	7.5044	25.392
16	MTNL	3	14.737	16.418	4	6.9521	17.603
17	NATIONALUM	3	16.954	20.581	4	6.1829	17.796
18	ONGC	6	19.636	22.818	3	9.6206	15.133
19	POLARIS	2	5.3930	17.216	5	5.2496	22.236
20	RANBAXY	2	12.093	22.312	5	6.9827	23.970
21	RELIANCE	2	9.3795	15.432	4	9.7677	31.263
22	SBIN	2	12.557	20.061	5	5.6844	19.381
23	TATAPOWER	2	14.350	18.653	4	5.8663	18.820
24	TATATEA	2	8.1510	12.899	4	8.1567	27.002
25	WIPRO	2	9.4717	12.350	5	4.9279	17.082

Note: LB (6) & LB (12) refers Ljung- Box Portmanteau statistic for uncorrelated residuals, over 6 and 12 lags, respectively

An autoregressive model of AR (p) was estimated for each of the stationary series and an ARIMA model was estimated for trading volume and open interest series to obtain residuals as a dependent variable in Table 3. Partitioning the series into expected and unexpected components was done to separate out information shocks that might otherwise enter the market. Trading volume and open interest were used to explain the lag length required to produce uncorrelated residuals for stock futures without over fitting the model. The residuals from ARIMA model were then used as the unexpected components. The Ljung Box Q- Statistics for unstandardized residual, over 6 and 12 lags did not reject the null hypothesis of no autocorrelation at any standard level for the unexpected components of trading volume and open interest in each period for stock future contracts.

The parameter estimates of the GARCH (1,1) model with the inclusion of expected and unexpected volume in the conditional variance. In the following models, an iterative procedure was used based upon the method of Bernd-Hall-Hall Hausman algorithm to maximize the log-likelihood function. Panel A shows the results for expected trading variable and Panel B shows the corresponding results for unexpected trading variables. The log likelihood function statistics were found large, which indicates that the AGARCH formulation is an appropriate presentation of daily stock future behaviour that captures the temporal dependence of return volatility. The F-statistics is significant at 1 per cent for all the stock future contracts.

Table: 4. GARCH (1,1) Model prediction for Returns on Trading Volume

Panel: A. Futures Returns on Expected Trading Volume

Sl. No:	Company	Coefficients						F - Statistic	Log Likelihood
		ø	R_{t-1}	α_0	α_1	β_2	ψ_3		
1	ACC	-0.000 (-0.30)	-0.468 (-16.86)*	4.92E-0 (5.77)*	0.153 (7.92)*	0.792 (31.54)*	0.000 (8.10)*	56.27	2769.54
2	BEL	-0.001 (-1.96)	-0.423 (-15.12)*	0.000 (7.59)*	0.260 (11.06)*	0.556 (14.06)*	0.000 (21.96)*	71.83	2711.35
3	BHEL	1.77E-0 (0.03)	-0.289 (-9.88)*	0.000 (7.99)*	1.043 (18.20)*	0.292 (10.32)*	0.000 (7.15)*	48.99	2653.47
4	BPCL	-0.000 (-0.63)	-0.503 (-19.69)*	2.6E-0 (3.65)*	0.114 (9.27)*	0.860 (55.99)*	0.000 (8.44)*	68.67	2709.33
5	CIPLA	0.000 (0.20)	-0.371 (-7.94)*	0.002 (12.46)*	0.075 (3.48)*	0.272 (4.86)*	-0.001 (45.44)*	73.22	1853.45
6	Dr. REDDY	0.003 (7.10)*	-0.424 (-16.45)*	0.000 (16.09)*	1.658 (14.58)*	0.028 (2.04)#	1.24E-0 (0.99)	74.69	2530.77
7	GRASIM	-0.000 (-0.66)	-0.479 (-16.93)*	3.10E-0 (4.86)*	0.160 (8.26)*	0.802 (36.61)*	0.000 (11.73)*	72.08	2875.11
8	HCLTECH	0.003 (2.61)*	-0.592 (-11.33)*	0.000 (70.85)*	0.643 (13.79)*	0.430 (12.92)*	0.000 (13.10)*	81.22	2367.65
9	HDFC	-0.000 (-0.80)	-0.467 (-16.94)*	8.25E-0 (5.07)*	0.226 (10.25)*	0.675 (21.15)*	0.000 (7.40)*	55.17	2804.91
10	HEROHONDA	-0.000 (-1.28)	-0.470 (-17.68)*	7.07E-0 (5.20)*	0.216 (7.59)*	0.693 (19.71)*	0.000 (10.87)*	55.96	2853.02
11	HINDPETRO	0.000 (0.62)	-0.530 (-17.43)*	-0.000 (-4.63)*	0.244 (8.44)*	0.670 (18.24)*	5.86E-0 (5.45)*	72.05	2675.97
12	ICICIBANK	-0.001 (-1.40)	-0.414 (-15.14)*	0.000 (6.69)*	0.198 (7.06)*	0.427 (6.33)*	0.000 (19.48)*	54.56	2738.47

Continued…..

13	INFOSYSTCH	-0.001 (-0.21)	-0.465 (-6.01)*	0.003 (3.04)*	0.092 (1.74)	0.587 (4.60)*	0.001 (30.29)*	82.69	1665.96
14	ITC	-0.009 (-0.59)	-0.322 (-2.71)*	0.004 (3.58)*	0.049 (2.24)#	0.719 (10.59)*	0.004 (36.65)*	63.42	1247.55
15	M & M	-0.004 (-1.90)	-0.543 (-11.38)*	0.000 (23.95)*	0.059 (3.46)*	0.822 (92.23)*	0.000 (5.70)*	59.88	2333.10
16	MTNL	-0.000 (-0.33)	-0.418 (-16.83)*	6.30E-0 (3.97)*	0.177 (10.53)*	0.758 (26.17)*	0.000 (96.80)*	52.08	2612.71
17	NATIONALUM	-0.000 (-0.19)	-0.481 (-17.90)*	4.82E-0 (5.98)*	0.186 (11.47)*	0.784 (51.79)*	0.000 (6.83)*	71.63	2536.30
18	ONGC	-0.005 (-3.71)*	-0.469 (-13.53)*	0.000 (22.22)*	0.060 (4.50)*	0.600 (85.17)*	0.000 (2.35)**	56.12	2516.20
19	POLARIS	-0.000 (-0.56)	-0.429 (-17.90)*	0.000 (6.57)*	0.313 (11.25)*	0.581 (15.13)*	0.000 (13.13)*	72.15	2331.50
20	RANBAXY	-0.000 (-0.65)	-0.450 (-13.57)*	0.000 (3.62)*	0.068 (3.15)*	0.406 (2.48)#	0.000 (12.01)*	78.40	2535.05
21	RELIANCE	-7.26E-0 (0.14)	-0.516 (-16.03)*	7.30E-0 (5.90)*	0.316 (19.51)*	0.608 (21.18)*	9.50E-0 (5.68)*	87.31	2914.26
22	SBIN	0.000 (0.39)	-0.483 (-17.87)*	9.48E-0 (4.19)*	0.200 (8.51)*	0.691 (15.98)*	0.000 (5.58)*	57.90	2750.44
23	TATAPOWER	-0.000 (-0.47)	-0.442 (-15.09)*	6.28E-0 (5.84)*	0.232 (11.01)*	0.722 (34.20)*	8.67E-0 (3.91)*	38.14	2667.29
24	TATATEA	-0.000 (-0.83)	-0.459 (-17.40)*	7.90E-0(6.30)*	0.327 (8.53)*	0.594 (14.13)*	0.000 (12.74)*	45.37	2887.12
25	WIPRO	-0.001 (-1.52)	-0.335 (-7.70)*	0.000 (24.96)*	1.340 (21.78)*	0.040 (1.95)	-0.000 (17.77)*	79.59	2175.91

Notes: Figures in the parenthesis report z-Statistics. * & # refers to 0.01 & 0.05 per cent level of Significance. Where R_t represents the rate of return I_{t-1} is the set of information available at the beginning of time t. The variance scaling parameter h_t now depends both on past and present values of the shocks, which are captured by the lagged residual terms and designated by ARCH (α_1) and GARCH effect (β_2) respectively. The explanatory variable was denoted by ψ_3

Panel: B. Futures Returns on Unexpected Trading Volume

Sl. No:	Company	Coefficients						F - Statistic	Log Likelihood
		ø	R_{t-1}	α_0	α_1	β_2	ψ_3		
1	ACC	-8.6E-0 (-0.14)	-0.464 (-16.86)*	4.11E-0 (5.27)*	0.135 (7.88)*	0.819 (35.61)*	0.000 (8.73)*	56.38	2770.33
2	BEL	-0.000 (-1.15)	-0.423 (-15.05)*	0.000 (7.20)*	0.251 (10.19)*	0.555 (12.78)*	0.000 (13.25)*	71.78	2710.03
3	BHEL	-0.001 (-1.28)	-0.202 (-3.58)*	0.000 (5.98)*	0.707 (9.05)*	0.438 (7.66)*	0.000 (29.96)*	37.57	2489.53
4	BPCL	0.000 (0.27)	-0.505 (-18.94)*	2.96E-0 (4.08)*	0.131 (8.05)*	0.840 (46.11)*	0.000 (10.37)*	68.52	2714.78
5	CIPLA	0.000 (0.30)	-0.288 (-7.60)*	0.003 (33.70)*	0.132 (2.69)*	-0.102 (-3.29)*	-0.001 (-38.38)*	62.45	1862.35
6	Dr. REDDY	0.001 (1.72)	-0.442 (-10.68)*	0.000 (11.84)*	0.409 (5.24)*	0.059 (0.85)	-7.700 (-9.84)*	78.54	2528.06
7	GRASIM	5.83E-0 (0.10)	-0.474 (-16.46)*	5.11E-0 (11.07)*	0.175 (12.96)*	0.755 (241.76)*	0.000 (7.72)*	72.01	2871.38
8	HCLTECH	0.000 (0.39)	-0.520 (-17.16)*	0.000 (9.36)*	0.766 (35.31)*	0.330 (11.59)*	0.000 (12.91)*	86.45	2513.70
9	HDFC	-0.000 (-0.78)	-0.467 (-16.92)*	8.46E-0 (5.28)*	0.233 (10.37)*	0.666 (21.48)*	0.000 (7.62)*	55.18	2808.04
10	HEROHONDA	-0.000 (-0.84)	-0.46 (-17.44)*	8.64E-0 (12.01)*	0.193 (10.25)*	0.675 (184.64)*	0.000 (7.50)*	56.29	2856.93
11	HINDPETRO	0.000 (0.21)	-0.529 (-18.29)*	9.79E-0 (5.77)*	0.222 (8.76)*	0.682 (19.36)*	0.000 (9.97)*	72.03	2688.74
12	ICICIBANK	-0.000 (-1.20)	-0.419 (-15.22)*	0.000 (7.14)*	0.164 (6.38)*	0.397 (5.45)*	0.000 (21.13)*	54.63	2725.73

Continued…..

13	INFOSYSTCH	-0.001 (-0.19)	-0.488 (-8.61)*	0.003 (3.28)*	0.064 (2.26)#	0.578 (4.90)*	0.001 (30.38)*	83.22	1695.83
14	ITC	-0.008 (-0.49)	-0.339 (-2.50)#	0.007 (3.99)*	0.071 (1.74)	0.533 (5.48)*	0.004 (49.27)*	66.17	1232.23
15	M & M	-0.004 (-2.73)*	-0.506 (-9.98)*	0.000 (6.18)*	0.121 (5.69)*	0.741 (21.95)*	0.000 (17.08)*	60.54	2377.93
16	MTNL	0.000 (1.02)	-0.423 (-20.04)*	5.11E-0 (3.72)*	0.172 (10.48)*	0.781 (31.15)*	0.000 (15.40)*	51.84	2620.21
17	NATIONALUM	-0.001 (-1.14)	-0.465 (-15.55)*	0.000 (11.50)*	0.202 (6.21)*	0.435 (9.18)*	0.000 (7.61)*	71.31	2462.09
18	ONGC	-0.001 (-1.19)	-0.460 (-13.46)*	0.000 (3.95)*	0.082 (3.67)*	0.471 (3.49)*	0.000 (4.43)*	65.00	2548.83
19	POLARIS	-0.000 (-0.33)	-0.419 (-17.09)*	0.000 (6.22)*	0.309 (11.47)*	0.604 (16.90)*	0.000 (15.83)*	71.74	2334.18
20	RANBAXY	-0.000 (-0.52)	-0.441 (-13.08)*	0.000 (3.86)*	0.070 (3.24)*	0.410 (2.69)*	0.000 (11.53)*	78.11	2534.41
21	RELIANCE	-7.890 (-0.15)	-0.515 (-15.99)*	7.09E-0 (6.03)*	0.314 (19.12)*	0.614 (21.99)*	9.48E-0 (5.17)*	87.32	2914.08
22	SBIN	0.000 (0.40)	-0.483 (-17.96)*	9.55E-0 (4.13)*	0.199 (8.48)*	0.691 (15.72)*	0.000 (5.61)*	57.91	2750.46
23	TATAPOWER	-0.000 (-0.31)	-0.441 (-15.07)*	6.15E-0 (5.88)*	0.230 (11.24)*	0.725 (35.40)*	8.79E-0 (4.07)*	38.21	2667.82
24	TATATEA	-0.000 (-0.33)	-0.457 (-17.44)*	8.45E-0 (6.90)*	0.346 (8.35)*	0.573 (13.31)*	0.000 (14.09)*	45.50	2884.38
25	WIPRO	-0.005 (-4.39)*	-0.221 (-15.22)*	0.002 (38.60)*	1.289 (18.39)*	-0.052 (-4.60)*	-0.001 (-31.74)*	53.66	2037.03

Notes: Figures in the parenthesis report z-Statistics. * & # refers to 0.01 & 0.05 per cent level of Significance. Where R_t represents the rate of return I_{t-1} is the set of information available at the beginning of time t. The variance scaling parameter h_t now depends both on past and present values of the shocks, which are captured by the lagged residual terms and designated by ARCH (α_1) and GARCH effect (β_2) respectively. The explanatory variable was denoted by ψ_3

In Panel A, the AGARCH model allowed us to add expected trading activity variable in the specification of the conditional variance equation. The expected trading activity variables were observed statistically significant at 1 per cent level. The coefficients of β_2 indicated that shocks to conditional variance take long time to die out for BPCL, GRASIM and M & M those were identified with statistically significant coefficient at 1 per cent level except Dr. REDDY and RANBAXY at 5 per cent level. Alternatively, a large error coefficients α_1 that can be inferred that volatility reacts quite intensely to market movements were observed for BHEL, Dr. REDDY and WIPRO. Finally, the sum of $\alpha_1 + \beta_1$ which is supposed to be less than one, was greater than one for BHEL, Dr. REDDY, HCLTECH and WIPRO. In Panel B, the coefficients of β_2 were identified with significance at one per cent level for all the stock futures except Dr. REDDY and the volatility shocks to conditional variance were found to take a long time to die out in ACC and BPCL. In α_1, the coefficients parameter estimates was higher for WIPRO at 1 per cent level and BHEL, HCLTECH, MTNL, RELIANCE, TATATEA and WIPRO have estimated greater than one. Moreover, the unexpected trading activity variable were observed with statistically significant coefficient at 1 per cent level for all the stock futures but Dr. REDDY identified with negatively significant value of 7.700. From the results observed, we can infer the unexpected trading volume has a greater impact on Dr. REDDY.

Table: 4, presents the results of selected parameters for estimating return prediction on expected open interest and return prediction on unexpected open interest that are envisaged in Panel A and Panel B. First, the log likelihood statistics were found very large, which implies that the AGARCH model is an attractive representation of daily return behaviour that successfully captures the temporal dependence of return volatility. Second, the F-statistics were found significant at 1 per cent level for all the stock future contracts in Panel A and Panel B.

Table: 5. GARCH (1,1) Model predictions for Return on Open Interest

Panel: A. Futures Returns on Expected Open Interest

Sl. No:	Company	Coefficients						F - Statistic	Log Likelihood
		ø	R_{t-1}	α_0	α_1	β_2	ψ_3		
1	ACC	0.000 (0.26)	-0.464 (-16.82)*	6.03E-0 (6.53)*	0.189 (8.26)*	0.752 (28.63)*	-0.000 (-1.55)	56.36	2757.92
2	BEL	-6.210 (-0.08)	-0.428 (-14.75)*	0.000 (7.08)*	0.286 (9.27)*	0.499 (9.66)*	-1.18E-0 (-0.22)	72.44	2685.84
3	BHEL	0.000 (1.40)	-0.269 (-8.93)*	0.000 (18.15)*	0.924 (16.98)*	0.155 (6.55)*	0.000 (7.07)*	46.68	2621.31
4	BPCL	0.000 (0.23)	-0.498 (-19.23)*	3.05E-0 (4.26)*	0.103 (8.52)*	0.867 (63.53)*	-3.62E-0 (-0.77)	68.82	2683.77
5	CIPLA	-0.000 (-0.17)	-0.299 (-27.03)*	0.003 (15.65)*	0.119 (3.12)*	-0.236 (-2.92)*	0.001 (11.12)*	64.23	1915.95
6	Dr. REDDY	0.000 (0.57)	-0.488 (-11.36)*	0.000 (8.68)*	0.249 (6.21)*	0.283 (3.81)*	-0.000 (-52.45)*	80.47	2579.38
7	GRASIM	5.33E-0 (0.09)	-0.475 (-16.69)*	4.10E-0 (5.53)*	0.190 (8.49)*	0.767 (33.45)*	4.64E-0 (1.18)	72.12	2849.92
8	HCLTECH	0.000 (1.46)	-0.540 (-17.97)*	0.000 (10.75)*	0.798 (34.71)*	0.310 (11.29)*	0.000 (3.33)*	86.39	2502.31
9	HDFC	0.000 (0.22)	-0.462 (-16.54)*	8.38E-0 (5.25)*	0.232 (10.30)*	0.675 (22.10)*	5.86E-0 (1.46)	55.36	2791.34
10	HEROHONDA	-0.000 (-0.20)	-0.477 (-16.93)*	8.01E-0 (6.02)*	0.231 (7.08)*	0.674 (19.38)*	4.78E-0 (0.13)	55.90	2833.01
11	HINDPETRO	0.000 (0.30)	-0.517 (-18.25)*	7.10E-0 (5.18)*	0.205 (8.99)*	0.736 (25.22)*	3.92E-0 (0.84)	72.61	2665.07
12	ICICIBANK	4.38E-0 (0.06)	-0.427 (-14.95)*	9.81E-0 (5.27)*	0.221 (8.27)*	0.675 (19.19)*	4.96E-0 (0.97)	54.89	2740.82

Continued…..

13	INFOSYSTCH	-0.000 (-0.10)	-0.496 (-9.38)*	0.002 (2.87)*	0.068 (2.26)#	0.506 (3.07)*	0.002 (29.94)*	83.47	1853.71
14	ITC	-0.001 (-0.14)	0.020 (0.11)	0.004 (4.18)*	0.129 (2.19)#	0.527 (4.82)*	0.003 (27.12)*	72.83	1466.61
15	M & M	0.000 (0.49)	-0.521 (-9.25)*	0.000 (28.45)*	0.216 (16.79)*	0.616 (50.62)*	0.000 (17.48)*	64.79	2402.42
16	MTNL	0.000 (0.94)	-0.429 (-16.17)*	8.70E-0 (5.12)*	0.213 (10.17)*	0.720 (23.81)*	9.15E-0 (1.44)	51.89	2586.22
17	NATIONALUM	0.000 (0.37)	-0.480 (-17.41)*	6.60E-0 (5.76)*	0.210 (10.79)*	0.756 (38.26)*	3.44E-0 (0.43)	71.61	2511.14
18	ONGC	-9.450 (-0.11)	-0.447 (-15.95)*	0.000 (6.14)*	0.165 (5.80)*	0.540 (7.51)*	0.000 (14.76)*	66.09	2642.41
19	POLARIS	0.000 (0.26)	-0.446 (-17.79)*	0.000 (7.31)*	0.352 (11.40)*	0.521 (12.64)*	0.000 (6.79)*	72.72	2298.09
20	RANBAXY	-0.000 (-0.62)	-0.462 (-16.52)*	0.000 (7.64)*	0.033 (4.82)*	0.414 (4.86)*	-0.001 (-39.18)*	78.72	2605.70
21	RELIANCE	0.000 (0.28)	-0.521 (-16.14)*	8.91E-0 (6.43)*	0.301 (14.80)*	0.594 (18.92)*	-0.000 (-3.44)*	87.26	2907.78
22	SBIN	0.000 (0.48)	-0.492 (-17.93)*	9.95E-0 (4.45)*	0.204 (8.18)*	0.686 (15.88)*	-6.99E-0 (-0.80)	57.58	2740.42
23	TATAPOWER	0.000 (0.18)	-0.443 (-14.95)*	6.42E-0 (5.74)*	0.242 (10.17)*	0.715 (30.80)*	-2.69E-0 (-0.42)	38.11	2662.24
24	TATATEA	0.000 (0.68)	-0.468 (-16.23)*	0.000 (7.12)*	0.323 (7.81)*	0.551 (11.34)*	8.61E-0 (6.93)*	44.96	2857.18
25	WIPRO	-0.004 (3.60)*	-0.153 (-4.68)*	0.001 (37.61)*	1.661 (20.71)*	-0.014 (-1.36)	-0.001 (-44.91)*	38.99	2169.61

Notes: Figures in the parenthesis report z-Statistics. * & # refers to 0.01 & 0.05 per cent level of Significance. Where R_t represents the rate of return I_{t-1} is the set of information available at the beginning of time t. The variance scaling parameter h_t now depends both on past and present values of the shocks, which are captured by the lagged residual terms and designated by ARCH (α_1) and GARCH effect (β_2) respectively. The explanatory variable was denoted by ψ_3

Panel: B. Futures Returns prediction on Unexpected Open Interest

Sl. No:	Company	Coefficients						F - Statistic	Log Likelihood
		ø	R_{t-1}	α_0	α_1	β_2	ψ_3		
1	ACC	9.73E-0 (0.16)	-0.464 (-16.78)*	6.32E-0(6.83)*	0.193 (8.27)*	0.745 (28.10)*	-5.92E-0 (-1.05)	56.26	2751.06
2	BEL	-7.74E-0 (-0.11)	-0.425 (-14.61)*	0.000 (7.06)*	0.286 (9.24)*	0.496 (9.48)*	-1.42E-0 (-0.02)	71.89	2679.98
3	BHEL	0.000 (1.05)	-0.323 (-11.09)*	0.000 (7.52)*	0.781 (18.87)*	0.377 (13.67)*	9.87E-0 (3.46 *	51.80	2642.66
4	BPCL	0.000 (0.19)	-0.499 (-19.27)*	3.03E-0 (4.22)*	0.103 (8.57)*	0.867 (63.61)*	-1.52E-0 (-0.39)	68.70	2677.91
5	CIPLA	0.008 (1.26)	-0.425 (-8.17)*	0.002 (27.68)*	0.052 (3.26)*	0.585 (31.48)*	0.002 (34.69)*	72.47	1692.76
6	Dr. REDDY	0.000 (0.84)	-0.483 (-11.25)*	0.000 (9.31)*	0.300 (5.72)*	0.193 (2.44)#	-0.000 (50.30)*	80.22	2572.89
7	GRASIM	7.93E-0 (0.14)	-0.475 (-16.69)*	4.12E-0 (5.53)*	0.191 (8.53)*	0.765 (33.42)*	3.37E-0 (1.08)	71.96	2840.37
8	HCLTECH	0.000 (1.43)	-0.534 (-17.76)*	0.000 (10.35)*	0.789 (35.56)*	0.316 (11.35)*	0.000 (4.00)*	86.07	2498.68
9	HDFC	0.000 (0.24)	-0.462 (-16.54)*	8.35E-0 (5.23)*	0.232 (10.30)*	0.674 (22.11)*	5.94E-0 (1.57)	55.36	2791.44
10	HEROHONDA	-6.06E-0 (-0.10)	-0.477 (-16.95)*	7.78E-0 (6.01)*	0.219 (7.02)*	0.685 (19.95)*	-4.72E-0 (-1.24)	55.88	2830.19
11	HINDPETRO	0.000 (0.31)	-0.518 (-18.18)*	7.31E-0 (5.14)*	0.208 (8.94)*	0.732 (24.37)*	4.55E-0 (1.02)	72.46	2658.61
12	ICICIBANK	3.13E-0 (0.04)	-0.427 (-14.95)*	9.65E-0 (5.27)*	0.221 (8.32)*	0.677 (19.55)*	6.84E-0 (1.47)	54.83	2735.77

Continued…..

13	INFOSYSTCH	-0.005 (-3.11)*	-0.489 (-9.37)*	0.002 (3.13)*	0.067 (2.49)#	0.504 (3.37)*	0.002 (13.58)*	80.98	1855.98
14	ITC	-0.005 (-0.43)	-0.341 (-3.65)*	0.006 (17.48)*	0.056 (2.45)#	0.449 (51.61)*	0.003 (16.98)*	68.11	1430.64
15	M & M	0.001 (1.04)	-0.494 (-10.01)*	0.000 (5.62)*	0.224 (7.61)*	0.740 (19.69)*	0.000 (33.30)*	65.23	2429.86
16	MTNL	0.000 (0.93)	-0.429 (-16.16)*	8.83E-0 (5.18)*	0.215 (10.19)*	0.717 (23.64)*	8.80E-0 (1.56)	51.91	2582.67
17	NATIONALUM	0.000 (0.43)	-0.479 (-17.41)*	6.38E-0(5.61)*	0.207 (10.81)*	0.761 (39.08)*	6.92E-0 (1.22)	71.54	2506.40
18	ONGC	-6.06E-0 (-0.07)	-0.446 (-15.93)*	0.000 (6.49)*	0.173 (5.76)*	0.515 (7.07)*	0.000 (15.31)*	65.99	2640.52
19	POLARIS	0.000 (0.36)	-0.443 (-17.69)*	0.000 (7.50)*	0.355 (11.75)*	0.517 (13.02)*	0.000 (6.91)*	72.47	2295.51
20	RANBAXY	8.28E-0 (0.10)	-0.447 (-14.22)*	0.000 (22.00)*	0.141 (5.31)*	0.354 (10.91)*	-0.001 (-79.09)*	78.26	2723.80
21	RELIANCE	0.000 (0.33)	-0.522 (-16.13)*	8.94E-0 (6.45)*	0.310 (15.46)*	0.587 (18.80)*	-0.000 (-2.75)*	87.13	2901.58
22	SBIN	0.000 (0.50)	-0.492 (-17.75)*	9.90E-0 (4.48)*	0.202 (8.12)*	0.688 (16.11)*	-6.76E-0 (-1.01)	57.45	2732.22
23	TATAPOWER	9.39E-0 (0.15)	-0.439 (-14.78)*	6.28E-0 (5.70)*	0.242 (10.24)*	0.717 (31.14)*	8.13E-0 (0.16)	38.13	2658.22
24	TATATEA	0.000 (0.70)	-0.466 (-16.18)*	0.000 (7.31)*	0.328 (7.83)*	0.546 (11.30)*	8.14E-0 (4.97)*	44.94	2848.84
25	WIPRO	-0.012 (-7.49)*	-0.218 (-10.05)*	0.002 (17.20)*	1.372 (13.83)*	0.051 (-61.31)*	-0.000 (-6.23)*	42.35	2044.13

Notes: Figures in the parenthesis report z-Statistics. * & # refers to 0.01 & 0.05 per cent level of Significance. Where R_t represents the rate of return I_{t-1} is the set of information available at the beginning of time t. The variance scaling parameter h_t now depends both on past and present values of the shocks, which are captured by the lagged residual terms and designated by ARCH (α_1) and GARCH effect (β_2) respectively. The explanatory variable was denoted by ψ_3

In Panel A the estimated coefficients for α_1 were statistically significant for all the futures contracts at 1 per cent level, except INFOSYSIS and ITC at 5 per cent level. The coefficients of β_2 envisaged with 1 per cent level of significance for all the stock futures contracts, except WIPRO with insignificant effect. The expected open interests were statistically significant at 1 per cent level for BHEL, CIPLA, Dr. REDDY, HCLTECH, INFOSYSTCH, ITC, ONGC, POLARIS, RANBAXY, RELIANCE, TATATEA and WIPRO. The average value of $\alpha_1 + \beta_2$ was found less than one except in the case of BHEL, HCLTECH and WIPRO. This indicates a greater persistence of shocks to volatility. In Panel B, the scaling parameters for estimating the ARCH (α_1) and GARCH (β_2) effect were found to be statistically significant at 1 per cent level for all the stock future contracts, but the ARCH (α_1) effect were found to be significant at 5 per cent level for INFOSYSTCH and ITC stock futures with the value 0.067 and 0.056 respectively. The shocks to conditional variance (i.e.) the GARCH (β_2) effect for Dr. REDDY were observed with the value 0.193 at 5 per cent significant level. The unexpected open interest series were included in the variance equation of the GARCH model specification to know the effect of open interest on futures return series. The coefficients results reveal that there was a significant change taking place in BHEL, CIPLA, Dr. REDDY, HCLTECH, INFOSYSTCH, ITC, M & M, ONGC, POLARIS, RANBAXY, RELIANCE, TATATEA and WIPRO at 1 per cent level of significance, but for other stock future contracts it was envisaged with insignificant effect. The sum of ARCH and GARCH effect were found higher for Dr. REDDY, HCLTECH, INFOSYSTCH and RELIANCE stock futures, which indicates that the shocks to conditional variance sustains for a long period and the shock leads to a permanent changes in all future values for BHEL, CIPLA, Dr. REDDY, HCLTECH, INFOSYSTCH, ITC, M & M, ONGC, POLARIS, RANBAXY, RELAINCE, TATATEA and WIPRO. Hence, it can be inferred from the result that shock to the conditional variance remains 'persistent' in these stock futures contracts.

4.4. Conclusion:

The uncertain nature and the relationship between price movements, trading volume and open interest for select stock future contracts were examined over the period from April 1, 2003 to December 31, 2008. The primary findings of the study showed significant positive relationship between return volatility, expected trading volume and expected open interest and vice versa. Furthermore, it was examined that there was strong positive correlation between price movements and trading volume for BHEL, Dr. REDDY, HCLTECH, MTNL, RELIANCE, TATATEA and WIPRO, respectively. On the other hand, the causal nexus between future return and trading volume were observed negative for ACC, BEL, BPCL, CIPLA, GRASIM, HEROHONDA, INFOSYSTCH, ITC, ICICIBANK, M & M, ONGC, POLARIS and RANBAXY.

Acceptance & Rejection MDH & SEQ Hypothesis

Null Hypothesis	Alternative Hypothesis
BHEL	ACC
Dr. REDDY	BEL
HCLTECH	BPCL
MTNL	CIPLA
RELIANCE	GRASIM
TATATEA	HEROHONDA
WIPRO	INFOSYSTCH
	ITC
	ICICIBANK
	M & M
	ONGC
	POLARIS
	RANBAXY

Therefore, the MDH and SEQ Hypothesis suggest that unexpected volume and open interest are more likely to have a greater impact on volatility than the expected trading volume and open interest. So, the return volatility was influencing both expected and unexpected trading volume and open interest, respectively. Specifically, the stock futures contract in India was found more likely to be influenced by lagged volatility, which is consistent with the conclusion of Mandelbrot (1963), Bessembinder and Seguin (1993) who found negative shocks have larger impact on volatility than the positive shocks. Finally, the result indicated that the market depth does not have any effect on volatility.

CHAPTER - V

MODELING AND FORECASTING STOCK FUTURES PRICES VOLATILITY THROUGH LINEAR AND NONLINEAR MODELS

5.1. Introduction

Volatility is the extent to which the return on an underlying asset fluctuates over a given period of time. It is most commonly calculated as the annualized standard deviation of returns and represents the risk associated with that particular asset. Historically, financial price series have shown great variation in volatility over time. Furthermore, there is significant evidence of volatility "clumping". This means that periods of high volatility tended to occur together, as do periods of low volatility. As volatility represents risk, the phenomenon of clumping is very relevant to market participants. This is because volatility is a key component of many financial decisions, asset pricing, risk management, portfolio selection and hedging strategies Jondeau and Rockinger (2003).

Modeling and forecasting volatility in financial markets is one of the most important and baffling task in financial research. Recently, a great deal of attention has been directed to this area by academicians, policy makers and practitioners over the globe, because it can be used as a measure of risk and also can exhibits some typical characteristics. Basically the volatility forecasts are sensitive to the specification of the volatility model. Hence, it is important to strike the right balance between capturing the salient features of the data and over fitting the data. As the estimated parameters are the true parameters of the volatilities models, which often changes the volatility forecasts it is difficult to observe the volatility estimate correctly. Further, volatility forecasts are anchored at noisy proxies or estimates of the current level of volatility. Even with a perfectly specified and estimated volatility model, forecasts of future volatility inherit and even amplify the uncertainty about the current level of volatility.

This dissertation can be considered as one of the few attempts made to examine the relative ability of various models to forecast volatility for daily stock futures contracts, such as volatility clustering, excess kurtosis, and fat tailed etc., to identify which model is the best model according to statistic and risk management evaluation criteria in the Indian context.

The data for this study consists of observations on the daily closing futures price for 25 stock futures contracts traded on NSE for the period beginning on 1st April 2003 and ending 31st December 2008, for a total of 1440 observations of the sample data NSE website. Contract specifications and trading details are available from (www. nseindia.com). The “in sample analysis” is carried out for the period from April 1, 2003 to march 31, 2008 (1257 observations) and the remaining 184 observations (from 1st April 2008 to 31st December 2008) are used to evaluate the “out-of-sample” forecasting performance of the model. Near month futures contracts are selected for this study, because they are the most actively traded futures contracts within their own classification. The price indices are converted to returns by the standard methods of calculating the log-difference as $R_t = \log (P_t/P_{t-1})$, where P_t represents the price of the future at time t. All the observations are transformed into natural logarithms so that the price changes in futures returns prevents the non-stationarity of the price level series approximately the futures price volatility.

The daily volatility of stock futures contracts returns are estimated by the model developed by Schwert (1990) and Schwert and Seguin (1990). The equation adopted is[1]:

$$\sigma^2 = \sqrt{\pi / 2}\ | R_t - \mu |$$

Where, R_t is the return for selected stock futures contracts and μ is mean of the series.

For model fitting exercise for volatility estimate, various Linear and Non linear models are attempted. The methodology adopted are discussed in the following section

[1] Cao and Tsay (1992) also point out that $\sigma_t = \sqrt{(\pi/2)}|R_t-\mu|$ is an unbiased estimator for the standard deviation

5.2 Econometric Methodology

5.2.1. Linear Models

5.2.1.1. Random Walk Model:

The random walk model is the simplest possible models, where the Ordinary Least Square (OLS) method is constructed on the assumption of constant variance. As per, efficient market hypothesis the competing market participants reflect information instantly hence are useless in predicting future prices. The basic model for estimating stock returns fluctuation by using OLS in the naïve random walk model is given below

$$R_t = \mu + \varepsilon_t$$

Where, μ is the mean value of the returns, it is expected to be insignificantly different from zero; and ε_t, the error term should not be serially correlated over time.

5.2.1.2. Simple Regression Model:

The simple regression model is the familiar model which provides one step-ahead forecasts for estimating the preceding volatility of the univariate series. The in-sample volatilities were estimated using ordinary least squares for observed actual volatility upon immediately preceding actual volatility of the time series data. The regression model follows the equation as;

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

Where, σ_t^2 is the volatility of futures market returns, α and β are the parameter to be estimated through one period lagged futures market returns, ε_t is an error term representing unexplained price changes. This methodology was followed to calculate the actual time-varying parameters for each day.

5.2.1.3. Moving Average Model

The simplest class of time series model that one could entertain is that of the moving average process. A moving average is a linear combination of white noise processes, where more recent observations receive more weight. A first order moving average, or MA (1) model was used to calculate the more recent forecast error and it is written as;

$$Y_t = \mu + (1 - \varphi_1 L)\varepsilon_t$$

Where, Y_t depends on the current and previous values of a white noise disturbance, φ denotes the moving average parameter, L is the backward shift operator, μ is constant term and ε_t is the error term at time t.

5.2.1.4. Autoregressive Model

An autoregressive model is one where the current value of a variable y, depends upon the values that the variable took in previous periods plus an error term. An first-order autoregressive model, AR (1) process is specified as follows

$$(1 - \varphi_1 B)\sigma_t(AR) = \mu + \varepsilon_t$$

Where, φ is the autoregressive parameter, B is backward shift operator, μ is constant term and ε_t is the error term at time t.

5.2.2. Nonlinear Models

5.2.2.1. GARCH Model

Bollerslev (1986) extended Engle's ARCH model to the GARCH model and it is based on the assumption that forecasts of time varying variance depend on the lagged variance. An unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period. The basic and the most widely accepted model GARCH can be expressed as;

$$
\begin{aligned}
&R_t = a + bR_{t-1} + \varepsilon_t \\
&\varepsilon_t \mid I_{t-1}\ N(0, h_t), \\
&h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \alpha_j u_{t-j}^2
\end{aligned}
$$

Where, $\alpha_j > 0$, $\beta_i \geq 0$, the GARCH is weakly stationery $\Sigma\beta_i + \Sigma\alpha_j < 1$, the latter two quantifying the persistence of shocks to volatility Nelson (1991).

Normally, volatility forecast are increased following a large positive and negative return, the GARCH specification that captures the well-documented volatility clustering evident in financial returns Engle (1982).

5.2.2.2. TGARCH Model

In TGARCH model, it has been observed that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to a " leverage effect" Black (1976). In the same sense, negative shocks are followed by higher volatility than positive shocks of the same magnitude Engle and Ng (1993). The threshold GARCH model was introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The main target of this model is to capture asymmetry in terms of negative and positive shocks and adds multiplicative dummy variable to check whether there is statistically significant difference when shocks are positive and negative. The conditional variance for the simple TGARCH model is defined by;

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid I_{t-1} \; N(0, h_t),$$

$$h_t = \omega + \sum_{i=1}^{p} \beta_i u_{t-i}^2 + \sum_{j=1}^{q} \lambda_j h_{t-j} + \delta_i u_{t-1}^2 d_{t-1}$$

Where, d_t takes the value of 1 if ε_t is negative, and 0 otherwise, identifying "good news" and "bad news" have a different impact.

5.2.2.3. EGARCH Model

The Exponential GARCH model specifies conditional variance in logarithmic form, which means that there is no need to impose estimation constraints in order to avoid negative variance Nelson (1991). The mean and variance equation for this model is given by;

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid I_{t-1}\ N(0, h_t),$$

$$\log\left(h_t\right) = \omega + \sum_{j=1}^{q} \beta_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \lambda_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i h_{t-1}$$

Where, δ captures the asymmetric effect. The exponential nature of EGARCH ensures that the conditional variance is always positive even if the parameter values are negative; thus there is no need for parameter restrictions to impose non-negativity.

5.2.2.4. IGARCH Model

The integrated GARCH (p,q) or IGARCH (p,q) model was originally developed by Engle and Bollerslev (1986). In many high-frequency financial time-series data, the conditional variance estimated using a GARCH (1,1) model exhibits a strong persistence. For stationary GARCH models, conditional variance forecasts converge upon the long-term average value of the variance with the increase in prediction horizon. For IGARCH processes, this convergence does not happen, while for $\beta_j + \alpha_i > 1$, the conditional variance forecast tends to infinity as the forecast horizon increases. The mean and variance equation for IGARCH model are as follows;

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid I_{t-1}\ N(0, h_t),$$

$$h_t = \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 = 1$$

Where, the estimated parameters of $\beta_j + \alpha_i$ are equal to one, then the IGARCH is a restricted version of the GARCH model, and therefore there is a unit root in the GARCH process and imply that current information remains of importance when forecasting the volatility for all horizons.

5.3. Results & Discussion

Table 1 summarizes the descriptive statistics for stock future price volatility series. The statistics reported are the mean, standard deviation, skewness, kurtosis, Jarque-Bera test and Ljung-box (1978) Q-Statistics were used to identify the autocorrelation of the series. The observations of result shows that average daily returns are very small in comparison to their standard deviation. The distribution of stock futures returns are positively skewed with a heavier tail to the right. Skewness close to the value of zero suggests that the return series exhibit a symmetrical distribution, while the skewness observed with asymmetrical effect. The value of kurtosis for select stock futures returns was observed to be very large. The probability values for the Jarque-Bera (1980) test statistics indicates that each variable is distributed non-normally. This shows that much of the non-normality is due to the special characteristics, might be due to volatility clustering, leptokurtosis and asymmetry effects associated with more advanced futures markets.

Table: 1 Descriptive Statistics for Volatility

Sl. No:	Company	Mean	S.D	Skewness	Kurtosis	Jarque Bera	Probability	LB-Q (5)	LB-Q (10)
1	ACC	0.02221	0.02209	2.23850	11.80881	5862.391	0.0000	268.3	357.12
2	BEL	0.02367	0.02394	2.85786	17.95362	15366.13	0.0000	206.4	267.44
3	BHEL	0.02453	0.03323	12.2168	279.9953	46394.04	0.0000	129.85	160.46
4	BPCL	0.02492	0.02351	2.07175	10.20509	4144.921	0.0000	175.73	315.11
5	CIPLA	0.02203	0.06343	25.0738	721.6155	31135382	0.0000	11.58	12.313
6	Dr. REDDY	0.01974	0.03083	16.3308	433.2637	11171617	0.0000	14.005	18.412
7	GRASIM	0.02189	0.02128	2.32565	11.46960	5602.130	0.0000	292.28	463.62
8	HCLTECH	0.02747	0.03454	10.3538	223.1482	2933642.	0.0000	88.426	169.96
9	HDFC	0.02396	0.02346	2.37397	12.97514	7322.781	0.0000	399.72	648.63
10	HEROHONDA	0.02026	0.01897	1.74493	6.902878	1644.697	0.0000	120.75	171.26
11	HINDPETRO	0.02509	0.02442	2.32443	11.15333	5285.333	0.0000	228.34	347.05
12	ICICIBANK	0.025857	0.02671	2.65738	15.16647	10576.18	0.0000	362.81	732.01
13	INFOSYSTCH	0.02236	0.05455	23.7827	688.9036	28343878	0.0000	6.4807	7.7114
14	ITC	0.02115	0.08864	35.6379	1323.746	1.05E+08	0.0000	0.4099	0.7873
15	M & M	0.02459	0.03284	13.1394	318.5435	6011319.	0.0000	109.94	163.62
16	MTNL	0.02488	0.02454	2.60101	15.20580	10562.56	0.0000	251.76	326.72
17	NATIONALUM	0.03034	0.03165	2.63158	14.84352	10078.19	0.0000	541.44	880.32
18	ONGC	0.02305	0.02554	5.50010	76.34132	329997.2	0.0000	173.5	244.99
19	POLARIS	0.03319	0.03625	3.26636	21.71931	23585.36	0.0000	315.34	368.35
20	RANBAXY	0.02174	0.03358	14.3586	353.2454	7404648.	0.0000	76.92	92.439
21	RELIANCE	0.02181	0.02315	4.55820	48.03586	126328.4	0.0000	409.96	618.35
22	SBIN	0.02427	0.02290	2.30732	12.47683	6666.310	0.0000	246.37	410.21
23	TATAPOWER	0.02621	0.02727	3.01422	19.68142	18876.72	0.0000	527.07	792.23
24	TATATEA	0.02115	0.02152	2.49164	12.52983	6939.046	0.0000	392.88	485.69
25	WIPRO	0.02630	0.04900	18.3770	460.1484	12620131	0.0000	24.145	33.259

Note: LB – Q refers to Ljung Box Q-Statistics, * Significance at 0.01 per cent level respectively.

Table: 2 Unit Root Test

Sl. No:	Company	ADF Test		PP Test	
		Intercept	Trend & Intercept	Intercept	Trend & Intercept
1	ACC	-10.61074	-11.74781	-36.01716	-35.62984
2	BEL	-11.35238	-11.45157	-33.93056	-33.85736
3	BHEL	-14.61881	-15.08222	-36.16696	-35.49959
4	BPCL	-5.590978	-6.184915	-36.84571	-36.27035
5	CIPLA	-16.89831	-16.89236	-37.58669	-37.57509
6	Dr. REDDY	-35.34392	-35.35584	-35.64737	-35.64783
7	GRASIM	-6.219426	-6.328350	-38.94136	-38.81747
8	HCLTECH	-5.694116	-6.007683	-37.66153	-37.20573
9	HDFC	-5.541808	-6.207713	-39.73625	-38.61276
10	HEROHONDA	-8.858530	-8.855722	-34.07336	-34.06591
11	HINDPETRO	-5.171961	-5.534925	-34.98169	-34.48881
12	ICICIBANK	-4.339780	-5.255879	-41.09709	-40.13047
13	INFOSYSTCH	-36.06770	-36.05537	-36.21679	-36.20515
14	ITC	-37.75843	-37.77546	-37.76299	-37.77769
15	M & M	-10.41734	-10.55933	-37.50359	-37.38761
16	MTNL	-6.072162	-6.127391	-32.86795	-32.82077
17	NATIONALUM	-6.347533	-6.713981	-34.64043	-34.14098
18	ONGC	-10.98955	-11.17860	-36.69149	-36.53095
19	POLARIS	-15.59077	-15.78609	-31.27781	-31.16306
20	RANBAXY	-14.63214	-15.27109	-36.16474	-35.68456
21	RELIANCE	-4.976078	-5.999626	-36.92888	-36.17682
22	SBIN	-5.810681	-7.324236	-36.95017	-35.89772
23	TATAPOWER	-7.434996	-7.582331	-33.13445	-32.82715
24	TATATEA	-13.19580	-13.28726	-32.71373	-32.66957
25	WIPRO	-34.44143	-34.45092	-35.21913	-35.20885

Note: The significant value at 1 % for Phillips-Perron test for intercept, trend and with both are – 2.5665, -3.4357 and -3.9667 respectively.

In the recent finance research, the explosion for testing the stationarity of the time series data is first attempted and testing the presence of unit root in the variables is considered first, otherwise the analysis is believed to produce spurious regression results. The select stock futures return series was examined for I(1), which was carried out in two steps process in Table: 2, by conducting the unit root test using both the Augmented Dickey Fuller (ADF) test and Phillip-Peron (PP) test, on the first differences for the volatility series. The unit root test results identifies that the stock futures return series are found to be stationary at first-order difference and integrated at the order of I(1).

The Random Walk, Linear regression, Autoregressive (1) and Moving average (1) models are estimated for the select stock futures contracts for the period from 1st April 2003 to 31st December 2008 and presented in Table: 3. The F-statistics and Durban Watson (DW) statistics were used to choose the volatility models that best fits the conditional variance of the stock futures returns.

Table: 3 Linear Models

Panel: A. Random Walk Model

Sl. No:	Company	μ	DW Statistics
1	ACC	0.022[a] (38.164)	1.512
2	BEL	0.024[a] (37.517)	1.517
3	BHEL	0.025[a] (28.019)	1.667
4	BPCL	0.025[a] (40.225)	1.572
5	CIPLA	0.022[a] (13.181)	1.967
6	Dr. REDDY	0.020[a] (24.304)	1.860
7	GRASIM	0.022[a] (39.034)	1.543
8	HCLTECH	0.027[a] (30.182)	1.710
9	HDFC	0.024[a] (38.759)	1.504
10	HEROHONDA	0.020[a] (40.515)	1.595
11	HINDPETRO	0.025[a] (38.981)	1.501
12	ICICIBANK	0.026[a] (36.731)	1.493
13	INFOSYSTCH	0.022[a] (15.551)	1.901
14	ITC	0.021[a] (9.055)	1.992
15	M & M	0.025[a] (28.406)	1.715
16	MTNL	0.025[a] (38.464)	1.440
17	NATIONALUM	0.030[a] (36.378)	1.252
18	ONGC	0.023[a] (34.255)	1.615
19	POLARIS	0.033[a] (34.749)	1.376
20	RANBAXY	0.022[a] (24.559)	1.758
21	RELIANCE	0.022[a] (35.709)	1.411
22	SBIN	0.024[a] (40.222)	1.504
23	TATAPOWER	0.026[a] (36.477)	1.256
24	TATATEA	0.021[a] (37.304)	1.360
25	WIPRO	0.026[a] (20.368)	1.809

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

Panel: B. Linear Regression Model

Sl. No:	Company	Coefficients		F - Statistics	DW Statistics
		α	β		
1	ACC	0.017[a] (20.971)	0.244[a] (9.547)	91.149	2.076
2	BEL	0.018[a] (20.877)	0.239[a] (9.346)	87.349	2.056
3	BHEL	0.020[a] (19.029)	0.166[a] (6.381)	40.717	2.048
4	BPCL	0.020[a] (22.217)	0.214[a] (8.300)	68.888	2.035
5	CIPLA	0.022[a] (12.234)	0.017[a] (0.629)	0.396	2.001
6	Dr. REDDY	0.018[a] (19.070)	0.070[a] (2.657)	7.057	2.002
7	GRASIM	0.017[a] (21.552)	0.229[a] (8.901)	79.224	2.074
8	HCLTECH	0.023[a] (20.378)	0.145[a] (5.550)	30.801	2.027
9	HDFC	0.018[a] (21.036)	0.248[a] (9.694)	93.973	2.078
10	HEROHONDA	0.016[a] (22.525)	0.202[a] (7.825)	61.237	2.032
11	HINDPETRO	0.019[a] (21.075)	0.249[a] (9.754)	95.138	2.044
12	ICICIBANK	0.019[a] (20.368)	0.253[a] (9.929)	98.585	2.095
13	INFOSYSTCH	0.021[a] (13.679)	0.049[a] (1.872)	3.506	2.001
14	ITC	0.021[a] (8.769)	0.004[a] (0.150)	0.022	2.000
15	M & M	0.021[a] (19.674)	0.143[a] (5.456)	29.769	2.027
16	MTNL	0.018[a] (20.262)	0.280[a] (11.036)	121.804	2.079
17	NATIONALUM	0.019[a] (17.700)	0.374[a] (15.269)	233.129	2.114
18	ONGC	0.019[a] (20.917)	0.192[a] (7.437)	55.308	2.043
19	POLARIS	0.023[a] (18.560)	0.311[a] (12.404)	153.859	2.104
20	RANBAXY	0.019[a] (18.259)	0.121[a] (4.613)	21.276	2.013
21	RELIANCE	0.015[a] (19.177)	0.294[a] (11.667)	136.107	2.086
22	SBIN	0.018[a] (21.398)	0.248[a] (9.704)	94.167	2.066
23	TATAPOWER	0.016[a] (17.773)	0.372[a] (15.192)	230.798	2.114
24	TATATEA	0.014[a] (19.070)	0.320[a] (12.802)	163.898	2.121
25	WIPRO	0.024[a] (16.276)	0.096[a] (3.643)	13.268	2.006

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

Panel: A reports the estimated parameters and the robustness of random walk model. The Ordinary Least Squares (OLS) of the constant random walk model suggest that the mean (μ) of the return series is statistically significant at 1 per cent level for all the estimates, which is inconsistent with the random walk hypothesis. The DW statistics presented in the last column of Panel: A reports that CIPLA, Dr. REDDY, INFOSYSTCH, ITC and WIPRO do not reject the null hypothesis of no autocorrelation. The linear regression results envisaged in Panel: B of Table: 3 suggest that the lagged value of the stock futures returns were significant for all the estimates at 1 per cent level. Further, a combination of information criteria such as F-statistics and DW statistics were used for testing volatility of the models. Here, the F-statistics best fit identifies the model and DW statistics have invariably two as critical values and thus reports no evidence of autocorrelation effect for the stock futures return series.

Panel: C. Autoregressive Model

Sl. No:	Company	Coefficients		F - Statistics	DW Statistics
		ø	R_{t-1}		
1	ACC	0.022[a] (29.736)	0.244[a] (9.547)	91.149	2.076
2	BEL	0.024[a] (29.360)	0.239[a] (9.346)	87.349	2.056
3	BHEL	0.025[a] (23.655)	0.166[a] (6.381)	40.717	2.048
4	BPCL	0.025[a] (32.375)	0.214[a] (8.300)	68.888	2.035
5	CIPLA	0.022[a] (12.952)	0.017 (0.629)	0.396	2.001
6	Dr. REDDY	0.020[a] (22.651)	0.070[a] (2.657)	7.057	2.002
7	GRASIM	0.022[a] (30.921)	0.229[a] (8.901)	79.224	2.074
8	HCLTECH	0.027[a] (26.044)	0.145[a] (5.550)	30.801	2.027
9	HDFC	0.024[a] (30.084)	0.248[a] (9.694)	93.973	2.078
10	HEROHONDA	0.020[a] (32.956)	0.202[a] (7.825)	61.237	2.032
11	HINDPETRO	0.025[a] (30.215)	0.249[a] (9.754)	95.138	2.044
12	ICICIBANK	0.026[a] (28.344)	0.253[a] (9.929)	98.585	2.095
13	INFOSYSTCH	0.022[a] (14.785)	0.049 (1.872)	3.506	2.001
14	ITC	0.021[a] (9.015)	0.004 (0.150)	0.022	2.000
15	M & M	0.025[a] (24.582)	0.143[a] (5.456)	29.769	2.027
16	MTNL	0.025[a] (28.858)	0.280[a] (11.036)	121.804	2.079
17	NATIONALUM	0.030[a] (24.523)	0.374[a] (15.269)	233.129	2.114
18	ONGC	0.023[a] (28.184)	0.192[a] (7.437)	55.308	2.043
19	POLARIS	0.033[a] (25.165)	0.311[a] (12.404)	153.859	2.104
20	RANBAXY	0.022[a] (21.747)	0.121[a] (4.613)	21.276	2.013
21	RELIANCE	0.022[a] (26.350)	0.294[a] (11.667)	136.107	2.086
22	SBIN	0.024[a] (31.192)	0.248[a] (9.704)	94.167	2.066
23	TATAPOWER	0.026[a] (24.659)	0.372[a] (15.192)	230.798	2.114
24	TATATEA	0.021[a] (26.754)	0.320[a] (12.802)	163.898	2.121
25	WIPRO	0.026[a] (18.474)	0.096[a] (3.643)	13.268	2.006

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

Panel: D. Moving Average Model

Sl. No:	Company	Coefficients		F - Statistics	DW Statistics
		μ	ε_{t-1}		
1	ACC	0.022[a] (32.847)	0.189[a] (7.296)	68.351	1.937
2	BEL	0.024[a] (32.191)	0.193[a] (7.457)	68.378	1.943
3	BHEL	0.025[a] (25.066)	0.130[a] (4.960)	31.318	1.961
4	BPCL	0.025[a] (34.585)	0.186[a] (7.187)	58.730	1.966
5	CIPLA	0.022[a] (12.976)	0.016 (0.589)	0.370	1.999
6	Dr. REDDY	0.020[a] (22.793)	0.068[a] (2.602)	6.901	1.998
7	GRASIM	0.022[a] (33.881)	0.175[a] (6.746)	59.043	1.941
8	HCLTECH	0.027[a] (27.113)	0.123[a] (4.693)	25.829	1.976
9	HDFC	0.024[a] (33.144)	0.198[a] (7.644)	71.775	1.944
10	HEROHONDA	0.020[a] (35.072)	0.176[a] (6.768)	52.276	1.968
11	HINDPETRO	0.025[a] (33.020)	0.212[a] (8.235)	79.122	1.953
12	ICICIBANK	0.026[a] (31.656)	0.188[a] (7.264)	70.589	1.927
13	INFOSYSTCH	0.022[a] (14.845)	0.048 (1.839)	3.440	1.999
14	ITC	0.021[a] (9.017)	0.004 (0.147)	0.022	2.000
15	M & M	0.025[a] (25.528)	0.122[a] (4.661)	25.133	1.979
16	MTNL	0.025[a] (32.429)	0.223[a] (8.689)	93.044	1.933
17	NATIONALUM	0.030[a] (29.881)	0.286[a] (11.312)	166.751	1.880
18	ONGC	0.023[a] (29.970)	0.160[a] (6.158)	45.112	1.964
19	POLARIS	0.033[a] (29.228)	0.234[a] (9.097)	109.739	1.903
20	RANBAXY	0.022[a] (22.259)	0.110[a] (4.212)	19.256	1.989
21	RELIANCE	0.022[a] (29.938)	0.235[a] (9.144)	103.466	1.927
22	SBIN	0.024[a] (34.402)	0.198[a] (7.661)	72.962	1.941
23	TATAPOWER	0.026[a] (29.879)	0.289[a] (11.458)	166.942	1.887
24	TATATEA	0.021[a] (31.296)	0.238[a] (9.296)	114.911	1.902
25	WIPRO	0.026[a] (18.765)	0.090[a] (3.418)	12.426	1.993

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

The results of AR (1) model specifications are provided in Panel: C. The highest lagged coefficient for NATIONALUM and TATAPOWER were observed at 1 per cent level of significance with value 0.374 and 0.372 respectively. But the coefficient parameters for CIPLA, INFOSYSTCH and ITC indicated insignificant effect. The null hypothesis for CIPLA, Dr. REDDY, INFOSYSTCH, ITC and WIPRO could not be rejected as DW was near to two. Hence, there exists a little evidence of autocorrelation for the stock futures returns. The simple class of linear combination of white noise series in the MA model is reported in Panel: D, from which it is observed that the estimated coefficients in terms of insignificance were found in CIPLA, INFOSYSTCH and ITC but the other parameters were observed with 1 per cent level of significance. The model was found to be more appropriate in ITC, CIPLA, INFOSYSTCH, Dr. REDDY and WIPRO.

In Table: 4, the parameter estimates for typical and parsimonious GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and IGARCH (1,1) models for the selected stock futures return series using still robust method of Bollerslev-Wooldridge's quasi maximum likelihood estimates assuming the Gaussian standard normal distribution. F-statistics were used to measure the best fits volatility model for examining the conditional variance of stock futures returns.

Table: 4 Non Linear Models

Panel: A. GARCH Model

Sl. No:	Company	Coefficients						F - Statistic
		$ø$	R_{t-1}	ω	α_j	β_i	$\alpha_j + \beta_i$	
1	ACC	0.015[a] (19.735)	0.184[a] (6.841)	4.21E-0[a] (7.324)	0.221[a] (9.862)	0.772[a] (36.473)	.993	16.94
2	BEL	0.018[a] (17.001)	0.190[a] (5.195)	0.000[a] (6.525)	0.301[a] (5.101)	0.696[a] (16.667)	.977	20.04
3	BHEL	0.018[a] (29.547)	-0.179[a] (-5.717)	0.000[a] (11.277)	0.728[a] (13.068)	0.300[a] (14.922)	1.028	58.49
4	BPCL	0.017[a] (20.145)	0.211[a] (8.098)	6.28E-0[a] (4.142)	0.041[a] (8.641)	0.957[a] (183.036)	.998	13.89
5	CIPLA	0.022[a] (3.073)	-0.009 (-0.103)	0.002[b] (2.116)	0.368[a] (-13.33)	0.590[a] (3.063)	.958	11.38
6	Dr. REDDY	0.016[a] (7.549)	0.163[a] (3.319)	0.001[a] (11.267)	0.235 (1.159)	0.740 (-1.388)	.975	18.13
7	GRASIM	0.015[a] (21.602)	0.173[a] (6.166)	9.15E-0[a] (5.898)	0.105[a] (12.283)	0.899[a] (171.363)	.994	12.28
8	HCLTECH	0.011[a] (16.616)	0.359[a] (9.237)	0.000[a] (13.741)	0.468[a] (29.371)	0.587[a] (26.715)	1.055	60.82
9	HDFC	0.016[a] (21.095)	0.174[a] (5.976)	1.81E-0[a] (4.995)	0.145[a] (10.301)	0.850[a] (65.110)	.995	14.78
10	HEROHONDA	0.014[a] (18.922)	0.220[a] (7.078)	4.32E-0[a] (6.298)	0.133[a] (6.754)	0.748[a] (26.025)	.881	13.64
11	HINDPETRO	0.017[a] (19.665)	0.193[a] (6.260)	2.06E-0[a] (5.865)	0.124[a] (8.908)	0.873[a] (70.081)	.997	18.28
12	ICICIBANK	0.018[a] (19.690)	0.177[a] (5.918)	3.08E-0[a] (6.368)	0.166[a] (9.065)	0.827[a] (47.288)	.993	16.36

Continued….

13	INFOSYSTCH	0.018b (2.326)	0.159 (0.739)	0.004[a] (13.061)	0.207[a] (3.591)	0.803 (-0.467)	1.010	55.63
14	ITC	0.019 (1.056)	0.001 (0.050)	0.005 (0.765)	0.179 (-0.600)	0.797 (1.136)	.976	28.64
15	M & M	0.019[a] (9.471)	0.213[a] (4.254)	0.000[a] (3.750)	0.266[a] (3.531)	0.672[a] (7.877)	.938	15.53
16	MTNL	0.019[a] (20.478)	0.161[a] (4.588)	0.000[a] (8.298)	0.184[a] (11.033)	0.620[a] (20.961)	.804	22.57
17	NATIONALUM	0.017[a] (18.730)	0.298[a] (9.687)	5.22E-0[a] (8.025)	0.196[a] (10.602)	0.798[a] (44.713)	.944	48.37
18	ONGC	0.019[a] (18.229)	0.163[a] (4.682)	0.000[a] (6.815)	0.385[a] (6.383)	0.578[a] (7.044)	.963	13.46
19	POLARIS	0.023[a] (17.373)	0.215[a] (5.585)	0.000[a] (10.559)	0.257[a] (11.274)	0.725[a] (46.461)	.982	32.02
20	RANBAXY	0.026[a] (35.416)	-0.129[a] (-5.340)	0.000[a] (12.647)	0.932[a] (19.147)	0.072[a] (3.936)	1.004	56.78
21	RELIANCE	0.015[a] (23.933)	0.166[a] (4.965)	3.92E-0[a] (7.150)	0.322[a] (33.574)	0.642[a] (36.407)	.964	19.68
22	SBIN	0.017[a] (25.626)	0.163[a] (6.273)	1.28E-0[a] (5.298)	0.079[a] (8.358)	0.898[a] (84.645)	.977	14.91
23	TATAPOWER	0.015[a] (19.840)	0.286[a] (9.772)	2.45E-0[a] (6.286)	0.182[a] (12.126)	0.815[a] (55.961)	.997	45.81
24	TATATEA	0.015[a] (19.434)	0.213[a] (6.868)	7.97E-0[a] (7.903)	0.300[a] (7.970)	0.608[a] (15.248)	.908	33.58
25	WIPRO	0.019[a] (5.510)	0.218[a] (2.289)	0.003[a] (14.382)	0.360 (0.925)	0.567 (-0.994)	.927	41.52

Note: Figures in the parenthesis report z-Statistics. a & b significance at the 0.01 & 0.05 per cent level respectively.

The GARCH (1,1) model for futures return series are presented in Panel: A. The lagged return in mean equation were found statistically significant for all the stock futures contracts, except CIPLA, INFOSYSTCH and ITC. The conditional variance found taking a long time to die out as the volatility is "persistence", indicated by larger coefficients in GARCH effect. The GARCH coefficients were higher for BPCL, GRASIM, HDFC, HINDPETRO, ICICIBANK, SBIN and TATAPOWER, which envisaged that new shocks will have the implication on prices for a longer period. In ARCH effect, the large coefficient for BHEL, HCLTECH, ONGC and RANBAXY indicated more persistence and were less reactive in volatility than the other stock futures. The sum of ARCH and GARCH estimates in variance equation were very close to one indicating that the volatility shocks were quite persistence, except in BHEL, HCLTECH, INFOSYSTCH and RELIANCE. The $\alpha + \beta$ for ACC, BPCL, HCLTECH, HDFC, HINDPETRO, ICICIBANK and TATAPOWER were close to one, which indicate that stock futures returns may be modeled better by a different GARCH models like IGARCH model. Moreover, the higher GARCH effect suggests that recent information is more important than old information and information decays very fast for BPCL, GRASIM, HDFC, HINDPETRO, ICICIBANK, INFOSYSTCH and SBIN futures return series.

Panel: B. TGARCH Model

Sl. No:	Company	Coefficients						F - Statistic
		ø	R_{t-1}	ω	β_i	δ_i	λ_j	
1	ACC	0.015[a] (18.117)	0.221[a] (7.564)	0.000[a] (6.441)	0.107[a] (9.045)	-0.286[a] (-5.195)	0.835[a] (41.623)	15.90
2	BEL	0.021[a] (26.901)	0.172[a] (30.822)	0.000[a] (9.796)	0.033[a] (4.856)	-0.581[a] (-7.831)	0.557[a] (11.895)	13.48
3	BHEL	0.020[a] (128.42)	0.097[a] (20.581)	0.001[a] (28.336)	0.914[a] (6.382)	-3.440[a] (-35.46)	0.297[a] (7.990)	15.57
4	BPCL	0.017[a] (19.187)	0.211[a] (7.966)	0.000[a] (4.227)	0.032[a] (8.294)	-0.072[a] (-3.562)	0.955[a] (154.47)	10.85
5	CIPLA	0.035[a] (4.824)	-0.015 (-0.158)	0.002 (2.551)	-0.001[a] (-113.9)	-0.759[a] (-3.031)	0.596[a] (3.173)	09.49
6	Dr. REDDY	0.015[a] (6.483)	0.263[a] (6.640)	0.000 (0.712)	0.005[a] (2.371)	-0.078[b] (-1.933)	0.673 (1.440)	11.55
7	GRASIM	0.015[a] (20.780)	0.172[a] (6.264)	0.000[a] (4.502)	0.088[a] (12.461)	-0.072[a] (-2.277)	0.891[a] (152.92)	10.25
8	HCLTECH	0.027[a] (147.51)	0.114[a] (8.343)	0.000[a] (10.785)	0.044[a] (3.129)	-1.284[a] (-12.787	0.660[a] (17.577)	13.76
9	HDFC	0.017[a] (19.923)	0.186[a] (5.661)	0.000[a] (5.505)	0.133[a] (10.071)	-0.252[a] (-4.517)	0.830[a] (50.698)	13.74
10	HEROHONDA	0.015[a] (18.558)	0.195[a] (5.815)	0.000[a] (6.712)	0.156[a] (6.824)	-0.263[a] (-4.542)	0.727[a] (23.290)	11.42
11	HINDPETRO	0.017[a] (19.466)	0.193[a] (6.249)	0.000[a] (3.985)	0.094[a] (8.262)	0.007 (0.294)	0.873[a] (66.312)	14.58
12	ICICIBANK	0.018[a] (18.305)	0.191[a] (5.935)	0.000[a] (5.235)	0.118[a] (8.007)	-0.175[a] (-4.025)	0.836[a] (40.147)	14.58

Continued…

13	INFOSYSTCH	0.018[a] (2.711)	0.232[b] (2.047)	0.002 (1.217)	0.043[a] (2.194)	-0.504 (-1.200)	0.563 (1.525)	06.95
14	ITC	0.022 (1.209)	0.005 (0.306)	0.005 (0.750)	-0.001 (-0.526)	0.360 (0.177)	0.595 (1.108)	03.45
15	M & M	0.019[a] (16.544)	0.166[a] (6.703)	0.000[a] (-2.537)	0.062[a] (9.121)	0.685[a] (7.778)	0.888[a] (74.874)	05.45
16	MTNL	0.019[a] (18.359)	0.179[a] (4.663)	0.000[a] (8.569)	0.239[a] (10.323)	-0.367[a] (-5.641)	0.548[a] (14.063)	20.30
17	NATIONALUM	0.017[a] (15.725)	0.324[a] (9.739)	0.000[a] (8.603)	0.147[a] (9.503)	-0.207[a] (-7.916)	0.808[a] (41.918)	42.03
18	ONGC	0.020[a] (15.950)	0.087[a] (2.325)	0.000[a] (7.505)	0.145[a] (7.710)	0.369[a] (4.671)	0.644[a] (20.027)	07.20
19	POLARIS	0.023[a] (19.422)	0.227[a] (8.178)	0.000[a] (12.493)	0.166[a] (11.274)	-0.549[a] (-8.514)	0.751[a] (45.715)	27.07
20	RANBAXY	0.017[a] (23.041)	0.034[a] (1.975)	0.000[a] (12.104)	0.354[a] (9.583)	6.086[a] (10.648)	0.104[a] (5.871)	24.73
21	RELIANCE	0.015[a] (19.441)	0.211[a] (5.192)	0.000[a] (10.542)	0.393[a] (27.616)	-0.571[a] (-10.96)	0.599[a] (30.463)	22.32
22	SBIN	0.017[a] (24.074)	0.162[a] (5.872)	0.000[a] (4.565)	0.086[a] (8.020)	-0.083[b] (-2.316)	0.888[a] (70.441)	12.55
23	TATAPOWER	0.015[a] (17.584)	0.266[a] (7.642)	0.000[a] (8.267)	0.191[a] (11.673)	-0.271[a] (-6.487)	0.801[a] (51.930)	36.31
24	TATATEA	0.015[a] (16.753)	0.215[a] (5.576)	0.000[a] (7.298)	0.221[a] (6.776)	-0.284[a] (-4.592)	0.590[a] (12.177)	27.58
25	WIPRO	0.022[a] (4.775)	0.181[a] (4.655)	0.001 (0.803)	0.003 (0.929)	-0.155[b] (-2.010)	0.593 (1.133)	05.27

Note: Figures in the parenthesis report z-Statistics. * & ** significance at the 0.01 & 0.05 per cent level respectively.

To capture the asymmetries in terms of positive and negative shocks TGARCH (1,1) model was envisaged in Panel: B. The ARCH and GARCH effect remained insignificant for ITC and WIPRO. A positive shock has an impact on $\boldsymbol{\lambda}$ while the negative shocks have an impact of ARCH (β) + $\boldsymbol{\lambda}$. If $\delta > 0$ we conclude that there is asymmetry while if $\delta = 0$ the news is symmetric. The results thus suggest that positive shocks were observed for ONGC and RANBAXY at one per cent level of significant, but the stock futures contracts like HINDPETRO, INFOSYSTCH and ITC were identified with insignificant effect. On the other side, the stock futures returns for Dr. REDDY, SBIN and WIPRO were envisaged with five per cent level of significance with negative shocks. The estimated parameter for all the variance envisaged that volatility is an asymmetric function of past innovation. Specifically, negative shocks have larger impact on the volatility of the series than positive shocks.

Panel: C. EGARCH Model

Sl. No:	Company	Coefficients						F - Statistic
		ø	R_{t-1}	ω	β_j	λ_j	δ_i	
1	ACC	0.015[a] (19.10)	0.219[a] (7.976)	-0.802[a] (-7.312)	0.025 (0.983)	0.141[a] (6.837)	0.900[a] (59.034)	15.24
2	BEL	0.019[a] (22.041)	0.223[a] (6.824)	-5.864[a] (-15.981)	-0.339[a] (-12.17)	0.509[a] (17.157)	0.198[a] (4.131)	17.31
3	BHEL	0.015[a] (22.852)	0.197[a] (4.562)	-2.846[a] (-19.763)	0.349[a] (12.050)	0.805[a] (39.069)	0.653[a] (33.092)	20.09
4	BPCL	0.017[a] (20.109)	0.216[a] (8.945)	-0.216[a] (-4.450)	0.066[a] (5.411)	0.031[b] (2.236)	0.978[a] (144.80)	11.23
5	CIPLA	0.024[a] (500.75)	-0.009 (-1.621)	-4.708[a] (-67.882)	-1.541[a] (-66.42)	1.422[a] (128.50)	0.096[a] (91.296)	18.79
6	Dr. REDDY	0.010[a] (31.231)	0.316[a] (17.351)	-7.556[a] (-31.610)	-1.001[a] (-38.42)	1.117[a] (35.714)	-0.081[a] (-2.510)	21.73
7	GRASIM	0.015[a] (21.823)	0.192[a] (6.981)	-0.304[a] (-7.887)	0.160[a] (11.079)	0.035[b] (2.339)	0.977[a] (177.73)	10.52
8	HCLTECH	0.018[a] (18.524)	0.340[a] (7.044)	-4.053[a] (-25.543)	0.163[b] (2.477)	0.945[a] (38.891)	0.445[a] (18.829)	16.65
9	HDFC	0.017[a] (20.637)	0.186[a] (5.807)	-0.689[a] (-7.087)	0.136[a] (5.801)	0.113[a] (4.793)	0.926[a] (67.601)	13.91
10	HEROHONDA	0.015[a] (18.308)	0.217[a] (5.833)	-2.227[a] (-7.257)	0.105[b] (2.392)	0.226[a] (6.623)	0.735[a] (19.233)	11.56
11	HINDPETRO	0.018[a] (18.781)	0.193[a] (5.872)	-0.555[a] (-7.191)	0.164[a] (7.618)	0.064[a] (3.835)	0.943[a] (90.579)	14.63
12	ICICIBANK	0.018[a] (21.640)	0.194[a] (6.521)	-0.537[a] (-7.580)	0.125[a] (5.169)	0.085[a] (4.284)	0.942[a] (91.988)	14.31

Continued…..

13	INFOSYSTCH	0.013[a] (20.349)	0.449[a] (13.39)	-5.982[a] (-28.079)	-1.005[a] (-16.59)	1.187[a] (18.705)	0.020 (0.663)	21.89
14	ITC	0.019[b] (2.328)	0.001 (0.272)	-4.952[a] (-6.066)	0.163 (0.447)	-0.766[a] (-4.815)	0.029 (0.170)	10.24
15	M & M	0.016[a] (23.260)	0.232[a] (15.68)	-7.687[a] (-24.645)	-0.652[a] (-15.52)	0.801[a] (21.096)	-0.082[b] (-2.146)	11.95
16	MTNL	0.019[a] (18.269)	0.176[a] (4.177)	-2.624[a] (-9.986)	0.217[a] (6.290)	0.194[a] (6.036)	0.679[a] (19.477)	20.14
17	NATIONALUM	0.017[a] (16.614)	0.321[a] (9.945)	-0.864[a] (-11.560)	0.125[a] (6.262)	0.145[a] (10.555)	0.895[a] (91.967)	41.47
18	ONGC	0.020[a] (16.876)	0.123[a] (3.693)	-1.120[a] (-7.721)	0.361[a] (20.436)	-0.098[a] (-5.160)	0.882[a] (45.999)	9.43
19	POLARIS	0.023[a] (17.235)	0.231[a] (6.025)	-1.246[a] (-11.784)	0.065[b] (2.040)	0.223[a] (8.277)	0.828[a] (49.025)	27.17
20	RANBAXY	0.016[a] (27.874)	0.046[a] (3.713)	-3.506[a] (-17.574)	1.768[a] (60.341)	-1.129[a] (-29.13)	0.627[a] (21.979)	31.45
21	RELIANCE	0.015[a] (20.990)	0.196[a] (5.401)	-1.538[a] (-13.657)	0.330[a] (10.403)	0.204[a] (7.582)	0.840[a] (54.552)	20.82
22	SBIN	0.018[a] (24.682)	0.158[a] (6.036)	-0.515[a] (-7.583)	0.125[a] (7.424)	0.081[a] (5.939)	0.946[a] (105.03)	12.19
23	TATAPOWER	0.016[a] (18.366)	0.283[a] (8.184)	-0.848[a] (-11.143)	0.169[a] (9.555)	0.153[a] (8.420)	0.907[a] (90.534)	37.8
24	TATATEA	0.014[a] (20.285)	0.258[a] (8.694)	-1.087[a] (-8.191)	-0.003 (-0.182)	0.213[a] (10.708)	0.864[a] (50.591)	29.51
25	WIPRO	0.017[a] (25.223)	-0.358[a] (-13.45)	-4.439[a] (-37.591)	3.026[a] (18.676)	-1.646[a] (10.640)	0.483[a] (25.749)	30.24

Note: Figures in the parenthesis report z-Statistics. * & ** significance at the 0.01 & 0.05 per cent level respectively.

To investigate the leverage effect EGARCH (1,1) model has been used and the statistical results are given in Panel: C. The lagged returns in mean equation were observed with positive sign and envisaged with one per cent level of significance. The presence of positive asymmetric effect were observed for ACC, BEL, BHEL, BPCL, CIPLA, Dr. REDDY, GRASIM, HCLTECH, HDFC, HEROHONDA, HINDPETRO, ICICIBANK, INFOSYSTCH, M & M, MTNL, NATIONALUM, POLARIS, RELIANCE, SBIN, TATAPOWER and TATATEA with one per cent and five per cent level of significance. But for ITC, ONGC, RANBAXY and WIPRO the negative asymmetric effect were identified. Moreover, the coefficient of δ_i term is positive and negative for all estimated parameters with one and five per cent level of significance, which indicates that there exist a leverage effect and asymmetric relationship between the select stock future contracts which indicated that “bad news has larger effects on the volatility of the series than good news”. Hence, it can be concluded that the persistence in volatility is very long and explosive and is suggestive of an integrated process.

Panel: D. IGARCH Model

Sl. No:	Company	Coefficients				F - Statistic
		ø	R_{t-1}	α_i	β_j	
1	ACC	0.0152[a] (29.288)	0.2399[a] (12.152)	0.0246[a] (20.183)	0.9754[a] (801.723)	40.62
2	BEL	0.0173[a] (22.631)	0.2545[a] (17.860)	0.0084[a] (10.454)	0.9916[a] (122.793)	43.27
3	BHEL	0.0311[a] (187.020)	0.1339[a] (290.609)	-0.0058[a] (-309.283)	1.0058[a] (541.900)	55.47
4	BPCL	0.0179[a] (31.044)	0.215[a] (10.478)	0.028[a] (16.105)	0.9712[a] (552.158)	30.38
5	CIPLA	0.060[a] (326.957)	-0.049[a] (-3.726)	0.000[a] (20.103)	0.9991[a] (2675.800)	36.92
6	Dr. REDDY	0.0328[a] (485.331)	-0.1290[a] (-21.072)	-0.0006[a] (-44.297)	1.0006[a] (704.990)	59.61
7	GRASIM	0.015[a] (35.095)	0.189[a] (9.110)	0.066[a] (19.239)	0.933[a] (271.628)	31.23
8	HCLTECH	0.0270[a] (11.571)	0.1091[a] (4.254)	0.0005[a] (33.760)	0.9995[a] (666.560)	10.33
9	HDFC	0.0176[a] (37.260)	0.1769[a] (8.295)	0.0850[a] (16.231)	0.9150[a] (174.701)	35.98
10	HEROHONDA	0.0168[a] (21.432)	0.1452[a] (7.618)	-0.0017[a] (-4.793)	1.0017[a] (280.620)	27.53
11	HINDPETRO	0.0180[a] (32.371)	0.2223[a] (10.716)	0.0603[a] (13.554)	0.9397[a] (211.359)	43.87
12	ICICIBANK	0.0191[a] (42.789)	0.1804[a] (8.945)	0.0694[a] (14.573)	0.9306[a] (195.458)	40.02

Continued…

13	INFOSYSTCH	0.0211[a] (4.484)	0.0349 (0.710)	0.0020[a] (61.652)	0.9980[a] (306.700)	51.53
14	ITC	0.0543[a] (42.505)	1.1967[a] (21.227)	0.6172[a] (31.602)	0.3828[a] (19.604)	87.15
15	M & M	0.0380[a] (78.155)	0.0521[a] (1.927)	0.1085[a] (9.628)	0.8915[a] (79.086)	89.57
16	MTNL	0.0192[a] (32.650)	0.2003[a] (10.251)	0.0635[a] (12.172)	0.9365[a] (179.545)	54.81
17	NATIONALUM	0.0194[a] (37.671)	0.3070[a] (15.637)	0.0707[a] (17.246)	0.9293[a] (226.596)	109.65
18	ONGC	0.0260[a] (166.314)	0.0987[a] (6.544)	0.0031[a] (10.908)	0.9969[a] (347.105)	71.82
19	POLARIS	0.0226[a] (20.919)	0.2969[a] (21.323)	0.0082[a] (16.612)	0.9918[a] (200.072)	76.28
20	RANBAXY	0.0409[a] (287.432)	-0.0852[a] (-5.578)	0.0000 (1.210)	1.0000[a] (365.850)	59.87
21	RELIANCE	0.0159[a] (39.072)	0.1731[a] (7.415)	0.1666[a] (55.141)	0.8334[a] (275.834)	48.52
22	SBIN	0.0176[a] (38.109)	0.1849[a] (10.706)	0.0470[a] (14.843)	0.9530[a] (300.663)	36.77
23	TATAPOWER	0.0157[a] (36.162)	0.3075[a] (17.548)	0.1007[a] (25.421)	0.8993[a] (227.015)	103.63
24	TATATEA	0.0146[a] (31.045)	0.2708[a] (13.899)	0.0480[a] (19.483)	0.9520[a] (386.006)	78.40
25	WIPRO	0.0225[a] (21.933)	0.0751[a] (9.776)	-0.0015[a] (-220.933)	1.0015[a] (145.900)	35.35

Note: Figures in the parenthesis report z-Statistics. * & ** significance at the 0.01 & 0.05 per cent level respectively.

The parameter estimates of the IGARCH (1,1) model are reported in Panel: D, where in conditional variance, the coefficients of β were found to be significant at 1 per cent level for all the estimates, inferring that the market takes some times to digest the full information into the prices and shocks to conditional variance takes a long time to die out. The α were found to be insignificant for RANBAXY, but for BHEL, Dr. REDDY, HEROHONDA, WIPRO and the stock futures returns were negatively significant at 1 per cent level which indicates less persistence and more reaction in volatility. Hence it can be inferred that the recent information is more important than the old information and the information decays very fast for all the stock futures returns except ITC.

5.4. Forecast Evaluation

In order to evaluate the forecasting performance of different models two forecasting error statistics were used by considering the root mean square error (RMSE) and the mean absolute percentage error (MAPE), which are formulated as follows:

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

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|(\sigma_t - \hat{\sigma}_t)|/\sigma_t$$

Where in all the above statistics *'n'* stand for the number of out of sample forecasts. Two most popular measures are analyzed to evaluate the forecasting capability of a model by using RMSE and MAPE. In RMSE, the mean of the squares deviations of the error is compared with the forecast demands and the actual demand values. Usually the effects on operations of small errors are not serious. But, the MAPE is the mean of percent deviations of the forecast from the actual series. In short, the model that exhibits the lowest values of the error measurement technique is considered to be the best model.

Table: 5. Out of Sample Forecast for Linear Models

Sl. No:	Company	Random Walk		Linear Regression		AR (1)		MA (1)	
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1	ACC	.027655	.019982	.026329	.019075	.026329	.019075	.026695	.019370
2	BEL	.028259	.018115	.027751	.017815	.027751	.017815	.027834	.017874
3	BHEL	.032044	.022808	.031469	.023264	.031469	.023264	.031628	.023174
4	BPCL	.030716	.022116	.029557	.021330	.029557	.021330	.029850	.021476
5	CIPLA	.021158	.014828	.021141	.014813	.021141	.014813	.021143	.014814
6	Dr. REDDY	.023679	.015479	.023251	.015216	.023251	.015216	.023278	.015224
7	GRASIM	.030469	.019621	.029614	.019574	.029614	.019574	.029788	.019540
8	HCLTECH	.039014	.027393	.038369	.027171	.038369	.027171	.038630	.027281
9	HDFC	.038055	.027561	.035749	.026484	.035749	.026484	.036470	.026960
10	HEROHONDA	.021386	.015508	.021203	.015879	.021203	.015879	.021283	.015954
11	HINDPETRO	.029212	.020882	.028900	.021061	.028900	.021061	.029046	.021008
12	ICICIBANK	.048764	.032890	.046152	.032439	.046152	.032439	.047060	.032670
13	INFOSYSTCH	.024339	.018696	.024127	.018691	.024127	.018691	.024142	.018699
14	ITC	.021369	.016299	.021352	.016293	.021352	.016293	.021354	.016293
15	M & M	.040421	.024967	.037963	.023682	.037963	.023682	.038472	.023878
16	MTNL	.024270	.017974	.022459	.016870	.022459	.016870	.022853	.016964
17	NATIONALUM	.048345	.031412	.042777	.028520	.042777	.028520	.044138	.029000
18	ONGC	.028837	.019689	.028050	.019553	.028050	.019553	.028160	.019551
19	POLARIS	.045214	.029822	.044093	.030142	.044093	.030142	.044195	.029912
20	RANBAXY	.046191	.026781	.044670	.026048	.044670	.026048	.044905	.026201
21	RELIANCE	.035898	.022692	.032946	.020911	.032946	.020911	.033719	.021190
22	SBIN	.034233	.024321	.032800	.023075	.032800	.023075	.033220	.023364
23	TATAPOWER	.034075	.023488	.032547	.023488	.032547	.023488	.033147	.023497
24	TATATEA	.021542	.015131	.020792	.015203	.020792	.015203	.021030	.015173
25	WIPRO	.033738	.024616	.032821	.024150	.032821	.024150	.032957	.024240

To assess the forecasting performance of selected stock futures contracts, out-of-sample forecasts were compared with Random Walk, Linear regression, AR (1) and MA (1) models are reported in Table: 5. The out-of-sample forecasts were performed by considering Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) statistics for the period from April 1, 2008 to December 31, 2008. The results suggest, that the RMSE statistics in AR (1) model and linear regression models rationally shared and ranked first for out-of-sample forecasts in the linear models. The results of MAE reveals that the AR (1) model dominates the entire set of models using MAE criteria. The linear regression model ranked second and MA (1) models ranked last.

Table: 6. Out of Sample Forecast for Non Linear Models

Sl. No:	Company	GARCH		TGARCH		EGARCH		IGARCH	
		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
1	ACC	.027082	.019227	.026800	.019108	.026876	.019125	.026732	.019066
2	BEL	.027886	.017598	.027519	.018147	.027707	.017818	.027820	.017790
3	BHEL	.039772	.028776	.032436	.023366	.033328	.024416	.029331	.023056
4	BPCL	.030271	.021466	.030307	.021476	.030237	.021459	.030092	.021420
5	CIPLA	.021151	.014939	.024331	.020119	.021143	.015217	.042326	.039471
6	Dr. REDDY	.022925	.014961	.022535	.015021	.023526	.015017	.024279	.018641
7	GRASIM	.030345	.019448	.030309	.019442	.030289	.019474	.030121	.019454
8	HCLTECH	.040759	.029237	.037548	.026902	.038917	.028282	.037651	.026921
9	HDFC	.037556	.027681	.037240	.027478	.037214	.027460	.037141	.027400
10	HEROHONDA	.021416	.015763	.021339	.015729	.021348	.015796	.021228	.015671
11	HINDPETRO	.029453	.020952	.029457	.020953	.029450	.020951	.029197	.020988
12	ICICIBANK	.048006	.033057	.047735	.032967	.047776	.033008	.047458	.032752
13	INFOSYSTCH	.023991	.018765	.023588	.018842	.024507	.019400	.024342	.018720
14	ITC	.021610	.016226	.021180	.016434	.021770	.016201	.066553	.059675
15	M & M	.037056	.023402	.037912	.023562	.037482	.023408	.037897	.027433
16	MTNL	.023187	.016970	.022996	.016946	.023008	.016968	.022846	.016909
17	NATIONALUM	.044709	.029154	.044133	.028905	.044231	.028942	.043804	.028776
18	ONGC	.028129	.019523	.028593	.019519	.028325	.019498	.027594	.020173
19	POLARIS	.044701	.029925	.044507	.029911	.044542	.029935	.044224	.030100
20	RANBAXY	.047870	.028101	.046958	.026961	.047102	.026993	.044531	.029774
21	RELIANCE	.035162	.022259	.034243	.021623	.034472	.021784	.034660	.021912
22	SBIN	.034156	.024084	.034067	.024024	.034108	.024061	.033792	.023792
23	TATAPOWER	.033541	.023408	.033476	.023311	.033405	.023343	.033131	.023326
24	TATATEA	.021079	.014967	.021015	.014972	.021026	.015000	.020889	.015050
25	WIPRO	.032448	.023961	.031859	.023901	.050270	.036842	.033629	.024410

The results reported in Table: 6 show that among non linear models the IGARCH model has outperformed all the other models and provides the most accurate forecast in terms of RMSE and MAE respectively. IGARCH model dominates the forecasting performance and it is considered as the best model followed by TGARCH model. On the other hand, the EGARCH model is the worst performing model under both the criteria. Despite its mathematical and statistical simplicity, the IGARCH model provides the most accurate forecast compared to other competing models in the study. Among both linear and non linear models IGARCH models performs the best fit in terms of forecasting ability.

5.5. Summary and Conclusion

This part of the analysis tried to shed light on the importance of modeling and forecasting stock futures contracts volatility and various linear and nonlinear models were used to undertake out-of-sample forecast. The dataset analyzed for the period from April 1, 2003 and ending on 31, December 2008. The forecasting models that were considered here ranged from random walk, linear regression, moving average, autoregressive, GARCH (1,1), TGARCH (1,1), EGARCH (1,1) and IGARCH (1,1) models. In order to evaluate the forecasting performance of different models two forecasting error statistics were used they were, Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) to identify which model is the best model according to statistic and risk management evaluation criteria. The results suggest that, in RMSE statistics the autoregressive model and linear regression models rationally shared and ranked first for out-of-sample forecasts in the linear models. In nonlinear model the IGARCH model dominates the forecasting performance and it is considered as the best model followed by TGARCH model. Despite its mathematical and statistical simplicity, the IGARCH model provides the most accurate forecast compared to other competing models in the study.

CHAPTER - VI

SUMMARY, CONCLUSION AND POLICY IMPLICATIONS

Over the last decade, many emerging and transition economies have started introducing derivative contracts. The introduction of it also has generated concerns of the policymakers, practitioners and regulators regarding its impact. One of the reasons for this concern is the belief that derivative trading may attracts speculators into the market who then destabilize spot prices.

Financial market liberalization since early 1990's has brought major changes in the financial system of our country. The creation and empowerment of Securities and Exchange Board of India (SEBI) has helped in providing higher level accountability in the market. New institutions like National Stock Exchange of India (NSEIL), National Securities Clearing Corporation (NSCCL), and National Securities Depository (NSDL) have been the change agents and helped cleaning the system and provided safety to investing public at large. With modern technology in hand, these institutions have set benchmarks and standards for others to follow. The microstructure changes brought about reduction in transaction cost that helped investors to lock in a deal faster and cheaper. The major changes in the capital market have resulted in the complete transformation of structure and composition of the market. In addition Indian capital markets also have started trading on derivative products in line with the developed countries.

Basically, a derivative is a product whose value is derived from the value of one or more basic variables called bases in a contractual manner. The underlying asset can be equity, commodities, interest rate or any other asset. The price of a derivative is contingent to the price of its underlying asset. Futures and Options are the different variants of derivative contract which are traded on exchanges, and they are standardized according to the rules and regulations of the exchange.

In India, the introduction of derivatives in its capital market started with Securities Exchange Board of India (SEBI) sets up a 24 member committee under the chairmanship of Dr. L. C. Gupta on November 18, 1996 to develop appropriate regulatory framework for derivatives trading in India. The committee submitted its report on March 17, 1998 prescribing necessary pre-conditions for introduction of derivatives trading in India. The committee recommended that derivatives should be declared as "securities" so that regulatory framework applicable to trading of "securities" could also govern trading of securities. SEBI also set up a group in June 1998 under the Chairmanship of Prof. J. R. Varma, to recommend measures for risk containment in derivatives market in India. The report, which was submitted in October 1998, worked out the operational details of the functioning of derivative market in terms of margining system, methodology for charging initial margins, broker net worth, deposit requirement and real - time monitoring requirements etc.

The derivatives trading flagged off in India in June 2000 after SEBI granted the final approval to this effect in May 2000. SEBI permitted the derivative segment in two stock exchanges viz. NSE and BSE, and approved trading in Index Futures contracts based on S & P CNX Nifty and BSE (Sensex) index. This was followed by approval for trading in Options based on the two indices and Options on individual securities. The trading in Index Options commenced in June 2001 and the trading in Options on individual securities commenced in July 2001. Futures contracts on individual stocks were launched in November 2001 and the Interest Rate Futures trading commenced in March 2003. Trading and settlement in Derivatives contracts regulated in accordance with the rules, byelaws, and regulations of the respective exchanges and their clearing houses duly approved by SEBI and notified in the official Gazette. NSE also introduced trading in futures and option contracts based on CNX - IT index and CNX Bank Nifty Index in 29th August, 2003 & 1st June, 2005 respectively. On 1st June 2007 NSE launched its trading on futures and options indexes on CNX 100 and CNX Nifty Junior. In January 2008 NSE initiated Mini derivatives (Futures & Options) Contracts on Nifty 50. In March 2008 NSE also launched

Long Term Option contracts on S & P CNX Nifty Index. Derivative contracts on DEFTY index was introduced in the year December 2008.

India's experience with of equity derivatives market has been extremely positive since its introduction. The derivatives turnover on the NSE has surpassed the equity market turnover. The turnover of derivatives on the NSE increased from Rs. 23,654 million in 2000-01 to Rs. 130,904,779 million in 2007-08. India has evidenced the world as one of the most successful developing countries in terms of a vibrant market for exchange-traded derivatives. This reiterates the strengths of the contemporary developments of India's securities markets, which are based on nationwide market access, anonymous electronic trading, and a predominant retail market. NSE proved itself the market leader in derivative trading contributing 99.9% of the total turnover in 2007-08 in India. There is an increasing belief that the derivatives market is playing a crucial role in accelerating the speed, quality of information flow and thus enhancing the overall market depth, increasing market liquidity and ultimately reducing informational asymmetries in market volatility.

As per details for the top 20 contracts for the year 2007 presented in Indian Securities Market Review of NSE, Kospi 200 options contract was the most traded in 2007 followed by Euro-Dollar Futures of CME with 621.47 million contracts. E-mini S&P 500 Futures, CME contract saw an increase of

61% in its traded volumes and moved to 3rd position in the list of top traded contracts in 2007 from 6th position in 2006. Another contract which witnessed a sharp increase in its volume in 2007 was the DJ Euro Stoxx 50 Futures contract leading to its positions' improvement from 8th to 6th in 2007. In terms of trading volumes in single stock futures, while the NSE ranked first (1st) in terms on number of contracts traded in 2006, it was shifted to second position as the Johannesburg Stock Exchange (JSE) overtook NSE with a 265.49 million contracts traded in 2007 at the JSE as against 179.33 contracts on the NSE. However, NSE faired very well in 2007 in terms of traded volumes in futures and options taken together, improving its worldwide ranking from 15th in 2006 to 9th in 2007. The traded volumes in the derivatives segment of the NSE saw an increase of 95 per cent in 2007 over the figure in 2006. In terms of trading volumes in single stock futures, while the NSE was ranked 1st in terms on number of contracts traded in 2006, it got shifted to second position as the Johannesburg Stock Exchange (JSE) overtook NSE with a 265.49 million contracts traded in 2007 at the JSE as against 179.33 contracts on the NSE.

The present research work has been developed on the background of earlier studies attempted in this area. In finance literature, there are many empirical papers that provide indirect evidence on the relationship between trading volume and stock returns. Clark (1973) examines Mixture of Distributions Hypothesis which plays a prominent role in the empirical finance arena. As suggested by Morgan (1976) volume is regarded as a major risk factor contributing to the volatility of returns, particularly in less liquid and thin markets, including emerging markets. In the mixture model of Epps and Epps (1976), trading volume is used to measure disagreement among traders, as investors revise their reservation prices based on the arrival of new information to the market. Similarly, positive contemporaneous relationship between variance of price change and trading volume was linked by Ragalski (1978), Figlewski and Cornell (1981) who studied the basic relationship between the variables. Tauchen and Pitts (1983), and Lastrapes and Lamoureux (1990) alleges that the conditional heteroskedasticity in stock returns can be explained by a serially correlated mixing variable that measures the rate at which information is transmitted to the market. These authors have shown that the information arrivals stemming from the existence of exogenous variables which can be identified by the mixture of distributions, and these variables exhibit time-varying ARCH effect.

There is quite strong body of literature advocating the use of the GARCH family of models to test the relationship between these variables. Lamoureux and Lastrapes (1990) examined the presence of ARCH/GARCH based on the hypothesis that daily returns are generated by a mixture of distributions using trading volume as a proxy for the rate of daily information arrival. They find that volatility persistence vanishes under the presence of trading volume series in the conditional variance equation. Brailsford (1996) found that the direction in price change was significant across three measures of daily trading volume for the aggregate market and was significant for individual stocks. An overwhelming number of studies have examined both theoretical and empirical relationship between future return, trading volume and open interest. Bessembinder and Seguin (1993) investigated the relations between volume, volatility, and market depth in eight physical and financial futures markets and suggested that unexpected volume shocks have a larger effect on volatility, the role of open interest provides information to mitigate volatility and he suggested that the volatility-volume relation in financial markets depends on the type of trader. A large number of studies have been conducted at international level to test the relationship between futures return, trading volume and open interest contacts, whereas in India the empirical works are quite limited. Pati & Kumar (2006) tested the maturity, volume effects and volatility dynamics for Indian futures market and suggested that time-to-maturity is not a strong determinant for futures price volatility, but rate of information arrival proxies by volume and open interest are the important sources of volatility. Finally, they concluded that Samuelson Hypothesis does not provide support for Indian futures market so the investors should not base their investment decision on time-to-maturity with the background of existing literature. The current study attempts to shed light on the chemistry among variables by examining the dynamic relationship between future return, trading volume and market depth for stock futures contracts in India.

As far as modelling and forecasting is concerned, there exist a strand of literature focusing on the modelling and forecasting of equity markets by Akgiray (1989), Dimson and Marsh (1990), Pagan and Schwert (1990), Bollerslev et.al (1992), Francis and Van Dijk (1996), Brailsford and Faff (1996), McMillan, Speight and Gwilym (2000) and Brooks and Persand (2002). The observations of these studies are; First, large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility clustering is observed in financial returns data. Secondly, financial time series data often exhibit leptokurtosis, which indicate that the return distribution is fat-tailed as observed by Mandelbrot (1963), Fama (1965), Laurent and Peters (2002). Finally, changes in stock prices tend to be negatively related to changes in stock volatility which is identified to be "leverage effect" Black (1976), Christie (1982), Nelson (1991), Koutmas and Saidi (1995).

There exist literature on modelling and forecasting volatility at international level, however only a limited attempt has been made the Indian stock market. Varma (1999) examined the volatility estimation models comparing GARCH and EWMA models in the risk management setting. Pandey (2002) analyzed the extreme value estimators and found the performance with

Parkinson estimator for forecasting volatility over these horizons. Karmakar (2005) has estimated that the movement in stock returns volatility is not explained by the fundamental economic factors, but reported the presence of 'fade' due to the actions of noise traders, liberalizing policies and procedures of the government. Kumar (2006) examined the comparative performance of volatility forecasting models in Indian markets and the results were found contrary to Brailsford and Faff (1996). Still, further research is needed to forecast the volatility of futures market for an in-depth understanding about the behavioural characteristics of Indian capital markets, and to fill the gap in the existing literature.

In India as of now there is no scientific study that used some of the modern econometric techniques to measure the relationship between price volatility, trading volume and market depth in stock futures market and to identify a suitable model for forecasting stock future markets volatility. There are some studies, which used Granger Causality test, GARCH (1,1) and EGARCH (1,1) model. Therefore, in this study Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test were used to check the stationarity of the series. The GARCH class family models and ARIMA model were used to evaluate the relationship, modeling and forecasting twenty five future securities.

On the above backdrop, the main objectives of the present study are;

1. To study the conceptual framework of derivatives and development of derivatives market in India.
2. To assess the dynamic relationship between price volatility, trading volume and market depth for select stock futures contracts in India.
3. To identify the suitable model to forecast volatility for stock futures contracts in India.
4. Finally, to summarize the findings and provide suggestions for the policy makers, academicians and research community.

The study is purely based on the secondary data for examining futures market in terms of relationship, modelling and forecasting volatility in India. The study period spanned from January 2003 to December 2008 with a sample of 25 stock futures contracts in India. During the sample period, the futures securities traded from 9:55 A.M to 3:30 P.M. All the required information for the stock futures contracts was collected from National Stock exchange (NSE) and their contract specifications, trading details were retrieved from their website terminal (www.nseindia.com). Out of the three types of contracts that are usually traded in the futures markets (i.e.) near month, middle month and far month futures contracts, near month futures contracts are considered for the purpose of analysis, because most trading activities take place in the near month contracts than on the other two types of contracts. The data were analyzed by using the econometric software package Eviews.

The earlier literature pertaining to the relationship between price volatility, trading volume and market depth in stock futures market and models for forecasting stock future markets volatility were reviewed which have formed the base of the present study. Most of the studies concluded that there exist a positive relationship between return and trading volume series. But, as far as modeling and forecasting futures market volatility is concerned, the Ordinary Least Square (OLS) model was found to be the earliest and simplest model to forecast the volatility behaviour of share market as per risk evaluation criteria. But, normally the OLS model does not takes into account of serial correlation problem. As far as non linear models, the asymmetric model is considered to be the more appropriate model to measure the effect of “good news” or “bad news” using in sample and out sample forecast error statistics criteria. It was also found out that most of the studies were related into the international level and Indian studies were found to be very limited related to testing the relationship between price volatility, trading volume and market depth in stock futures market and to identify a suitable model for forecasting stock future markets volatility. At the national level, further study can be conducted by taking the latest available data.

In Chapter III, the study discussed the concept and types of the derivatives and its instruments such as: forwards, futures and options. A forward or futures contracts involves an obligation to buy or sell an asset at a certain time in future for a certain price which are called calls and puts, respectively. A call option gives the holder the right to buy an asset by a certain date for a certain price. Derivatives have been very successful innovations in capital markets. Three types of traders can be identified in these markets (i.e.) hedgers, speculators and arbitragers. Hedgers are in the position where they face risk associated with the price asset. They use derivatives to reduce this risk. Speculators wish to bet on future movements in the price of an asset. They use derivatives to get extra leverage. Arbitragers are in business to take advantage of a discrepancy between prices in two different markets. This chapter discussed more detailed about futures market. Along with this, the relationship between spot and futures prices that can be explained by two models they are Cost of Carry model and Expectations model. Indian derivative market along with the mechanics of trading, its economic and social functions of derivative market and the various factors affecting futures markets are discussed in this chapter.

In Chapter IV investigates various unresolved issues regarding futures markets, using formal methods appropriate for inferring causal relationships between price movements, trading volume and market depth for stock future contracts. The initial results of the study were observed with various characteristics like volatility clustering, leptokurtosis and asymmetry effects etc. However, an attempt was made to estimate the market depth and volatility by using various GARCH types of models to draw valid conclusion. The findings of the analysis suggest that the information in trading volume is simultaneous for all investors except HCLTECH and ONGC stock futures contracts. Only, for these two stock futures contracts the information was found to have taken a long time to die out, indicates that information is persistent. On the other hand the major market moves towards the end of each day were observed with a lagging period of four days for all the contracts except ITC stock futures. This shows that the contracts are not closed at the end of a day and the information gets carried till the end of fourth day. Our findings indicate that there is a positive relationship between return volatility, trading volume and open interest variables. The futures return volatility is influenced by both expected and unexpected trading volume and open interest respectively, but the unexpected components has more impact on volatility than the expected components. In addition, the returns were found to be influenced by lagged volatility. The market depth was found not having any effect on volatility. Finally, our results indicated that unexpected components prices to be more important information for both practitioners and researchers which supports sequential information arrival hypothesis and mixture of distribution hypothesis in stock futures contracts.

In Chapter V compares the performances of various volatility forecasting models through linear and nonlinear approach by using in-sample and out-sample forecast error statistics Root Mean Square Error and Mean Absolute Error. Our analysis attempted to forecast volatility and to identify which model is the appropriate model for forecasting the volatility characteristics according to statistic and risk management evaluation criteria, the autoregressive model and linear regression models rationally shared and ranked first for out-of-sample forecasts in the Root Mean Square Error (RMSE) statistics. In nonlinear model the IGARCH model dominates the forecasting performance and it was considered as the best model followed by TGARCH model. Despite its mathematical and statistical simplicity, the IGARCH model provided the most accurate forecast compared to other competing models in the study.

Policy Implication from the Study:

1. The results pave the way for the investors that negative shocks have larger impact on volatility than the positive shocks and unexpected components will have a greater impact on futures market returns which is due to the structural changes, global impact and herding behaviour in stock markets.

2. The results of the study suggest that open interest does not have any effect on volatility, so the market players can understand that the market depth does not influence the volatility.

3. The study observes that the futures market increase the efficiency of the market by providing information to decision-makers and planners to carter the needs of the market participants.

4. The study reveals that volatility in futures market is due to the powerful influence of exogenous factors like interest rates, discount rates etc.

5. The fluctuations in underlying assets is mainly based upon the margin requirements, which seduced the market participants to play a dominant role in derivative market, So Clearing house should increase the margin requirements for membership in terms of capital adequacy (Net Worth, Security Deposits).

6. Hedgers and Speculators are the two market participants interested in knowing the results, Hedgers enters the futures market to offset the risk of substantial loss in the future, while speculators take positions based on their expectation of the movements of that contract. So, investors should base their decision based upon trading volume.

7. In the light of results and recent developments in derivatives market, the open positions of the members are marked to market based on contract settlement price for each contract at the end of the day, so SEBI should consider to settle difference on cash basis at T+1.

8. Clearing members serves as a trading terminal for monitoring the open positions for all the trading members in clearing and settlement system. A clearing member may set limits for a trading members clearing and settling through him. National Security Clearing Corporation Limited (NSCCL) assists the clearing member to monitor the intra-day limits set up by a clearing member and whenever a trading member exceeds the limits, it stops that particular trading member from further trading.

9. Finally, the findings of this study has a message for the market regulators that risk management practices should be further strengthened to take care of greater market volatility associated with an increase in the volume of trading.

Limitation of the Study:

Since this study is based upon the secondary data, all the limitations inherent to the secondary data will also be applicable to this study. In this research work, our special focus is to examine the relationship, modelling and forecasting volatility for select stock futures securities in India. The overall structural patterns, volatility behaviour and persistence of information for stock futures contracts are alone considered for the period. The research opens an area for further study of using other key determining variables like Inflation Rates, Industrial Production Index, Gross Domestic Product, Money Supply and Exchange Rate etc. are the factors not taken into account. This might have resulted in more consolidated results than the univariate analysis employed in this research.

Broader and long term issues involving Foreign Institutional Investment, Foreign Direct Investment and Global Meltdown impact in India and their Nation wide implications have not been discussed in this research. The micro structure aspects of stock futures contracts returns have not been attempted. Moreover, the analysis is done on stock futures of National Stock Exchange (NSE) alone which only constitutes 99 per cent of the market share rather than Bombay Stock Exchange's Sensitive Index (Sensex) which contains thirty major companies of India. The thesis work is limited to the period from January 2003 to December 2008 and is based on daily data. In spite of these limitations, it is hoped that the findings will be applicable to identify the status for developing derivative markets.

Agenda for Further Research:

The results of this dissertation present several questions that deserve further research. Some of these issues relate directly to the futures market volatility while others do not. So, an in depth analysis is required at International level between the developed and emerging markets, will be an interesting areas yet to be answered by the researchers for the investors community. Finally, several directions for future research could be investigated to improve the volatility behaviour of Indian financial time series; they are

1. International comparison between futures contract returns and trading volume will be useful to predict the characteristics of Indian stock markets.
2. Relationship between returns and volume change by considering the seasonality effect.
3. Long run persistence of shocks in the volatility with fractionally integrated models would certainly allow catching better dynamic of the series.
4. Forecasting volatility by using the macro economic variables like Inflation, Money Supply, Foreign Institutional Investors and Industrial Production Index.
5. Measuring the impact of derivatives on the underlying spot market.
6. Price discovery and volatility spillovers between spot and futures market.
7. Testing the hedging effectiveness of stock futures contracts.

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