Empirical Investigation and Analysis of Volatility Forecasting Models for the Indian Stock Market

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CERTIFICATE

This is to certify that the thesis entitled **"Empirical Investigation and Analysis of Volatility Forecasting Models for the Indian Stock Market"** submitted by **Mr. Rajan Pandey** ID No. **2008PHXF023P** for award of Ph.D. degree of the Institute embodies original work done by him under my supervision.

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Abstract

For the asset pricing theories, the estimate of volatility of returns is of paramount interest. Volatility estimation is crucial for making investment decisions as well as safeguarding the value of portfolios. This estimate of conditional variance from a generalized auto-regressive conditional heteroscedasticity (henceforth, GARCH) approach is a combination of weighted average of unconditional variance, the news surprise in the preceding period, and lagged period conditional variance. The news arrival not only plays a dominant role in the evolution of conditional volatility but also in appraising reliable forecasts therefrom.

Research studies on volatility forecasting models indicate superior performance of GARCH-*type*[1] models in modeling conditional variance of asset returns. In this thesis a comprehensive empirical investigation on the utility of GARCH models for estimating the volatility of the Indian stock market is undertaken. Time series data are known to exhibit common statistical properties, in this study, empirical evidence on the presence of properties on the volatility of stock market returns is provided. In particular, the focus is given to measure the time varying persistence of volatility using data from the Indian stock market. The economic value of GARCH parameters lies in their ability in explaining the persistence of the conditional variance. The estimate of persistence provides a quantitative measure about the impact of a sudden significant change in the asset return on its future volatility. This study attempts to analyze the magnitude and time evolving pattern in the persistence of conditional volatility using data on S&P CNX NIFTY 50 (henceforth, Nifty) benchmark index. The GARCH (1, 1) model is fitted on daily returns and a simple iterative scheme is used to re-estimate GARCH parameters on

[1] Various extensions of GARCH models are collectively referred to as GARCH-*type* models.

samples of different sizes and different time periods. The GARCH estimates obtained through repeated estimations furnish empirical evidences on the nature and consistency of the persistence parameter. Findings of the study confirm high persistence in the volatility process and indicate a positive relationship between the conditional volatility and volatility persistence.

Another vital statistical feature of volatility is its asymmetric response to news arrival. Research studies document that stock market volatility is more sensitive to stock market decline following a negative news arrival. If such property holds, then the volatility reacts asymmetrically to positive and negative news. For the analysis of the asymmetric response of volatility to news arrival; econometric techniques such as Exponential GARCH (EGARCH), Exponential GARCH-in Mean (EGARCH-M) and GJR-GARCH (Threshold-GARCH) models are used. Conditional volatility estimates using daily sampled return series on BSE Sensex for the period 01 Jan 1985 to 31 Dec 2014 confirms asymmetric response of volatility to shocks in the news arrival. However, since of GARCH model estimation based on a large data set has potential drawbacks and therefore the volatility models are subsequently estimated on the data divided into smaller sample periods of five years each. The findings of the study conclude that symmetric models of conditional volatility underperform the asymmetric models in modeling variance of index returns. This result is in contrast to other empirical findings where symmetric models perform better than asymmetric models.

Research studies show that the local and global factors also contribute to stock market volatility. Following the landmark economic reforms proposed in the year 1991, several key capital market reforms have been initiated in India. Over the long-run the markets have benefitted from these reforms and the participation of local and foreign investors in the Indian stock market has steadily increased. However, several instances of global stock market crashes and phases of consolidation are also argued to influence the volatility of the Indian stock market. To assess the impact of these local and global factors the sample periods are resized that overlaps with periods of turmoil and euphoria. Both symmetric and asymmetric GARCH models are estimated on these samples and results of the model estimations are compared with the findings in the previous analysis. The key finding that emerges from the analysis is that both the symmetric and asymmetric GARCH models equally perform well in modeling the volatility in the Indian stock market.

With reasonable degree of acceptance, studies on the influence of macroeconomic variables on stock market suggest presence of a long-run relationship between economic variables and the stock prices. On the contrary, few have questioned these claims and documented either a weak association or an insignificant influence of these economic variables on stock prices. The analysis undertaken in this study provides empirical evidence on the long-run and short-run causality between macroeconomic variables and volatility of Indian stocks. Proxies for six macroeconomic variables i.e. long-term interest rate, consumer price index, money supply, exchange rate, crude oil prices and exports are considered for the analysis. Using the Johansen and Juselius (1990) and Johansen (1991) multivariate co-integration framework and the vector error correction the existence of significant long-run equilibrium relationship between the macroeconomic variables and stock prices emerge. The study demonstrates the existence of both the long-run relationship and the transitory nature of the self-adjusting short-run disequilibrium that prevents the time-series from permanently meandering apart. The findings of this analysis are then used for estimating the volatility of the Indian stock market. We observe that the macroeconomic variables selected in this study carry useful information about the conditional volatility of domestic stock market. The analysis discovers that the macroeconomic variables contain significant long-run associations and significant short-term lead-lag relationship with the Indian stock market.

The findings of the study suggests that no single model uniformly outperform all other models in improving conditional volatility forecasts and the identification of the optimal GARCH model for the Indian stock market is left for further exploration. This study makes no attempt for explaining the possible reasons behind the high degree of persistence and accurate implications of the high persistence can be studied further by estimating the half-life of a shock in the return process. Further study on the half-life of a random shock will be useful in quantifying the number of trading days a shock takes to completely die out. The results of this study indicate presence of incremental informational content in the macroeconomic variables and further empirical investigations will be useful for identifying more macroeconomic variable that adequately explains the volatility of stock market.

A major contribution of the study is that, it employs the long-run association between select macroeconomic variables and stock market index for estimating and forecasting the volatility of stock returns. However, one limitation of this finding emanates from the fact that the variables that are considered for analyzing the impact of macroeconomic variables on stock market volatility are based on the past literature studies. The economic theory does not propound any clear guideline for variables selection and several competing variables qualify as desirable candidates. Hence, this finding can be further extended by exploring such association by including host of other macroeconomic variables to investigate the structural dependence between the real sector and the financial sector. Several other frontiers of further research for enhancing the forecasts of volatility conclude the discussion.

Key words: Conditional variance, asymmetric volatility, volatility persistence, leptokurtosis, volatility feedback, conditional heteroscedasticity, long memory; volatility clustering, volatility asymmetry, GARCH-*type* models, co-integration, vector error correction model.

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Chapter 1 Introduction

1.1 Actors in the Financial Markets

The cornerstone of financial economics is the dynamic interplay between the law of demand and supply that satisfies the utility maximizing principle of the market participants.[2] The demand-supply equilibrium in the financial markets requires liquidity seekers and providers to trade financial securities, on a designated platform, and make decisions that are coherent to their objectives of utility maximization. The stock market is one such platform where agents in large number participate and transact securities. Modern share market is host to different kinds of market participants, a significant number of daily transactions and extensively well-regulated norms and procedures. It is, therefore, an attractive and a real place to study the behavior of agents and the resulting impact on the prices of the instruments being traded. Since the wealth of investors changes as the asset price change the market participants take a keen interest in analyzing the price fluctuations. The unpredictable change in asset prices is also one of the most debated and yet unresolved issues of research in finance.

The financial market participants are of four major kinds namely sellers, buyers, intermediaries and the government. For financial transaction, the first two kinds are the most relevant entities and the rest two perform their auxiliary but vital roles. The first constitutes suppliers of capital i.e. the investors, and by investors, it is meant both the current investors as well as the prospective investors. The second entity encompasses all those who demand capital for financing their investment needs and for meeting the expenditure requirements, e.g.

[2] Market participants here are referred to as agents participating in financial transactions either on their behalf or behalf of their clients or principals.

corporations. The third consists of market intermediaries who bring together providers and demanders of capital on a common platform and facilitate financial transactions and also provide specialized financial services. Few examples of an intermediary include banking and other financial institutions, professional fund managers, traders and brokers in capital markets, investment bankers, and investment consultants. The fourth entity comprises of the regulatory bodies that engage in the policy-making practices to stabilize the financial markets and also act as a market watchdog to ensure fair participation and protection of the interests of all the stakeholders as mentioned above. A complete and a well-functioning capital market without any of these four is rather inconceivable.

One of the most baffling challenges faced by all of these market participants is the accurate estimation and forecasting of the **'*uncertainty of the variability'*** of future returns that investment is expected to earn over the investment horizon (Alexander, 2001). The corporate agents in their pursuit of maximizing the shareholder's wealth must undertake investments that yield superior *risk-adjusted* returns. Like, an investment decision is taken, if the project's net present value (NPV) is positive i.e. the current value of all projected future cash flows, discounted at rate consistent with the risk of expected cash flows, exceeds the initial outlay. On the other hand, rational individual investors pursuing utility maximization choose optimal investments according to their degree of *risk-aversion*. Specifically, an investment in security A is preferred over security B only if security A generates a higher positive return for the same level of risk. Hence, the agents' allegiance to shareholder's wealth maximization principle and the individual's choice in optimal portfolio selection is always commensurate with the degree of uncertainty involved in holding that asset. This continuous interplay between the supply and demand actions of agents along with their utility maximization principle mandates a thorough analysis of the uncertainty component inherent in the investment.

The intermediaries engaged in providing specialized investment services to investors must also give heed to the unprotected exposure in an investment. And finally, on the policy-making front the regulators are engaged with controlling market-wide factors such as the level of interest rates through monetary policy actions, managing exchange rate fluctuations, and curbing the fraudulent activities of traders and corporate agents. The regulators through the Basel accord of 1996 have prescribed mandatory requirements for the firms to undertake the investment risk management exercise through the use of adequate volatility estimation and forecasting tools (Léon, 2015). For example, the value-at-risk (VaR) measure for tail-risk exposure (developed by *Risk Metrics* at JP Morgan in the 1980s) has become a popular yardstick used by financial institutions as a risk management tool and as a method that is a precursor to firm's regulatory capital requirements (Holton, 2002). Corradi *et al.* (2013), and Fornari and Mele (2013) note that Policy makers and monetary authorities must give credence to the fact that the stock market volatility contains information about future business cycle fluctuations.

In a nutshell, the risk manifests itself as the volatility of future outcomes and the above discussion portrays the implications of market volatility to *all* the members of the investing community. Modeling and forecasting of the volatility of returns on financial securities are therefore imperative to sound investment decision making and invariably attracts an enormous interest of academicians as well as practitioners (Miah & Rahman, 2016).[3]

In recent decades, phenomenal innovations in the financial sector riding on the rapid growth of financial engineering, computation and information technologies, along with the surge in trading

[3] In this thesis, the term volatility is throughout used as synonymous to the risk inherent in an investment.

of financial securities and derivatives instruments on commodities, foreign exchange, and financial assets have afforded numerous tailor-made investment avenues. Investors today have, at their disposal, the flexibility in choosing their preferred investment route depending on their risk appetite, holding period, and timing of cash flows. However, a serious concern remains that in the event of a market crash, due to the deep integration of the modern financial markets, a negative trickle-down effect often causes quick contagion followed by a large-scale market collapse (Hammoudeh, Kang, Mensi, & Nguyen, 2016; Tampakoudis, Subeniotis, & Kroustalis, 2012). The liquidity crisis (aka subprime crisis) of the year 2008 is a classic case of the fault lines that exist in modern financial markets. Given the extent of risk exposure facing investors, it is a preeminent requirement that the volatility of future outcomes inherent in investments is rigorously assessed and adequate hedging strategies are adopted to neutralize any downside hazard. As we later elaborate on the impact of local and global triggers on stock market volatility - and in particular the Indian experience - a convincing case can be put forth suggesting that while creating an investment plan the investor must embrace risk-management practices.

1.2 The Indian Stock Market

The stock market plays a pivotal role in global financial markets by providing a secondary market platform for trading of shares issued by the firms.[4] Upon the completion of the share issuance and subscription process in the initial public offering (IPO), the shares are subsequently listed on the stock exchange(s) and thereupon the share market assumes the role of a financial intermediary, providing access to the needs of the suppliers and the demanders of capital. The

[4] Though the usage of stock and share differs when seen from an accounting perspective, in this thesis, following the general terminology used in Finance literature the sense in which stock, share, equity and common stock are used is synonymous.

historical presence of stock market in India along with a host of capital market reforms in recent decades has not only facilitated the growth and development of the Indian corporate sector but as well succeeded in cementing the faith and sentiments of domestic and global investors in Indian capital markets.

The Bombay Stock Exchange (BSE) is Asia's oldest stock exchange and was established in the year 1875. Promoted by leading financial institutions such as banks and insurance companies, the National Stock Exchange (NSE) was incorporated in November 1992, and trading in equity at NSE commenced from November 1994. The Over-the-Counter Exchange of India (OTCEI), based in Mumbai, was the designated stock exchange for small firms till it wound up its operations starting 1st April 2015.[5] Almost all trading in domestic equities takes place at the BSE (Bombay Stock Exchange) and the NSE (National Stock Exchange) have complete domination in the market. Besides equities, investors can trade in government securities (G-Sec), debentures (NCDs), and a variety of exchange traded funds (ETFs), *etc.* Trading in financial derivatives such as futures and options on stock indices and individual stocks are also operationalized on the NSE starting from the year 2000.

Both BSE and NSE are the two most active secondary stock market platforms in the country and compete relentlessly for market share and thus progressively strive to provide state-of-the-art services to its members. The result is a rapid increase in the market turnover along with an array of technological progress of both the exchanges, leading to the reduction in the trade settlement cycle, the transaction costs, and the volatility of asset prices. The NSE is India's first electronic exchange, and despite being a recent entry in the Indian capital market space it has outperformed the BSE compared with its business growth over the last two decades (Gokarn, 1996). Both stock

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[5] Refer to SEBI circular dated 31st March 2015 regarding discontinuation of OTCEI.

exchanges are well characterized by factors crucial for the operational efficiency of any stock market. Tobin (1984) discusses several prerequisites for an informationally efficient market, which include high liquidity, price continuity, competitive transaction costs (functional efficiency), the absence of arbitrage opportunities, pricing efficiency, and insurance efficiency i.e. the ability to fully hedge against contingent liabilities. Indian stock markets satisfactorily qualify all the above prerequisites and share features compatible with global standards.

The capital mobilization by corporate bodies via an IPO and the subsequent listing of shares on the stock exchanges involves a lengthy and a bureaucratic process requiring numerous regulatory filings and approvals. These compliance requirements ensure investor's protection to a great extent by debarring incompetent firms that fail to meet the necessary criteria. As on 31st March 2016, more than 5,500 companies are listed on the BSE and 1,500 firms are listed on the NSE, and the market capitalization of the firms listed on both exchanges is over $1.4 trillion as on March 2016. The stock market grants the approval of listing of securities under the provisions of Securities Contracts Regulations Act, 1956, Securities Contracts Regulation Rules, 1957, Companies Act, 1956, and guidelines issued by the market regulator. Despite an increase in the stock market listing of the firms over the years, more than 90% of the total market capitalization is still dominated by top ten-percent of the firms and these firms are usually the most actively traded scrips on the exchange. One of the probable explanations of this skewed distribution of market share is that the companies utilize the majority of funds mobilized through IPOs in recent years for either providing an exit route to private equity investors or toward repayment of outstanding debt, rather than creating new capital.[6]

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[6] Financial Express dated 12, December 2015.

1.2.1 BSE Sensex and NSE Nifty

The BSE's flagship index is BSE Sensex, and that of the NSE is Nifty 50. Both are recognized benchmark indices in the country and are tracked by fund managers, financial institutions, and retail investors worldwide for making investment decisions and also for benchmarking the performance of the Indian economy. BSE Sensex is a well-diversified benchmark portfolio comprising of leading 30-stocks listed on the BSE and the Nifty 50 consists of 51 constituent stocks.[7] Both these indices are considered to be the representative index for the India stock market. The BSE Sensex and Nifty 50 are free-float-market-weighted indices and contain the most liquid and valued firms spread across various sectors.[8] As majority of the shares that are constituents of these indices are same, the percentage change in the values of both the indices is not significantly different from each other. The difference in the absolute values of BSE Sensex and Nifty 50 index is purely on account of choice of different base-year for each.[9]

Stock market reforms in India have centered on addressing the aspects vital to the overall efficiency of the stock exchange that includes the issue of regulation and governance, turnover and liquidity, settlement time, openness to foreign investment, and trading of futures and options. Studies in the global context also attempt to draw relations between stock market reforms and its impact on market volatility. Though the benchmark indices and sectoral indices cannot be bought or sold in the cash segment, the derivatives contracts are frequently traded by investors, speculators, hedgers, and arbitrageurs.

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[7] Starting April 1, 2016, Tata Motors DVR (Diluted Voting Rights) is included as 51st stock in the index.

[8] Refer to https://www.nseindia.com/content/indices/nifty_freefloat_method_new.pdf for Nifty index calculation methodology.

[9] The base year for Sensex is 1978, and that of Nifty 50 is 1995.

1.2.2 Reforms in the Indian Capital Markets

Indian stock market experienced spectacular returns in the second half of the 1980s but these gains were quickly eliminated due to many stock market scams, and by the year 2001 the index was at mere seven percent, in rupee terms, above the post 1992-scam levels (Varma, 2002). The period following the economic liberalization, beginning mid-1991, has been historically the most volatile period in the Indian stock market (Karmakar, 2006). The decade of 1990 saw a significant number of market reforms, but several detrimental factors such as structural weakness in the Indian economy and scams in the capital markets caused frequent panic among the investors leading to significant increase in market volatility. The study by Batra (2004) also claims that the period following India's economic crisis and the liberalization that followed was historically the most volatile period in India’s stock market history and attributes this increase in volatility to local political and economic factors rather than the global events. Shah and Thomas (2001) provide eight significant episodes of alleged market manipulations during the 1990s in the Indian stock market.

The capital market reforms mainly focused on the twin issues of governance and technological modernization. Transactions in the Indian financial markets are regulated by the market regulator, the Securities and Exchange Board of Indian (SEBI) that came into existence in the year 1988. It was empowered with statutory authority through the SEBI Act, 1992. It is believed that Harshad Mehta's securities scam of 1992 was one of the prominent triggers that significantly resulted in the consolidation of the regulatory authority of SEBI to curb fraudulent activities on the exchange. The increase in the fraudulent activities of stock brokers also expedited the creation of the NSE (Gompers, Ishii, & Metrick, 2003; Krishnamurti, Sequeira, & Fangjian, 2003; Shah & Thomas, 2001; Uppal & Mangla, 2006). The traditional way in which the securities were settled in the Indian stock market engendered several hassles as the securities were held in a physical form and needed to be transferred from one location to another. The typical settlement cycle used to range from 14 to 30 days which was a major obstacle to the market liquidity. The landmark market reform to take effect in the Indian stock market in the mid-1990s was entirely designed to address the issue of the settlement of financial securities. The trading and settlement process that hitherto was carried out in the physical market was gradually migrated to a nation-wide electronic trading platform. The dematerialization process of all the physical securities was earnestly undertaken to successfully achieve the objectives of the complete migration to on-line trading. This entirely on-line fully automated screen-based trading system remarkably enhanced the trading and settlement efficiencies and significantly reduced the counter-party risk as well as the risk of mutilation of the physical securities. The first electronic exchange in the country, the National Stock Exchange, played a pioneering role in the creation of the electronic-based trading system and single-handedly disbanded the draconian practices ushering in a new era of high-speed trading. It was a major initiative that markedly reduced the trading and settlement hurdles by providing instant order matching and execution of the trade instructions. It also allowed traders to see real-time quotes online and take trading decisions thereby increasing the informational efficiency of the markets and reducing the market volatility. Starting April 2003 the trading settlement cycle was reduced to T+2 days, and a further reduction of trade settlement to T+1 day is quite likely to happen soon. On an operational level, the Indian stock market provides state-of-the-art trading technologies to its members and traders and so far no major incident of failure of the trading networks and software has occurred.

Shah and Thomas (2001) in their study on the evolution of the Indian stock market post-liberalization commented that the equity market design for the Indian stock market was complete by the year 2001 and emphasized the need to focus more on issues of corporate governance and the need to strengthen the Government bond market. They explicitly mention that beginning years of the 1990s were marred by several scams owing to lack of regulatory oversight and restrictions on speculative activities such as *Badla* transaction and leveraged trading. Lack of accessibility to corporate debt market has skewed the fundraising preference towards equity route, and a majority of the borrowing requirements were conveniently arranged as unsecured loans from financial intermediaries. The slow growth of debt market has led to a reduced depth of the issuance, reach, and the popularity of debt markets in India. At the same time, the risk exposures of the financial institutions and the stock markets have considerably increased since a majority of the loans issued were unsecured. Also, the absence of debt market deprives investors of an attractive alternative investment avenue in the case of weakness in the stock markets, and hence investors are forcibly driven out of the secondary market in search for safer havens such as gold or bank deposits.

A flourishing and active debt market will not only reduce the risk exposure of financial intermediaries but will also allow investors to migrate from equity to debt segment swiftly and vice-versa at a manageable cost. Such flexibility will be welcomed by investors and would instil further confidence of domestic and foreign investors in the Indian capital markets. The financial sector reforms that were undertaken in the first decade after the reforms of 1991 concentrated primarily on the commercial banking and the stock exchange.

Ahluwalia (2002) observes that the insurance and the mutual fund sector picked up growth in the first decade of the twenty-first century. In the years following the beginning of new millennium significant reforms and developments, participation, fundraising possibilities, regulation, improvement in credit rating practices have been witnessed in the Indian context

(Varma, 2009). There is no doubt that such inclusive capital market reforms will improve and strengthen the secondary markets in India which will further stabilize the Indian financial markets and curb high volatility.

Financial sector reforms undertaken in the post-liberalization era are not only intended to empower domestic financial institutions such as banking, mutual funds, and insurance sector but are also targeted at attracting foreign investors to our markets. Following Tobin's q, a positive relationship exists between stock prices and capital investment by the firms (Henry, 2000) which depends on the accessibility of capital (both local as well as foreign). However, in the years following the economic liberalization in different countries the researchers tried to establish a relationship between the foreign investor's participation and the domestic equity market performance. Bhole (1995) conjectures a positive and significant relationship between volatility in the equity market and the number of licenses issued to foreign institutional investors (FIIs) to participate in the Indian capital markets.

The study conducted by Miles (2002) also documents an increase in volatility in the Indian stock market during the periods following the liberalization after considering a dummy variable for policy reforms. Much of the market volatility is attributed to the actions of foreign portfolio investors, in particular, because of their unpredictable and erratic decisions. This unusually high degree of dependence is a matter of concern because FII actions are sensitive to global events. IMF Country Report, February 2014 commented "The principal risk facing India remains the inward spill-over from global financial market volatility, involving a reversal of capital flows."[10]

Volatility in financial markets is a dynamic process that corresponds to price fluctuations. Globally, the financial markets have witnessed periods of abnormally high levels of volatility

[10] Source: IMF Country Report No. 14/57, February 2014 (Item No. 46, p. 20). (Available at: http://www.imf.org/external/ pubs/ft/scr/2014/cr1457.pdf)

leading to massive erosion in investor's wealth. Recent episodes such as the 2008 sub-prime crisis, the Euro-Zone crisis of 2010, the flash crash of May 2010 in the United States and an unprecedented weakening of Chinese's economy in the initial months of 2016 have caused high volatility in the markets. It is not surprising to observe that the volatility in global markets during the troubled times have also spilled over to Indian markets (Rastogi 2014; Li & Giles 2015). For instance, during the sub-prime crisis the Indian stock market witnessed a fall of approximately sixty-three percent, from its intra-day high of 21,078 points to intra-day low of 7,697 points, within a ten-month period. The worth of shares sold by the FIIs during this period amounted to Rs 52,000 crore (Srinivas, 2016). The Euro-zone crisis beginning the year 2009 that followed the US sub-prime liquidity crisis resulted in a near twenty-seven percent fall in the Indian stock market returns from November 2011 to December 2012. During this period the net buying by foreign institutional investors was negative (i.e. value of shares sold exceeded the value of total purchases). Apart from this the on-going debt crisis in Greece, frequent devaluation of the Chinese currency, and the recent interest-rate hike by the US Federal Reserve continue to disrupt the stability among the foreign investors. It is implausible to reasonably predict the actions of the foreign investors and therefore the Indian markets are expected to remain volatile in the coming years. Hence, the estimation of volatility and its prediction for future periods is a desirable prerequisite for adopting risk management strategies.

To rein in market speculators, one of the most significant market reform undertaken in recent years is the launch of futures and options (F&O) on benchmark indices, individual stocks, and sectoral indices starting June 2000. Notable studies such as (Varma 2002b, Vashishtha & Kumar, 2010) provide empirical evidence favoring a decline in volatility in the years following the launch of derivatives trading in India. Over the years the stock exchanges in India have launched specialized products such as interest rates derivatives and currency derivatives to meet increasing demands from traders for hedging cash flows uncertainties. In the year 2013, the National Stock Exchange launched futures on India VIX allowing investors to hedge the volatility of the volatility.

Despite a phenomenal increase in turnover in the derivatives segment, these recent initiatives have not been able to marshal adequate steam and the highest activity in derivatives trading is on conventional products such as futures and options on the benchmark indices and large-capitalization equities. The popularity of derivatives products can be imagined from the fact that the combined average daily turnover of BSE and NSE in the spot segment in cash segment is roughly Rs. 2,500 crore and Rs. 15,000 crore respectively. However, in the F&O segment the daily turnover is around Rs 300,000 crore on NSE and almost entire trading in derivatives contracts takes place at the NSE.

Table 1.1 contains key local and global events that have caused substantial fluctuations in the Indian stock market.

Year	Financial Sector Reforms (1992 - 1996)
1990-91	Imminent threat of insolvency of the banking sector and balance of payment crisis. India pledges tonnes of gold with IMF to acquire capital for survival. Government extends support of Rs 200 billion to public sector banks. Gulf-war between United States and Iraq after Iraq invades Kuwait.
1991-92	New government is formed under the leadership of Shri P V Narsimha Rao. Series of economic reforms are unleashed by the government emphasising on globalization, abolishing of license raj, privatization of banking sector and several financial sector reforms.
1992-93	SEBI becomes sole authority of new capital issues. Financial market intermediaries come under purview of SEBI.. FIIs allowed access to Indian stock market. Indian firms allowed to issue foreign depository receipts to attract foreign investors (first listing in Nov 1992 by Reliance Industries Ltd). Harshad Mehta's stock market scam is exposed.
1993-94	Private mutual funds permitted. NSE and OTCEI created. Trading in wholesale debt market (WDM) commences. Trading in equities commences. Migration to electronic trading from physical settlement.

	Badla transactions abolished.
1994-95	UTI brought under SEBI's authority. Disclosure norms expanded for lead managers to public issues. Introduction of the electronic order book by the exchange
1995-96	NSCCL (National Securities Clearing Corporation Ltd.) incorporated as wholly owned subsidiary of NSE.
1996-97	Basal committee recommends 99% daily VaR level for financial institutions.
1997-98	Asian economic crisis (real estate crisis that began in July 1997). Global stock market crash October 1997 because of Asian economic crisis. RBI increases interest rates to check foreign currency outflows.
1998-99	Compulsory dematerialisation of shares for institutional and retail investors in a phased manner. RBI increases interest rate to control capital outflows after India's conducts nuclear test in Pokharan. Domestic money market was severely hit as a result of RBI's liquidity tightening outlook followed between August 1997 to August 1998. August 1998 – The Russian default on domestic debt and the Rouble currency crisis Brazilian devaluation of Jan 1999.
1999-00	Mandatory corporate governance was introduced by SEBI. Dot-com bubble bursts in March 2000 (10 March 2000). Suspension of opening and closing call auctions by the NSE – 09 Jun 1999.
2000-01	Derivatives (futures) trading commences on NSE (June, 2000). Privatization of insurance companies.
2001-02	Implementation of index-based market-wide circuit breakers to contain excessive volatility. Enron's accounting fraud is uncovered. Arthur Andersen surrenders its license to practice as Certified Public Accountant following Enron scandal. Index options launched in June 2001. Complete ban on *badla* transaction by July 2001. Futures in individual securities commences on NSE. Terror attack on September 11, 2001 caused a negative reaction in global stock markets.
2002-03	Year 2002 witnessed further decline in global stock exchanges and stock prices reverted to 1997 levels by Sept, 2002.
2006-07	Feb 2007 saw sharp decline in Shanghai stock exchange; a fall of 9%. May 2006 saw more than 1,000 points decline in BSE Sensex By December, 2006 Sensex levels were in excess of 14,000 points.
2007-08	October, 2007 to June 2009 subprime crisis phase in US stock market Indian stock market continues to outperform and reaches peak of 17,000 points in September, 2007. By October, 2007 Sensex was trading over 19,000 points. Participatory notes issues and statement from SEBI caused panic among the FIIs that triggered increase in volatility for several trading sessions. In December, 2007 Sensex breached 20,000 points. In the month of January, 2008 due to weakness in global stock markets the volatility in Indian stock markets also increased resulting in significant decline in asset prices. Episodes of free fall in Indian stock markets observed frequently in January 2008 and March 2008. Sensex traded at 14,000 levels by March 31, 2008.

Year	Financial Sector Reforms (1992 - 1996) contd..
2008-09	September, 2008 collapse of Lehman Brothers triggers a global contagion and stock markets around the world experience massive decline. October, 2008 Sensex fell to 8,500 points and to 8,500 points by March, 2009.
2009-10	May 2009 post election results Sensex gained over 2,000 points in a single trading session before trading was halted due to excessive volatility.
2010-11	April 2010 Economic crisis in Greece following its rating downgraded to junk by Standard and Poor’s. May 2010, US stock market fell sharply (Dow Jones crashed 1,000 points) due to technical reasons. Markets recover partially thereafter.
2011-12	August 2011 stock markets around the world fall sharply and remain volatile for several months.
2014-15	May 2014 Bhartiya Janata Party gets overwhelming majority in the Indian parliament to form government at the centre.
2015-16	March 2015 Sensex crossed 30,000 level intra-day. June 2015 the Chinese stock market crashes causing panic in the global markets. January 2016 witnesses worst beginning of year performance of global stock markets due to weakness in Chinese stock market.
2016-17	June 2016 global stock markets decline after Britain votes to exit from the European Union. The episode is popularly known as Brexit.

Table 1.1 Key local and global events in the past two and half decades[11]

1.2.3 Risk Assessment of Indian Markets

As discussed above, the stock market has been extremely volatile in the early 1990s. BSE Sensex which was trading at 730 points at the beginning of the year 1990 in subsequent years witnessed abnormally high intra-year positive and negative movements to close at 3,500 points by the end of the year 1993. Changes such as 250 percent positive in one year followed by over 50 percent fall in another year and subsequent annual increase of 135 percent are indications of the presence of exceptionally high volatility at that time. Such erratic variations cannot be explained alone by the economic fundamentals of a country and are neither forecast-able unless statistical tools of time-series analysis are employed to examine the time-varying evolution of such variables. From

[11] Source: Bhole (1995), Gokarn (1996), Varma (2002b), Allen *et al.* (2007), nseindia.com, sebi.gov.in

Fig. 1-1 one can observe wild swings in the Indian stock market in the past. The figure contains the daily closing values of the BSE Sensex (the representative index) for the earliest date from which the data is available i.e. 03 April 1979 and the ending date is 30 May 2016.[12]

The beginning of an upward momentum in the Sensex immediately follows the year 1991 which was the year the landmark economic reforms were tabled in the parliament.[13] The initial upsurge in the market shows a positive feedback of the market to economic liberalization policies. However, the euphoria was short-lived and during the eleven year period starting from the Jan 1992 to Dec 2002 the markets struggled to maintain the initial momentum and remained oscillating within a wide range (2,000 points to 6,000 points).

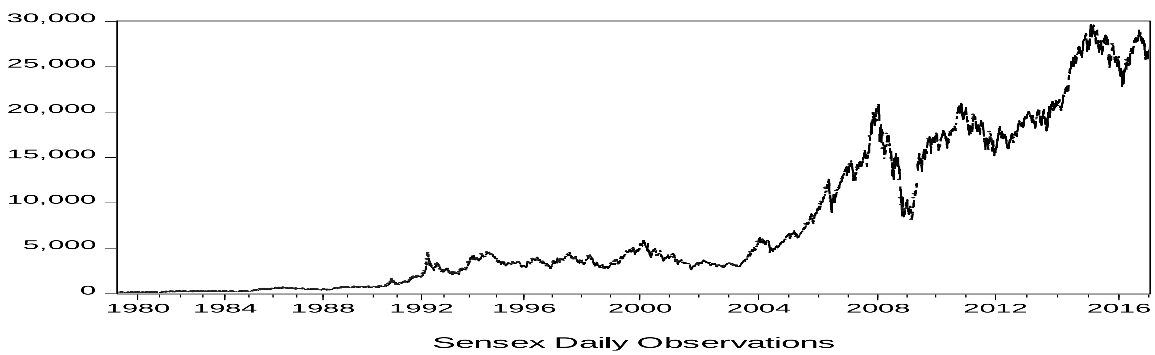

Fig. 1-1 Sensex daily closing from Apr 1989 to Dec 2016

There were wild fluctuations in the intervening periods and by the end of the year 2002 the Sensex was trading at approx. 3,300 levels which translate to a mere 5% (approx.) compounded annualized return during this eleven-year holding period. The sluggish performance was primarily due of the lack of modern trading infrastructure and governance oversight along with a weakness in the global markets emanating from the east-Asian real-estate crisis and the collapse of the dot-com bubble in early 2000. The markets during this entire period remained highly

[12] In this thesis, the data sample period considered is from Jan 1991 to May 2016. However, only for the sake of illustration in particular cases graphs containing longer time-periods appear.
[13] The year is taken as the calendar year.

volatile and especially around the time of the bursting of the tech bubble in the year 2000 (Fig. 1-2).

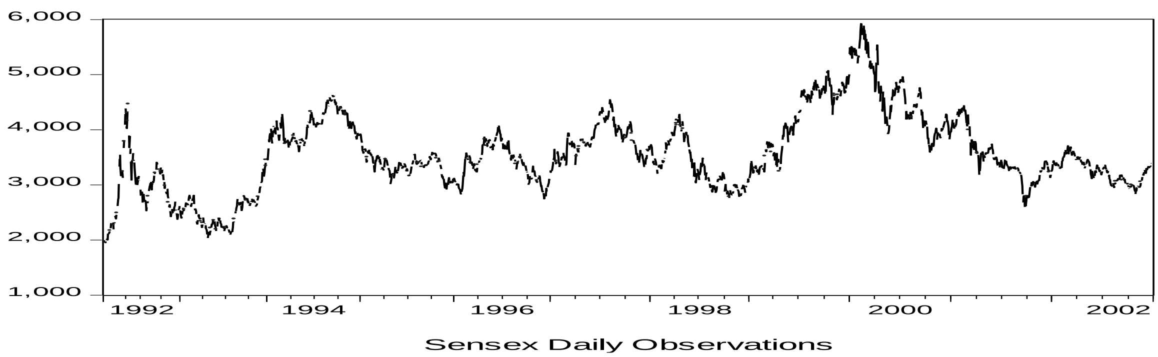

Fig. 1-2 Daily movement in BSE Sensex from Jan 1992 to Dec 2002

The years following 2002 till the beginning of the housing crisis in the United States are considered as the golden years for the Indian stock market (Fig. 1-3). The market from the January 2003 till the end of the year 2007 provided a holding period return of two hundred and forty percent that corresponds to a compounded annualized return of (approx.) thirty percent over the five years. This phenomenal performance witnessed in the Indian stock market consistently for these five years overlap increasing business integration with the world markets and the restoration of the faith of foreign investors in the Indian economy.

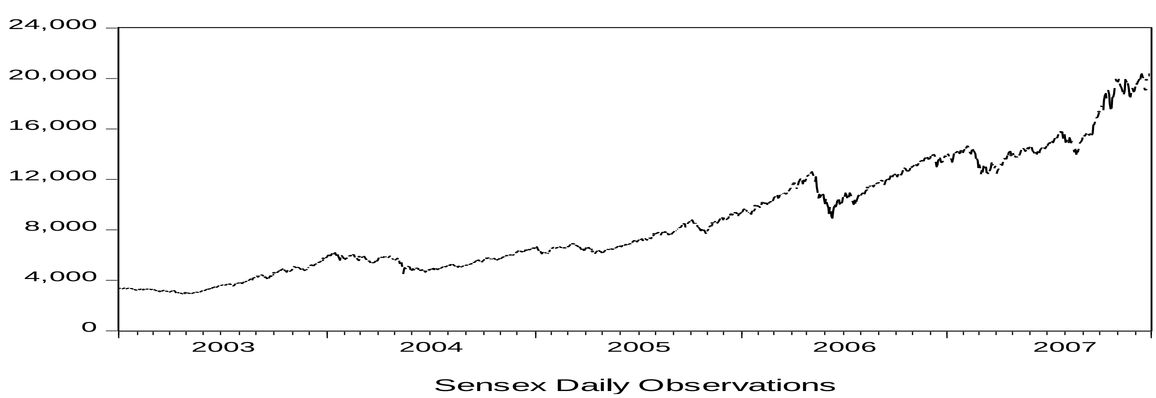

Fig. 1-3 Daily Sensex performance during Jan 2003 to Dec 2007

Fig. 1-4 contains the annual holding period returns on Sensex for each year starting the year 1991 till the end of the year 2016. The distribution of the annual returns prevalent in the Indian stock market provides a substantial evidence of highly persistent nature of volatility in the market and to model such time-series behavior the statistical models capable of capturing the persistence property with a reasonable accuracy may prove to be profitable. The annual returns in the figure appear to fluctuate in a random fashion, and a mere graphical illustration is insufficient to rationalize its future outcomes. The average annual change in Sensex over this twenty-six year period was 12.44% per annum with a range of -74.33% to 59.93% in the most extreme cases. In the entire twenty-six year sample period the annual returns witnessed a decline in eight cases compared to eighteen cases when the markets ended the calendar year higher than the previous year's closing value.

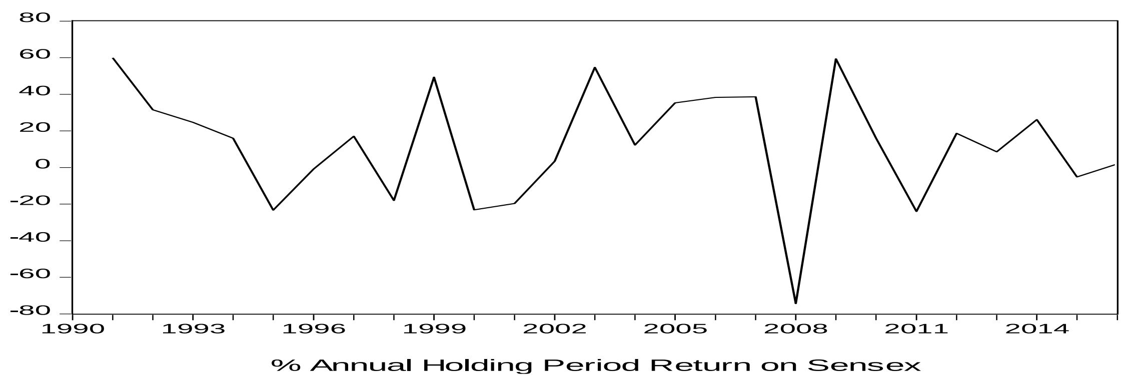

Fig. 1-4 Percent-age annual returns on BSE Sensex

Fig. 1-5 illustrates the frequency distribution of annual returns along with their descriptive statistics. The standard deviation of 31% in annual returns indicates the degree to which the holding period returns have fluctuated in the past. Should one considers, the past performance to be indicative for likely future movements, then the applications of such volatility models for risk management that utilize their lagged values to estimate volatility becomes inevitable and undoubtedly relevant.

Fig. 1-5 Sensex percent annual holding period returns from 1991 to 2016

The biggest fall in the annual returns (approx. negative 75%) coincided with the financial crisis of the year 2008 (see Fig. 1-6).

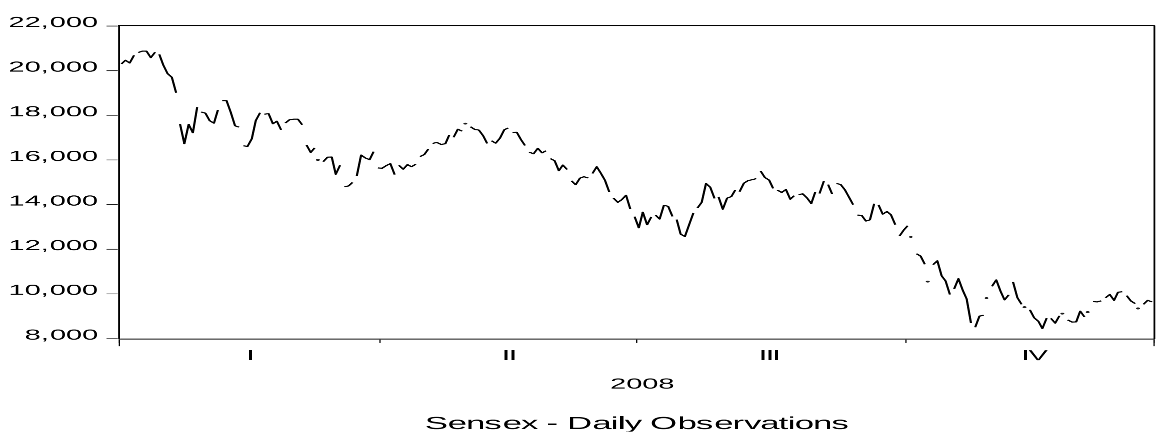

Fig. 1-6 BSE Sensex performance during the sub-prime mortgage crisis

However, due to the strong domestic economic fundamentals and victory of the Congress party in the general elections of 2009, a high upside momentum lasted throughout the year which resulted in an unexpected recovery of eighty percent from previous year close (Fig. 1-7). On a closer observation both Fig. 1-6 and Fig. 1-7 appear as mirror images of each other.

The post sub-prime recovery phase (Fig. 1-8 and Fig. 1-9) has been a mixed-bag of experience for the Indian markets with global factors such as the Euro-zone debt crisis and an increase in domestic consumer price index kept the market under check (Fig. 1-8). However, positive factors such as domestic political stability and attractive rate of productivity have diffused an overall confident outlook of investors toward the Indian economy and the stock markets.

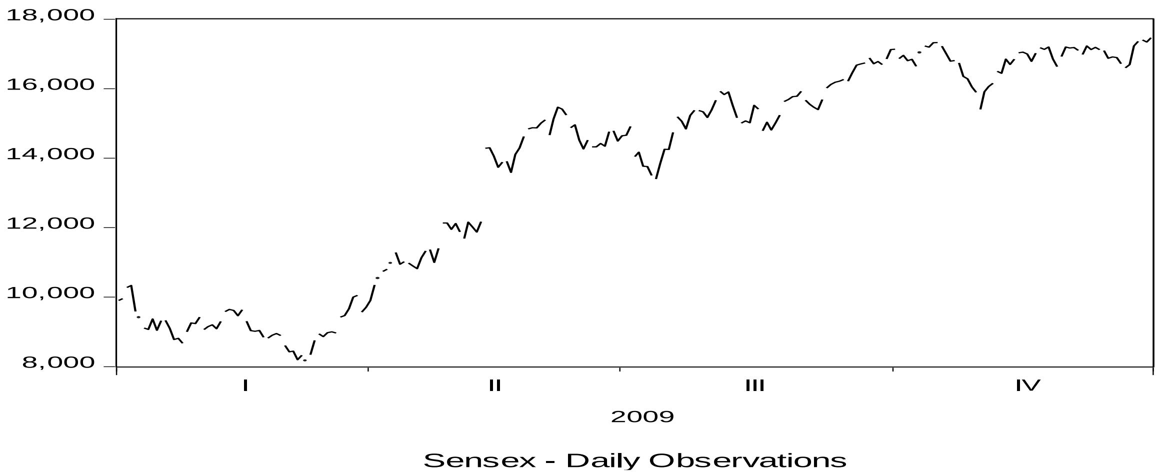

Fig. 1-7 BSE Sensex performance in the year 2009

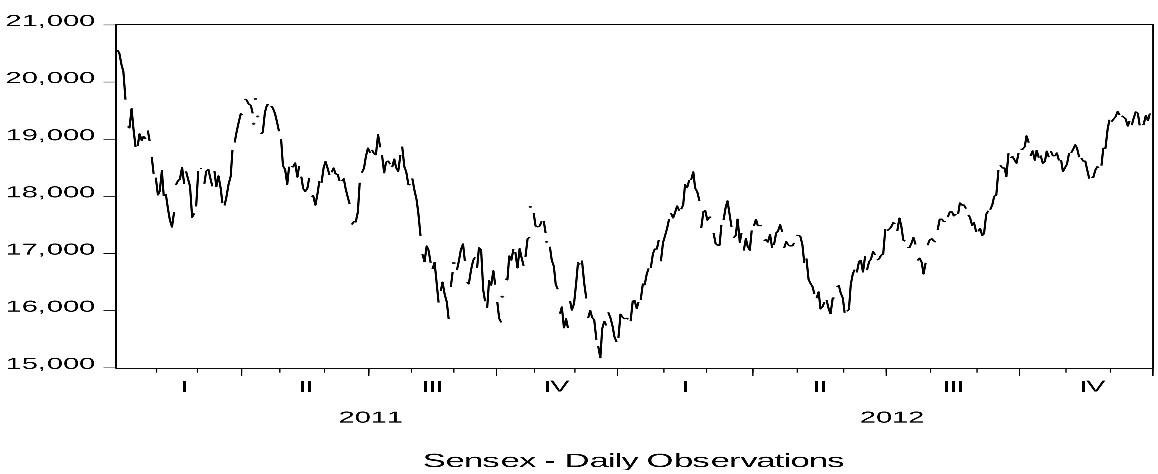

Fig. 1-8 Euro-zone debt crisis 2011-12

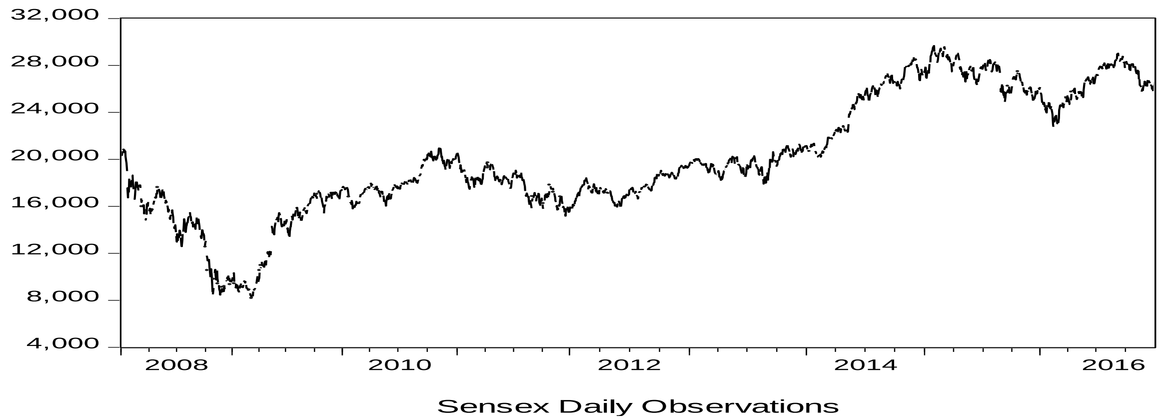

Fig. 1-9 Post sub-prime crisis recovery phase

The perspective in which the concept of volatility in general interpreted is its association only with a fall in the general price levels. This interpretation is erroneous because the statistical intuition of volatility regards both positive as well as negative changes to be contributing factors for volatility. Hence from the above discussion, it appears that instances of high volatility in the Indian stock markets occur frequently, and such a manifestation of volatility as a function of significant positive or negative returns cannot be ruled out. Such dynamic price movements require an accurate statistical model capable of describing its time-evolving nature and project outcomes, *ex-ante*.

1.3 Significance of Volatility Models

Volatility is associated with variation in prices of assets over time. Since investors' wealth fluctuates with a change in price levels, volatility is considered synonymous to risk. Since shares of a company represent residual ownership and are subject to rapid price movement, these instruments contain the high-risk component. Larger variations indicate greater volatility which enhances the investment risk and results in migration of investors from risky assets to safer havens such as the fixed income instruments. Availability of alternative investments makes these high-risk assets vulnerable to a rapid decline in value when investors panic.

The real time information on the market variables such as security prices, trading volume, and open interest are accessible whereas any information on the volatility inherent in these variables remains latent. Therefore, reasonable proxies of volatility are the only suitable candidates for analysis. The ideal proxy of volatility remains elusive and researchers over the years have proposed alternative measures as an attempt to capture the hidden volatility process. Both statistical, as well as econometric tools are modern devices used for volatility model building.

Forecasting of returns on financial assets requires precise econometric specification of the precise underlying data generating process for modeling the conditional moments of the probability density of these variables. Alternative model specifications and endless inquiry into the statistical properties of time-series data have drawn considerable interests from econometricians over the past three decades (Starica, 2003). Reliable predictions of the volatility of asset prices are crucial to several interrelated areas in investment science including pricing of financial assets, financial risk management, and portfolio selection for asset allocation, to name a few.

Investors at every stage of the investment lifecycle demand a risk premium for the uncertainties associated with the investment which determines the required rate of return. Conventional asset pricing theories estimate the current price of an asset by discounting the expected stream of future cash flows with the required rate of return commensurate with the perceived risk; as the required rate of return increases the present value of an asset falls due to volatility feedback hypothesis. Consequently, the firm's market value falls, and its debt-equity (financial leverage) ratio increases. An increase in financial leverage is perceived as a risk by existing and prospective investors and is referred to as the leverage effect. The debt-equity ratio has a positive relationship with the required return of the asset, and due to the feedback hypothesis, an inverse relationship exists between the risk premium and the price of the security.

Since the knowledge on appropriate risk premium is of paramount importance and because of the invisible nature of volatility, many models are proposed in pursuit of finding the actual model that adequately captures the time-varying nature of volatility. Historical standard deviation, traditionally, the most widely used measure, provides a point estimate for a particular sample period such as past 30-day volatility or 90-day volatility, etc. The option implied volatility (IV) or the implied volatility index (India VIX), now a widely traded index in many developed markets, provides a forward-looking estimate of expected volatility till the option expiry date. Studies on other conventional methods such as the moving average (MA), the exponentially-weighted moving average (EWMA) and the VaR measures are undertaken to quantify the volatility to mitigate its implications on the value of the portfolio (Poon & Granger, 2003). Numerous approaches to model volatility exist, and therefore it is not feasible to undertake each and every method for analysis. The class of models considered in this thesis for estimating and forecasting volatility are known as the auto-regressive conditional heteroscedasticity models (henceforth, ARCH) developed by Engle (1982).

1.3.1 ARCH Modeling in Finance

A fundamental law of investment is "risk and return go hand-in-hand." This statement only implies that the risk of investment has a positive relation with the investor's preference for higher yields and vice-versa. Modern econometric tools considered for empirical data analysis focus on the modeling of both returns and risk. The effective application of traditional regression-based econometric approaches such as the ordinary least squares (OLS) and auto-regressive moving average (ARMA) process remained confined only to the modeling of returns. The introduction of ARCH model made it possible to estimate the variance of asset returns conditional on its historical prices. Following its introduction, the ARCH model became a recognized approach for determining the conditional second moments (i.e. variance dependent on past data) and resulted in a paradigm shift in the way the time-series data are now studied. The original ARCH model was modified by several researchers, most notably by Bollerslev (1986), Nelson (1991), Glosten, Jagannathan, and Runkle (1993), and Zakoian (1994). Numerous empirical studies have attempted to investigate into the nature of time-varying volatility in financial markets by applying these models in different markets and on different asset classes ever since the introduction of the ARCH model.

Though the extant literature on ARCH models is remarkably comprehensive encompassing global markets and numerous asset classes, the empirical findings therein, en masse, are not unanimous for a single and the most desirable model for volatility modeling and thus it remains an active area of research.

1.3.2 Prominent Theories in Financial Economics

The entire financial ecosystem rests firmly grounded on vigorous theories and risk management principles. Louis Bachelier in his doctoral dissertation titled "The theory of speculation" published in the year 1900 described the movement of the stock prices as a stochastic Brownian motion. Though his work was immediately not well received, decades later his treatise on the randomness of asset prices became the foundation of the option pricing theory. His doctoral dissertation is argued to be the first published account of the erratic behavior of asset prices and associating its fluctuations to natural random processes. Mandelbrot (1963) recognized the works of Louis Bachelier and formulated his theory of the behavior of financial assets. His work is considered as a breakthrough in the modeling of the stochastic nature of asset prices. Mandelbrot and Fama (1965) were among the earlier researchers to document the presence of clustering of returns in financial assets.[14]

Modern theories in Finance first appeared in the mid-twentieth century beginning with the work of Harry Markowitz (Markowitz, 1952) on mean-variance portfolio theory that led to the development of the Markowitz's efficient frontier consisting of a portfolio of only risky assets. This work was remarkable, since it was the first mathematical exposition on how a portfolio's risk is negatively related to its extent of diversification. This work was followed by the Miller and Modigliani's (popularly known as M&M) capital structure theory (Modigliani & Miller, 1958). Their work stimulated tremendous interest in corporate finance and investment theory. William Sharpe (Sharpe, 1964) and John Lintner (Lintner, 1965) independently developed the Capital Asset Pricing Model (CAPM) that extended the Markowitz's mean-variance portfolio theory by considering borrowing and lending opportunities at a risk-free rate. Eugene Fama (Fama, 1965, 1970) proposed the Efficient Market Hypothesis (EMH) and challenged the conventional notion of the possibilities of consistently generating abnormal returns by a systematic analysis of financial securities. Fisher Black, Myron Scholes, and Robert Merton proposed the acclaimed theory on the pricing of contingent liabilities (Black & Scholes, 1973; Merton, 1973) and their work is said to have played a pivotal role in the explosive growth of financial markets worldwide. At present, a promising area in financial economics is behavioral

[14] Mandelbrot (1963) pp. 418, noted that "large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes." This tendency of returns to cluster together is commonly referred to as volatility clustering.

finance that studies the financial decision making of agents by applying behavioral aspects and cognitive psychology to finance.[15]

These early works outlined the theoretical framework that enabled the researchers to unravel the dynamics governing the collective decision making of corporate agents and participants in financial markets. Modern day finance acknowledges the importance of these theories, and it would not have been possible unless the validity and reliability of these models qualified the empirical litmus-test using actual data and econometric methods. Hence, besides the development of these theories, the applications of econometric methods to test these models became integral to financial economics. This tandem of theoretical underpinnings with rigorous empirical studies brought the field of financial economics to a stage of prominence and repute.

The interest of econometricians in the behavior of speculative assets gathered momentum after the introduction of the auto-regressive integrated moving average (ARIMA) specification of the time-series data. Box and Jenkins (1970) formulated a statistical procedure for modeling time-varying properties of asset returns that significantly improved understanding of stochastic processes and their time-varying properties. However, their work neither involved the influence of economy-wide variables like the interest rate or the national productivity nor considered the firm-specific variables such as the size of the firm or the earnings per share (EPS).

The ARIMA model is considered a useful specification for explaining the return generating processes that allow both the lagged dependent variables and the lagged error terms simultaneously in the regression function. Alternative combinations of the lagged variable, the lagged error terms, and the freedom to include exogenous variables in the model allow greater flexibility compared to a simple linear regression (OLS) method. However, the predictive ability

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[15] Behavioral Finance is a sub-field within Behavioral Economics.

of ARIMA models remained low and subsequent research for a model that explains the time varying nature of the conditional moments of a stochastic process culminated in the introduction of the ARCH model in Engle (1982).

The introduction of the ARCH model sparked a paradigm shift in the formalization of time-series models that are particularly useful for modeling the second moments of asset returns. The ARCH model considers a simple auto-regressive specification for the conditional variance and simultaneously allows ARIMA-type specification for the conditional mean. ARCH model outperform ARIMA model because of their built-in superiority that allows the variance of the process dependent on past information (conditional) to be modeled. It was a remarkable improvement over standard econometric models that hitherto permitted only the estimation of conditional mean.

Time-series literature before the introduction of ARCH model made an unreasonable assumption of constant variance (homoscedasticity) in asset returns. ARCH model provides a parsimonious specification for modeling the conditional mean and the time-varying conditional variance simultaneously and hence provides an estimate of the current level of volatility. The model can be subsequently employed to obtain the volatility forecasts from the model parameters. Bollerslev (1986) generalized the ARCH model and introduced the GARCH model, and further extensions of GARCH (known as GARCH-*type* models) model were introduced. As researchers became aware of properties of the time-series data new models were proposed. Econometricians undertook the modeling of these salient features inherent in the time-series data referred as the conditional distribution of returns, volatility clustering, volatility persistence, volatility asymmetry, etc.

A significant contribution in time-series econometrics is due to Sir Clive Granger, who "... picked up on the importance of the Box and Jenkins' work on integrated data to devise methods for modeling evolving relationships between non-stationary economic variables that would transform the discipline of econometrics" [16]. Non-stationary variables have means and variances that change over time and exhibit trends and cycles. A variable is said to be integrated of order one i.e. I (1) if it is non-stationary in its level form and the first order log-difference transformation makes the series stationary. Following Engle and Granger (1987), two variables are *cointegrated* if they are both I (1) but their linear combination is stationary i.e. an I (0) process. This relationship is useful in establishing long-run equilibrium relationships between co-integrating variables since such variables have potential to influence each other over time. This technique opened new frontiers for researchers interested in dynamic and long-run causal linkages between macroeconomic variables and stock markets. Several studies using co-integration approach have attempted to describe underlying relationships between macroeconomic fundamentals and the movement in stock prices.

1.3.3 Why ARCH Model?

Alternative formulations to estimate volatility in asset returns exist. Non-regression based approaches like sample variance of stock returns, historical volatility, VaR estimate, and option implied volatility, etc. are popular sample statistic used by investors and professional fund managers to quantify risk exposure. The standard regression-based models such as the random walk (RW), MA and EWMA processes, and the ARCH-type of models remains popular choices for describing the underlying data generating process. The superiority of ARCH models lies in their ability to utilize the information set available till the point of model estimation i.e. allowing

[16]The Guardian, Monday 1, 2009: Obituary to Sir Clive Granger

modeling the volatility conditional on past information. The time-series of interest here is the first order lag-difference of the natural log of stock index values. This log transformed series is also referred to as the continuously compounded returns of the stock index prices.

Well-known empirical evidence concerning time-series data is that many stochastic variables share important statistical properties. These time-series properties are referred to as the *stylized facts*. Stylized features of a financial time-series are universally accepted as the general properties that manifest themselves in time-series data such as daily returns. *Volatility clustering*, the persistent impact of a random shock on future outcomes, instances of extreme observations resulting in a *fat-tailed distribution* of returns, and *serial correlation* of asset returns on their lagged values are commonly observed in time-series data. Other statistical features are *the asymmetric response* of future returns to lagged positive and negative returns and the *mean reversion* of the conditional mean and volatility to their long-term averages.[17] The ability of ARCH-type models in capturing these statistical features surpasses that of the traditional models discussed above and provides useful information on the true data generating process.

1.4 Plan of Work

The empirical analysis carried out in this thesis attempts to document the time-varying behavior of financial market volatility with particular concentration to the Indian stock market. From the initial discussion, it emerges that the Indian stock market over the past twenty-five years has been subject to intense speculation resulting in high levels of volatility. We surmise that the study on the patterns of volatility on Indian stock market is an area of research having many

[17] Some authors argue that due to an increase in the debt-to-market-value ratio following a price decline the *leverage effect* causes a downward bias in volatility's response to news and therefore the volatility responds asymmetrically to the good and bad news.

research frontiers unexplored. This thesis is divided into six chapters, and the chapter-wise plan is as follows.

Following chapter one which gives an overall background on the broad topic of study, the second chapter on literature review contains a comprehensive review of research studies done on both developed as well as developing markets covering various aspects of volatility modeling over past decades. The review of related literature is done with a view to identify gaps in the existing body of research and set-forth research objectives to address the research gaps. Review of literature is followed by the third chapter on research design and methodology. This chapter describes in detail research design and methodology and focuses on vital issues such as data, sampling, and econometric tools and techniques considered for answering the research questions. Chapter four undertakes an in-depth discussion on the statistical properties of the time-series data to rule out any statistical anomaly in the data. A comprehensive discussion on two key properties of volatility viz. persistence and volatility asymmetry are discussed in detailed. The comparative analysis of several volatility forecasting models, under different distributional assumptions, is done to identify the most reliable model specification for the Indian stock market. Subsequently, chapter five extends the study on the performance of volatility models by analyzing the impact of macroeconomic variables on the stock market returns and utilize the information content of macroeconomic variables to estimate volatility within the GARCH framework. Overall conclusions and limitations of this study are discussed in chapter six. The chapter concludes by offering a critical assessment of the research work by highlighting the findings of the study, the limitations of research work, and scope for further research work.

Chapter 2 Literature Review

2.1 Introduction

The aim of this chapter is to review the literature on significant aspects surrounding the estimation and forecasting of the conditional volatility to get an overall picture of the existing body of literature and identify the research gaps. The majority of studies concerning the performance of GARCH-type models across both the developed and the emerging markets indicate that the GARCH models have a better predictive ability regarding capturing the volatility inherent in asset prices. However, review of a vast number of such empirical studies also provides concrete evidence that forecasting of volatility remains a notoriously difficult task. The standard econometric models used for forecasting volatility are influenced by the time-series properties of asset returns, reforms in the capital markets, significant global events, and the impact of macroeconomic variables. Hence, for approximately describing the volatility using stock market data may require incorporating these factors to enable a better understanding of the behavior of the speculative assets.

2.2 Auto-regressive Conditional Heteroscedasticity (ARCH) Model

Financial economics studies the distribution of resources in the financial markets where agents make decisions under uncertainty; therefore, it is inevitable to ignore the volatility of returns that emanates itself from the uncertain components of the time-series variables. Andersen *et al.* (2006) define volatility as the variability of the unforeseen random component of the time series hidden in the asset prices and are therefore forecastable. Sharpe (1964) and Merton (1973, 1980) confirm a positive relationship between stock's expected return and its conditional variance.

Therefore, a model that captures the time varying heteroscedasticity in asset price fluctuations may provide superior forecasts of asset returns and minimize the investment risk.

A popular class of time series model that assume constant time-varying conditional variance is the Auto-regressive Moving Average (ARMA) model. In contrast, the models of conditional heteroscedasticity such the ARCH-type models permit time-varying variance conditional on past realizations. Traditional time series specifications like ARMA models make an implausible assumption of a constant variance in asset returns, whereas, Auto-regressive Conditional Heteroscedasticity (ARCH) class of models, introduced by Engle (1982), allow simultaneous modeling of both the conditional mean and the conditional variance that evolves with time.

The ARCH model estimates the time-varying conditional volatility at time *t* by utilizing past period's information on asset prices. Given that the econometric specification of the model is correct, then not only do the estimates of conditional variance appropriately capture the current period volatility but also provide reliable forecasts. These estimates of future volatility are used for pricing contingent liabilities like stock options. Early literature e.g. Hsu *et al.* (1974) on the time-series analysis of stochastic processes, provides the foundation on the need for ARCH-type models. They argue that probability distributions used for describing the rates of return assuming an unchanging variance in the process might yield misleading results, and therefore, stress on considering a probability model for explaining the return process by hypothesizing a dynamic variance in the process. Hence, the academic debates and discussions on the time-series analysis during the 1970s eventually led to the development of ARCH model.

The estimation and forecasting of volatility have a range of applications in finance, and therefore, its accurate estimation and forecasting are of prime consideration. Estimation of the variance of a process, conditioned on its past values, which is also referred to as the conditional volatility, was first introduced in the year 1982 by Robert Engle. The model came to be known as auto-regressive conditional heteroscedasticity or the ARCH model. In his seminal work, Engle (1982) proposed presence of an ARCH process in the time-series data, that described the conditional variance of the innovations in the underlying time series as realizations of past values. He also showed that typical time-series data suffer from heteroscedasticity and for such processes a homoscedastic variance assumption was implausible.

The introduction of the ARCH model by Engle (1982) brought about a paradigm shift in the outlook toward the modeling of the conditional second moments of a time-evolving process. Its utility in generating the forecasts of conditional volatility by utilizing available information was immediately recognized by researchers. The ARCH model permits simultaneous modeling of the mean and the variance of the stochastic process, conditional on the information set, and requires the time-series to be weakly-stationary, under the assumption of normality. It was remarkable because it allowed the simultaneous modeling of the return and the variance of a range of time-series variables that shared common statistical properties.

It is a well-known fact that for a normally distributed variable the first two moments of the process i.e. the mean and the variance are required to describe its probability density function. Poon and Granger (2003) note that the skewness value for a normally distributed process is zero and kurtosis is always three and therefore, the first two moments that describe the return and risk respectively are sufficient to characterize the entire distribution. Hence, under the assumption of a normally distributed variable the ARCH model may be considered a representative model with reliable predictive abilities.

2.3 Variants of the ARCH Model

A major impediment in the ARCH model was the requirement of a lengthy and arbitrary lag-length selection which rendered the model undesirable by reducing its number of degrees of freedom and thereby costing dearly on its economic value. Bollerslev (1986) addressed this issue of arbitrary lag-length selection by proposing a more parsimonious description of the stochastic process by introducing the generalized ARCH or the GARCH model. The Generalized Auto-regressive Conditional Heteroscedasticity (GARCH) model, proposed by Bollerslev (1986), addresses the issue of arbitrary lag length selection in the ARCH model by allowing a linearly declining infinite order lag structure.

Number of studies available on conditional heteroscedasticity clearly shows an explosion in the studies in the modeling of the conditional volatility following the introduction of the GARCH model. Bollerslev *et al.* (1992) in their review of studies on ARCH models suggested using ARCH models for estimating and forecasting volatility in developed and emerging markets. Bollerslev *et al.* (1992, 1994), Poon and Granger (2003), Hansen and Lunde (2005), and Cont (2007) provide excellent reviews on advances in volatility forecasting literature following the introduction of the GARCH model.

Empirical evidences in research studies on GARCH model overwhelmingly indicates that the plain-vanilla GARCH (1, 1) model performs better than other stochastic volatility and random walk models (McMillan and Speight 2004, Hansen and Lunde 2005). Studies have also confirmed the presence of heteroscedasticity in asset returns (Aggarwal & Goodell 2008). Also, Andersen *et al.* (2006) mention that volatility forecasting has been the most active and fruitful areas of research in time series econometrics. These studies have focused on the comparative performance of GARCH models from the perspective of symmetric treatment to volatility as well as a comparison to non-normal density with the normal ones.

Several empirical studies have focused on exploring the relation between returns and volatility, the role of risk premium in asset pricing, and the expected and unexpected changes in the risk premium on account of dynamic variability in asset returns. Notable studies such as by French *et al.,* (1987), Glosten *et al.,* (1993) and Poterba and Summers (1986) find that volatility has little or no effect on stock returns in the periods of low volatility and argue that models of conditional volatility are suitable only during economic recessions. Many relevant studies on stock-specific volatility include Lintner (1965), Christie (1982), French *et al.* (1987), Bekaert and Wu (2000), and Campbell (2001).

Earlier studies like Sharpe (1964) and Merton (1980, 1973), confirm a positive relationship between stock's expected return and its conditional variance. Hence, econometric models that capture the time varying heteroscedasticity, dependent on past information, are preferred over the unconditional estimates both as a measure of current volatility and for forecasting volatility. The GARCH model successfully captures common time-series properties such as the persistent impact of a large shock on future volatility, clustering of high and low returns, and frequent instances of a fat-tailed probability distribution. But the GARCH model fails to capture the leverage effect since the model assumes a symmetric impact of both positive and negative news on volatility.

Research studies by Christie (1982), French *et al.* (1987), Nelson (1989, 1991) and Glosten *et al.* (1993) argue that stock market volatility increase subsequent to fall in prices, and therefore symmetric volatility model may not be able to explain the exact nature of the underlying process. Black (1976) attributes the asymmetric response of volatility to negative returns which is commonly known as the leverage effect. Poterba and Summers (1986) also confirm that rise in volatility causes stock prices to fall as the discount factor governing the present value of future cash flows increases. The exponential GARCH (EGARCH) model proposed by Nelson (1991) includes a coefficient for past period news in the conditional variance equation. This quantifies the impact of positive and negative returns on subsequent volatility and allows identification of the asymmetric response of volatility to previous period's good news or bad news. Other specifications for asymmetric volatility modeling include GJR-GARCH by Glosten *et al.* (1993) and TARCH model by Zakoian (1994).

The asymmetric response of volatility to good and bad news is extensively studied both in different markets as well as across a range of asset classes. As mentioned below, the studies focusing on the Indian stock markets also confirm that the conditional volatility is more sensitive to bad news and hence leverage effects cause sharp and biased investors reactions to negative innovations in the past period.

In addition to the asymmetric GARCH specifications, Engle *et al.* (1987) proposed the GARCH-in-mean (GARCH-M) model to quantify the influence of lagged period conditional volatility on risk premium. In the GARCH-M specification the conditional mean equation is specified by including the lagged period conditional volatility estimate. If the sign of the lagged volatility is positive and significant, it suggests that investors attach a risk premium depending on the most recent observation on the volatility and in such cases the ARCH-M model is proper for describing the return generating process. To circumvent the problem of coefficient restriction and the collapse of GARCH model under the presence of an approximate unit root in the conditional variance led Engle and Bollerslev (1986) to propose the Integrated-GARCH (IGARCH) model.

2.4 Comparative Analysis of Volatility Forecasting Models

A large number of studies concerning the performance of GARCH models in modeling and forecasting of volatility exist in the literature. Akgiray (1989) finds that GARCH models perform better than ARCH and exponentially weighted moving average (EWMA), and the models of historical mean using data from United States index stock volatility. Day and Lewis (1992) study the relative performance of GARCH and EGARCH models over the predictive ability of information contained within the volatility implied in option prices. They find substantial within-sample evidence favoring GARCH and EGARCH models relative to the implied volatility and considering the out-of-sample forecasts, find that GARCH model performs better than the EGARCH model. Engle and Ng (1993) in their comparative study of symmetric and asymmetric models conclude that both the symmetric and asymmetric models of conditional volatility respond differently to news arrival (also see Hentschel, 1995, for similar results). They claim that the GJR-GARCH model of Glosten, Jagannathan, and Runkle (1993) which explicitly incorporates asymmetry into volatility by allowing different effects of positive and negative forecast errors is more suitable for stock market data.

Ng, Chang, and Chou (1991) find that the ARCH process is appropriate for capturing the characteristics of the time-varying variance of stock returns. A study conducted by Corhay and Rad (1994) on European markets also provide overwhelming evidence favoring the GARCH (1, 1) model as the ideal candidate for modeling stock returns volatility. On exchange rate data similar results are documented in West and Cho (1995). However, the comparative analysis by Pagan and Schwert (1990) between parametric and non-parametric models indicate the poor performance of GARCH and EGARCH models in forecasting monthly stock returns in the United States. Yu (1996) and Franses and Van Dijk (1996) reject the TARCH model and conclude that non-linear GARCH models such as QGARCH are better suited for forecasting stock return volatility.

Research studies on volatility forecasting remain divided concerning the relative quality of stock market volatility forecasts, and both the complex models of conditional volatility such as ARCH-type models as well as traditional models provide reliable results (Brailsford & Faff, 1996). Their study is useful in the sense that no single model outperforms other models across different data sets and they found some evidence favoring the GJR-GARCH specification.

Noh and Kim (2006), Duffee (1995), Franses and Van Dijk (1996), Akgiray (1989), French *et al.* (1987) found that the expected market risk premium is positively related to the volatility of stock returns. Cheung and Ng (1992) used the EGARCH model but observed that the parameter estimate depends on the time-period. Theodossiou and Lee (1995) highlight that past studies relating the asset returns with its volatility have confined to a linear framework for modeling risk-return relationship. However, they note that results on studying the nature of volatility have been inconclusive and non-linear specifications such as GARCH-M have greater potential in describing the interrelationship between risk and return.

Other studies also conclude similar results but there is a general agreement in these empirical studies that the models that capture the conditional heteroscedasticity in time-series data do have economic value in terms of estimating and forecasting stock returns volatility (Balaban, Bayar, & Kan, 2001; Loudon, Watt, & Yadav, 2000; Gokcan, 2000). Analysis of the asymmetric nature of conditional volatility by Pagan and Schwert (1990), Loudon *et al.* (2000), Siourounis (2002), and Yu (2002) finds that EGARCH model is the best and the study is done on daily sampled data ranging over a twelve year period.

West & Cho (1995) document superiority of GARCH model in forecasting dollar exchange rate volatility. The advantage of conditional heteroscedasticity models over exponentially weighted moving average and historical mean models for forecasting monthly US index stock volatility is demonstrated in Akgiray (1989). Brailsford & Faff (1996) find GJR-GARCH (Glosten, Jagannathan & Runkle, 1993) superior to other models in predicting Australian stock index volatility. From option pricing to risk management to monetary policy decisions the role of volatility estimation and forecasting becomes very crucial.

Akgiray (1989) favors GARCH model over traditional models. Brailsford and Faff (1996) also document similar results under both symmetric and asymmetric loss functions. Similar results appear in Balaban et al. (2001) in which they include the GARCH effects in the conditional mean equation to investigate the impact of variance on asset returns. Balaban (2004) compares symmetric and asymmetric volatility models and finds exponential GARCH (EGARCH), introduced by Nelson (1991), as the best model. Their results document the poor performance of GJR-GARCH models in forecasting volatility. The volatility models are capable of capturing the risks associated with volatility in option prices, stock and bond prices, and in the foreign exchange rates and volatility based asset pricing models well predict the future market returns (Ang, Hodrick, Xing, & Zhang, 2006; Bollerslev, Tauchen, & Zhou, 2009; Christiansen, Ranaldo, & Söderlind, 2011; Da & Schaumburg, 2011; Menkhoff, Sarno, Schmeling, & Schrimpf, 2012). Loudon, Watt, and Yadav (2000) study several parametric GARCH models and claim that optimal choice of model is inconsistent and unique to sample periods. Studies comparing linear and non-linear GARCH models (Franses & Van Dijk, 2000) conclude that non-linear GARCH models are unable to outperform standard GARCH models. Pagan and Schwert (1990), study over ninety-year sample period and compare the performance of non-parametric modeling techniques with GARCH-type models and conclude that in the out-of-sample forecasting the non-parametric models fare worse than the parametric ones.

The conditional heteroscedasticity models are extensively surveyed in Andersen and Bollerslev (2004), Andersen *et al.* (2006, 2001). Bollerslev *et al.* (1992), Bollerslev *et al.*(1994), Diebold and Lopez (1995), Engle and Patton (2001), Pagan (1996), Palm (1996), and Shephard (1996), Bera and Higgins (1993). A very comprehensive work covering results of vast models is presented in Hansen and Lunde (2005). They compare 330 ARCH-type models to compare their ability in describing conditional variance. GARCH models outperform all other and GARCH models that account for the presence of leverage effects are even more desirable.

From the review of literature it emerges that several GARCH specifications exists that are capable of describing the return-volatility relationship. The economic value of such models lies in their efficiency in forecasting future volatility. The empirical studies covered in this section indicate that many researchers have tried to model the time-series data (primarily the stock market returns) and the volatility inherent in the stock returns using the GARCH and its several variants. The studies revolve around two major focus areas one is the symmetric volatility model and the other is the asymmetric response of volatility to news arrival. It is interesting to note that the research studies indicate conflicting results and no model consistently outperforms the other in all the studies, done in developed markets, reviewed above. The assessment of the outcomes of studies on the forecasting ability of GARCH-type models in the context of the Indian stock markets and other emerging markets follows in the next section.

2.5 Conditional Volatility in the Indian and Other Emerging Markets

Study on the Indian markets by Vijayalakshmi and Gaur (2013) shows that the models of asymmetric volatility fared better than the symmetric ones. Banumathy and Azhagaiah (2015) note that most studies in the Indian context found GARCH (1,1) to be best performing models for symmetric volatility and EGARCH-M as best performing model for capturing asymmetry in volatility. They also document the presence of high persistence in volatility in the Indian stock returns but does not consider out of sample data for forecast evaluation. Lama *et al.* (2015) study agricultural products such as edible oil, cotton and find the presence of ARCH effects in their historical prices and find EGARCH as the ideal specification for predicting volatility in commodity prices. Song *et al.* (1998) and Kaur (2004) document that models of asymmetric volatility such as EGARCH and TARCH are the best candidates for capturing volatility in the Indian stock market. Similar results are recorded in Karmakar (2006), Banerjee and Sarkar (2006), Kumar (2006), and Goudarzi and Ramanarayanan (2011).

Chand *et al.*(2012) and Tah (2013) provide a good review of work done on ARCH modeling on financial data in emerging markets. Abdalla and Winker (2012) study African markets and document superior performance of ARCH-M models. Floros (2008) studies middle-east emerging markets and reports presence of leverage effects and the EGARCH models better capture the volatility compared to symmetric models. Abd Elaal (2011) find asymmetric GARCH model i.e. the EGARCH model is found to be the most suitable model for modeling volatility in Egyptian stock returns. Karmakar (2005, 2007) found EGARCH-M as the best model in the context of Indian markets. Goudarzi and Ramanarayanan (2011) consider the Akaike Information Criteria and the Schwarz Information Criteria and find that the GARCH (1,1) model is the most suitable specification for modeling the volatility in the Indian stock market. They argue that the symmetric GARCH (1,1) model most suitably describes the salient features of volatility clustering and the mean reversion in its process. Using similar information criteria, they also found the TARCH model to contain predictability of future volatility.

Divecha *et al.* (1992), Barry and Lockwood (1995), and Barry *et al.* (1998) find that emerging markets have historically experienced a high level of mean returns and volatility but the extent of correlation with the developed markets is low. Aggarwal *et al.* (1999) study the ten largest emerging markets in Asia and Africa and observe that the emerging markets are characterized by high volatility and this high volatility is usually caused by local rather than global factors (also see Bekaert & Wu 2000, Kassimatis 2002, Goudarzi & Ramanarayanan 2011, Léon 2015). Bekaert and Wu (2000) emphasize the need to study emerging markets as these markets usually provide higher sample average returns, have low correlations with developed markets, contain higher volatility component in time-series returns and are more predictable than developed markets. Other studies that have focused on emerging market volatility include Bekaert and Harvey (1997) and Abdalla and Winker (2012). In the context of Indian markets, some recent studies on the predictive ability of GARCH models include Mishra (2010), Chand *et al.* (2012), and Banumathy and Azhagaiah (2015) and Tripathi and Chaudhary (2016).

2.6 Studies on Properties of Conditional Volatility

One of the commonly observed and statistically useful features of time series data is the clustering of high and low returns. Mandelbrot (1963) was the first to document, and other researchers such as Fisher Black, Eugene Fama seconded B.B. Mandelbrot's finding. They also confirm the presence of other statistical properties such as volatility clustering, leverage effects, leptokurtosis. Several studies have documented commonly observed properties in time-series data such as the non-normal distribution of returns and clustering of high and low returns.

The presence of clustering in returns suggests rejection of the weak-form Efficient Market Hypothesis (EMH) and allows return predictions using historical data. Seminal works by Mandelbrot (1963) and Fama (1965) concentrated in the identification latent properties of asset returns such as clustering of returns and lack of statistical dependence structure. They argue that in spite of the absence of serial correlation there exists a higher order dependence structure that manifests itself as clustering of returns. This phenomenon can be exhibited by showing that the *Q-stat* of the auto-correlation of returns are though highly significant the ACF and PACF of squared and absolute returns are not significant at 5% level (Cont, 2007).

Mandelbrot (1963) and Fama (1963, 1965, 1967) argued that the empirical distribution of asset returns is significantly different from that of an independent and identically distributed (iid) normal variable. For example, Fama (1965) concluded the absence of serial correlation in asset returns and argued that asset returns are statistically independent and the return generating process is representable as a pure martingale process. Mandelbrot (1963), however, noticed serial dependence in stock returns and identified the presence of volatility clustering in asset returns and this statistical property provides a useful interpretation in the analysis of time series data.

Ammermann and Patterson (2003) provide substantial evidence favoring non-linear intertemporal dependencies in the conditional volatility. They argue that such non-linear serial dependencies influence the dynamic return and volatility process across several stock markets. However, clustering of volatility is a non-parametric feature of the time series and may be present in time series data that do not exhibit ARCH effects. The presence of volatility clustering indicates that asset returns are not independent and therefore models that can capture this property are likely to perform better than others. Since the sum of ARCH and GARCH parameter in GARCH specification on stock returns are usually very close to unity the volatility-clustering phenomenon is sometimes called a GARCH effect. McNees (1972, pp: 52) suggests "the inherent uncertainty or randomness associated with different forecast periods seems to vary widely over time." He also documents that, "large and small errors tend to cluster together (in contiguous time-periods)". The presence of serial correlation (especially) during episodes of high variances confirms clustering.

Subsequently, several research studies have documented common statistical properties of stock returns that emerge from empirical studies on asset returns are asymmetric response of stock return volatility to positive and negative returns (Glosten, Jagannathan, & Runkle, 1993; Nelson, 1991), clustering in asset returns (Daal et al. 2007; Fama 1965; Zivot 2008), and persistence in volatility (Charles & Darné, 2014; Chou, 1988; P. R. Hansen & Lunde, 2005; Poterba & Summers, 1986).

Various studies (French, Schwert, & Stambaugh, 1987; Nelson, 1989) argue that stock market volatility increases subsequent to fall in prices. However, they suspect whether future stock returns are related to stock market volatility. Poterba & Summers (1986) also confirm that rise in volatility causes stock prices to fall due to increase in risk premium which drives the present value of future cash flows downwards and hence fall in its price. Bekaert and Wu (2000) explain this phenomenon as the time varying risk premium on account of change in the conditional variance. Though in GARCH (p, q) model many possible values of p and q can be considered, studies find GARCH (1, 1) formulation as very satisfactory (Hansen & Lunde, 2005).

Other simple extensions are the models of asymmetric volatility and GARCH-in-mean specification. GARCH-type models succeed in capturing salient statistical properties, that manifest in time series data, like higher order dependence, occurrences of extreme observations, and long memory. In an ARCH (q) specification, the conditional variance of the residuals from a regression model evolves as a function of q lagged squared residuals. These lagged terms are called ARCH terms. ARCH formulation involves specifying a conditional mean specification for modeling returns and uses the residuals of this regression in conditional variance equation to estimate the volatility of returns. Modeling volatility with models of conditional heteroscedasticity has a wide range of applications. Notable examples include option valuation, estimation of optimal hedge ratios for dynamic hedging, and VAR (Value-at-Risk) forecast for portfolios (Engle & Patton, 2001).

Extensive empirical studies on the performance of volatility models across different asset classes in both developed and emerging markets are available. Prominent studies on forecasting volatility include aspects like alternative specifications of underlying volatility process, statistical properties of financial time series data and comparative analysis of econometric approaches in modeling and forecasting volatility of asset returns (Bera & Higgins, 1993; Bollerslev et al., 1992, 1994; R Cont, 2001; Teräsvirta, 2009).

Knowledge of volatility in asset prices is crucial to market participants such as risk managers, stock traders, analysts, regulators, etc. Since volatility is not directly observable, practitioners consider a proxy for volatility to estimate investment exposures and variability in asset returns. This estimate of volatility proxy must be reliable to use so that it allows agents to adopt desirable trading strategies and take investment decisions based on levels of market volatility. However, the latent nature of volatility confounds researcher in estimating its true value and hence numerous estimation approaches of volatility estimates are considered as the approximation of underlying data generating process. These include plain vanilla sample standard deviation (historical volatility), rolling standard deviation, volatility implied in prices of contingent liabilities (implied volatility), and, historical means of squared or absolute returns. These proxies serve adequate, but their performance is inconsistent in empirical studies, which casts doubts over their reliability especially in forecasting future volatility (Brooks & Burke, 1998). Poon and

Granger (2003) discuss the performance of several volatility proxies and argue for estimating volatility estimates based on the models of conditional heteroscedasticity.

The dynamic ARCH formulation appropriately deals with time-dependent volatilities. In his seminal paper, Bollerslev (1986), recognizes the weakness of these unconditional volatility proxies and suggests a simple generalization of ARCH model by introducing *p* lags of past volatility estimates to compute the variance of returns conditional on past fluctuations. This model is popularly known as generalized auto-regressive conditional heteroscedasticity, GARCH (*p*, *q*) where *p* is the order of lagged GARCH terms and *q* is the number of ARCH terms. GARCH allows for a parsimonious parameterization of conditional variance and is, therefore, more flexible. The conditional variance estimate of a GARCH model is a weighted average of unconditional long-run variance, the news surprise in the preceding periods and lagged conditional variance. In many empirical studies, the time varying estimate of volatility using GARCH formulation emerges as a preferred choice (Corhay & Rad, 1994; De Gooijer & Hyndman, 2006; So & Yu, 2006).

Statistical aspects such as specification of the conditional mean and the conditional variance equation, probability density assumptions of the innovation terms, nature of time-varying persistence in GARCH parameters, and debates on the symmetric behavior of volatility process have encouraged researchers to propose alternative approaches that can better explain the underlying data generating process. Econometricians have attempted to model several statistical properties of asset returns, and many such features are considered in developing the ARCH model and its various extensions. Forecasting of returns on financial assets requires precise econometric specification, of the true underlying data generating process, for modeling the conditional moments of the distribution of asset prices. Alternative model specifications and inquiry into the statistical properties of time series data have drawn considerable interests from econometricians over the past three decades (Starica, 2003).

Several statistical properties of time series data are considered for explaining the behavior of asset prices and provide insights into the latent structure of historical asset returns. One such salient feature commonly encountered in the time series data is referred to as the *persistence* of volatility that measures the influence of a sudden significant change in asset returns on future volatility. A significant value of persistence suggests that the shocks to the volatility process die out gradually and a large change in volatility today is likely to impact the future volatility for several periods. If the value of persistence exceeds one, the volatility process is said to be non-stationary, and GARCH formulation breaks down in that case. Over the past few years, we have witnessed dramatic interest in modeling asset returns and volatility using GARCH approach.

Persistence of Volatility is the extent to which a large shock in the return process can carry its impact on the future volatility of returns. If the persistence is high, a shock in the volatility process temporarily increases the variance of expected returns before it reverts towards its long-term mean. The econometric models of conditional volatility assume volatility to be highly persistent and hence the presence of persistence property in time series data is desirable. Poterba and Summers (1986) mention that determining the degree of persistence in the volatility is crucial for financial analysis. The tendency of volatility to persist over time is widely studied by Bollerslev et al., (1992), Pagan and Schwert (1990), Schwert (1989), Chou (1988), and Engle and Bollerslev (1986). Earlier works, (e.g. Poterba and Summers, 1986), rejected the hypothesis of non-stationarity in the volatility process and suggested that shock to volatility does not persist for long. Officer (1973), on the other hand, noticed high persistence and high volatility during periods of Great Depression.

Lamoureux and Lastrapes (1990) indicate an increase in the persistence of GARCH coefficients under the presence of structural breaks. Hamilton (1989) considers permitting sudden and discrete changes in the GARCH model to account for structural breaks in volatility. Several authors (Klaassen, 2002; Cai, 1994; Hamilton and Susmel, 1994; Brunner, 1991) use Markov switching model to permit regime switches within the volatility forecasting framework for obtaining reliable forecasts. Chou (1988) studies the persistence of GARCH parameter estimates and its impact on volatility forecasting using stock returns.

Review of literature on volatility forecasting suggests that conditional volatility estimates of a GARCH process exhibit high persistence. The tendency of volatility to persist over time is widely studied, and Bollerslev *et al.* (1992) provide a review of work concerning with the persistence of volatility. Other notable works include Pagan and Schwert (1990), Schwert (1989), Chou (1988), and Engle and Bollerslev (1986). Studies also indicate an upward bias in volatility persistence when regime changes or structural breaks are ignored while modeling the conditional volatility. The Iterated Cumulative Sums of Squares (ICSS) algorithm of Inclán and Tiao (1994) is used extensively for detection of structural breaks in the volatility process. Emerging markets are typically characterized by high levels of volatility, and empirical results confirm this fact (Aggarwal et al., 1999; Bekaert and Harvey, 1997). Studies conducted on crude prices by Kang et al. (2009), Ewing and Malik (2010) and Ozdemir et al., (2013) also provides evidence on the high association between persistence in the volatility of returns in crude prices and structural breaks in the variance. As pointed out by Poon and Granger (2005) the auto-correlation of variances remains significantly above zero beyond 1000 lags, suggesting strong “long memory” effect.

Malik (2003) studies sudden changes in variance and persistence in currency movements and documents positive relation between persistence of volatility and structural breaks in the underlying series. Various studies on stock returns in emerging markets developed markets, and the domestic market provides evidence correlating the presence of structural breaks and overestimation of persistence (Kumar and Maheswaran, 2012; Wang and Moore, 2009; Hammoudeh and Li, 2008; Malik et al., 2005). Several studies indicate that the persistence of volatility reduces, if the models are augmented with the structural breaks or regime switches. However, none of the studies offer any theoretical explanation behind this phenomenon.

Several studies also suggest a significant influence of domestic macroeconomic events causing a permanent change in the variance structure (Reena Aggarwal et al., 1999). Choudhry (1996) demonstrates a change in ARCH parameter before and after the crash of 1987 and points out that changes are not uniform across markets. In the Indian context study by (Karmakar, 2005) argues that GARCH (1, 1) model is a better predictor of volatility compared to other models. Other studies in the Indian context (Banumathy & Azhagaiah, 2015; Goudarzi & Ramanarayanan, 2011; Vijayalakshmi & Gaur, 2013) provide contradictory conclusions regarding the most suitable model for estimating conditional volatility. As the period of study and the nature of capital markets differ across these empirical findings, it is unlikely that similar generalizations will qualify for all markets. This uncertainty is further heightened in the wake of dramatic globalization in the last decade-and-half, and the 2008 global financial crisis affirms volatility spill-over from developed markets to emerging markets. However, the impact of the sub-prime crisis on the volatility of emerging markets is mixed, and both symmetric and asymmetric models provide reliable estimates for conditional volatility (Rastogi, 2014). Thus, it is doubtful that presence of structural breaks in return series will continue to be primarily driven by local factors. These studies on volatility persistence have mainly focused on structural breaks and regime switches to estimate long memory property of stock returns and augment GARCH models to accommodate structural breaks for achieving stable estimates.

Aggarwal *et al.* (1999) explicitly mention that time series of stock returns are leptokurtic (fat-tailed), distribution of returns is skewed, and the variance changes with time (i.e. heteroscedasticity). The squared values of the returns exhibit a high level of correlation whereas the values of the returns do not have much correlation. Financial time series data show significant heteroscedasticity and the ARCH models correct the heteroscedasticity. The plots of the daily returns exhibit a high kurtosis having peaks centered on the mean and instances of fat tails. Figlewski (1997) noted that volatility inherent in asset prices has a tendency to revert to its long-term mean. He argues that the volatility clustering may also be considered as an explanation behind sentimental trading as a shock in volatility structure persists for given period before reverting to long-run average and demonstrates mean reversion of conditional volatility (see also, Hull, 2006).

Randolph (1991) also considers a mean reversion model for forecasting the stock market volatility. Knowledge about probabilistic properties of stock returns is critical to forming expectations about returns generation process. Several papers, including Pandey *et al.* (1997), have documented the presence of nonlinear dependencies in stock returns, that challenges the weak-form efficient market hypothesis, as mentioned above. Such studies confirm the fact that using ARCH type models have economic value as evidence of non-linear dependencies in asset returns is overwhelming. This presence of the nonlinear dependence structure in the data permits some degree of predictability using non-linear models such as ARCH.

Malkiel (2003) and Shiller (2003) argue that stock market prices are predictable by suggesting that agents suffer from inherent biases in their decision making and that these behavioral choices determine stock prices. Poshakwale (2002) documents that the predictability aspect of stock returns is extensively documented in the developed markets but is relatively less known about the nature of stock market efficiency in the developing markets. Fama argues that in a well functioning efficient stock market the asset prices are adjusted based on well-informed decisions of all agents. Since the arrival of news is random, the markets rapidly adapt to new information, and it is not possible to consistently make abnormal returns. The presence of linear or non-linear dependence structure in the data is an indicator of predictability of future asset prices. The rate of growth of emerging stock markets in the past two decades had been astonishing but academic research on stock market return predictability had lacked similar enthusiasm as documented by Poshakwale (2002). In another study, Poshakwale (1996), performs runs test and tests for serial correlation to reject the weak-form efficient market hypothesis. Cutler *et al.*(1989) argue that statistical properties of volatility play a vital role in quantifying observed volatility which otherwise may not be explainable by variations in fundamental economic variables.

Above results indicate that it is important that any typical time-series data conforms to these observed statistical properties. For proper application of conditional volatility models, it is essential that the intertemporal behavior of the time-series data under consideration is well characterized by these statistical properties.

So far the discussion involved the understanding of the time-series nature of stochastic processes and the ability of GARCH-type models in explaining the mechanism of variations in asset prices that follow such processes. In the next section, we discuss the financial sector reforms that have been implemented in the last two-and-half decades and its potential influence on the variability of the shares listed on the Indian stock market.

2.7 Market Reforms and Volatility in Indian Stock Market

It is believed that volatility in the stock market is caused by both local as well as global events. In the introductory chapter, we discussed several instances of recent global shocks that have, in the past, aggravated the volatility in the Indian markets. However, whether volatility in Indian markets increased or reduced following liberalization is a topic of debate and not yet resolved. Since the period undertaken in this study coincides with the era of financial liberalization and the opening of the Indian economy to foreign investors, we conducted a review of literature studies that have analyzed the impact of these reforms on the volatility in the Indian markets. The motivation for undertaking such a study originates from the fact that the economic and financial liberalization reforms of the 1990s are considered as catalyzing factors that have not only enabled the growth of the Indian economy but have also fostered faith of the investors in the Indian stock markets.

Bekaert and Harvey (1997) and DeSantis and Imrohoroğlu (1997) provide empirical evidence highlighting fall in stock market volatility following capital market reforms, whereas Huang and Yang (2000) detect an increase in unconditional volatility following liberalization. In the context of Indian markets, Debasish (2008) documents no significant change in the volatility of the underlying spot market segment following the introduction of Nifty index futures. Krishnamurti *et al.* (2003) in their study on stock market governance highlighted that better governance partially enhances stock market quality regarding efficiency and pricing of securities. They provide insights into the nitty-gritty of Indian stock market and its evolution, and technological improvements in trading platforms and its impact on market turnover. A study conducted by

Uppal and Mangla (2006) provides comparisons in stock market volatility in the Bombay Stock Exchange and the Karachi Stock Exchange. They also stress the need for strengthening the role of SEBI for mitigating pricing uncertainties in Bombay Stock Exchange and find a significant decrease in volatility in the Indian stock market following regulatory intervention after Harshad Mehta's securities scam and the scam of early 2000 involving Ketan Parekh, an Indian stock broker.

Many authors argue that volatility has gone down while rest are of the opinion that it has increased but not reduced markedly. The study conducted by Miles (2002) also documents an increase in volatility in Indian stock market during the periods following the liberalization after considering a dummy variable for policy reforms. A study conducted by Bekaert and Harvey (1997) fail to find conclusive evidence supporting the hypothesis of an increase in market integration following liberalization in the context of emerging markets. Shastri *et al.* (1996) show that market volatility declines as foreign participation increases and the value of the stock market index which tends to increase in the initial phase of economic liberalization before declining later on.

It is also argued whether empirical evidences are consistent with the fact that whether the volatility of financial markets reduces or increases following financial liberalization policies adopted by the markets and increased openness to foreign investment (e.g. see Reinhart and Tokatlidis, 2003) as a proponent of financial market liberalization. In November 1992, India took landmark reform to encourage participation of foreign investors (Bekaert & Harvey, 2000 and Kim & Singal, 2000). The impact of the financial sector is found to be positive for the growth and development of the financial markets which in turn has led to domestic economic growth. For example, using the auto-regressive distributed lag (ARDL) approach Sehrawat and Giri

(2015) and Palamalai and Prakasam (2014) document that domestic financial development stimulates India's economic growth. In the context of emerging markets, Aggarwal *et al.* (1999) particularly stress the role of local factors behind the stock market volatility. A study conducted by Hamao and Mei (2001) find no evidence of an increase in volatility as a function of domestic and foreign trading in Japan. Kaminsky and Schmukler (2001) observe a transitory increase in volatility immediately following a period of market liberalization in 28 countries. A host of the studies discussed above provides evidence favoring a positive relation between stock market volatility and capital market reforms. Paramati and Gupta (2011) highlight stock market efficiency and increased global participation as key objectives of the Indian stock market.

Kaminsky *et al.* (2000) found evidence of increased behavioral biases in the actions of the investors in these developing economies undergoing financial liberalization, resulting in increased stock market volatility. They also document lower volatility in closed economies compared to open economies during the time of financial crisis. Froot *et al.* (2001) argue that there is an increased faith of institutional investors in open economies compared to closed ones and this lowers the stock market volatility in open economies. The lifting of official restrictions coupled with low-interest rates and stock returns in developed economies such as Japan and European markets caused foreign investors' interest in exploiting profit opportunities in these markets.

Notable studies such as Varma (2002) and Vashishtha and Kumar (2010) provide empirical evidence favoring a decline in volatility after the launch of futures and options trading in the Indian stock market. The turnover in derivatives trading has increased substantially over the years. The study conducted by them also analyzes the growth of derivatives in the Indian market and their impact on the volatility of the Indian market. Gupta (2002) examines the impact of commencement of futures trading on the volatility of Indian stock market and documents a decline in volatility in the Indian stock market upon introduction of futures and options trading. Varma (2002) discusses the mispricing of futures and options in Indian stock market and therefore the initial years of derivatives launch are considered separately. Other subsequent studies confirm a fall in volatility and therefore starting the year 2003 is discussed under separate sub-sample (e.g. Vashishtha and Kumar, 2010). Many authors have also attempted to explain market volatility considering market microstructure factors such as bid-ask spread, call auctions versus continuous pricing, etc. Areas within market microstructure such as the bid-ask spread and non-synchronous trading etc. are useful measures of stock's liquidity, volatility and investor sentiments.

As pointed out in Demsetz (1968) bid-ask spread - an implicit transaction cost - is indirectly proportional to the stock's liquidity and hence high liquidity is a necessary condition for minimizing transaction costs. Bid-ask spread also widen during volatile times as well as on account of information asymmetry between informed and naive traders. Studies have attempted to compare and contrast two pricing mechanisms namely call auctions and continuous trading. On this market microstructure issue, mixed evidence from the empirical work emerge. Central to the pricing mechanism is the subject of asset price volatility, and changes in asset values after any particular pricing mechanism is introduced. Indian stock markets follow a continuous price discovery mechanism where prices dynamically change by orders for trading arriving at different prices and the best orders are executed.

NSE suspended opening and closing call auctions in the year 1999, and the study conducted by Camilleri and Green (2004) analyzed its impact on the asset price volatility but could not find evidence favoring call auction pricing over continuous price discovery adopted at the NSE.

Shastri *et al.* (1995) investigated the impact on the volatility of opening call auction and observed increased volatility at the beginning of trading. One argument that holds is that because of accumulation of overnight news this high volatility is not unusual and not necessarily due to call auctions. Call auctions are pricing mechanism better suited for emerging markets because of their low liquidity Madhavan (1992). However, it is argued that prices tend to fluctuate more at the time of market opening and therefore from October 2010 only the market opening prices are arrived at through the call auction followed by the continuous pricing mechanism for the rest of the day. Market microstructure effects such as non-synchronous trading and bid-ask effects only provides an isolated view of their impact on stock market volatility and more so since these microstructure effects are stock specific assessing their impact on broader stock market volatility is complex. Therefore, these market microstructure factors are not considered for assessing the volatility in the Indian stock market.

2.8 Macroeconomic Variables and Stock Market Volatility

Numerous studies are available that have documented the impact of macroeconomic variables on the stock market returns. Most frequently occurring variables in literature are proxies for consumer price index, foreign exchange rates, money supply, interest rates, bank credit, dividend yields, price-to-earnings ratios, book-to-market value ratios, industrial production, crude oil price, exports, business confidence index and gross domestic product. An earlier discussion on the impact of exogenous variables on stock returns is available in Ross (1976) Arbitrage Pricing Theory (APT) and by Fama and French (1989). These studies on individual stocks are also further extended in the context of broader stock market index (Chaudhuri & Smiles, 2004; Cheung & Ng, 1998; Gan, Lee, Yong, & Zhang, 2006; Humpe & Macmillan, 2009; Mukherjee & Naka, 1995).

Studies documenting the influence of macroeconomic variables on stock returns in the developed markets are aplenty, and recently this has become a research issue of interest in the less developed and emerging economies (Fifield *et al.* 2000; Lovatt & Parikh 2000; Hondroyiannis & Papapetrou 2001; Lu *et al.* 2001). Conflicting evidence emerge, and there are no clearly defined macroeconomic variables as the desirable candidates for establishing their relationship with stock returns, refer to these review papers for a summary of studies done on macro variables and their impact on stock returns (Balvers *et al.* 1990; Flannery & Protopapadakis 2015).

Mele (2007) argues that variables that have the ability to capture the time-varying risk premium are ideal candidates for understanding and forecasting asset return volatility. The study also notes that a broad range of variables such as valuation ratios, profitability ratios, industry, and economy performance indicators and macroeconomic variables such as interest rates, the rate of inflation and currency exchange rates are promising candidates for future research on stock market volatility forecasting. Other studies such as Goyal and Welch (2003), Welch and Goyal (2008), Ang and Bekaert (2007), Lustig *et al.* (2011), Ludvigson and Ng (2009), and Paye (2012) have also contributed to the recent literature on using financial and macroeconomic information in predicting volatility. In a related study, Christiansen *et al.* (2012) provide evidence on the predictability of financial market volatility considering a broad range of macroeconomic variables. They, however, recognize the challenges in reaching consensus amongst researchers on the choice of macroeconomic variables for forecasting volatility and due to this model uncertainty, the results may vary across different market regimes and asset classes.

Gan *et al.* (2006) employed the Johansen co-integration test in the vector error correction model (VECM) and found evidence of co-integration between New Zealand stock market and seven macroeconomic variables. Other empirical studies concerning the long-run association between macroeconomic variables and stock market include Patra and Poshakwale (2006) on Athens stock exchange, Maysami and Koh (2000) carry out similar analysis in the Singaporean market with five macroeconomic variables. Gan *et al.* (2006) mention that there does not appear to be a unified theory regarding the selection of these macroeconomic variables and in most of the studies, the approach is rather arbitrary. Other studies on emerging markets include Patra and Poshakwale (2006), Gunasekarage *et al.* (2004), and Prabu *et al.* (2016).

A number of studies on influence of macroeconomic variables on stock returns have focused on the developed markets. Studies by Cheung and Ng (1998) for example provide useful references to studies conducted in Japanese market. Mukherjee and Naka (1995) find presence of long-term equilibrium relationships among macroeconomic variables and stock market. It is often argued that macroeconomic variables such as inflation rate, rate of interest, and foreign exchange rates influence the movement in stock markets. Chen *et al.* (1986) provide empirical evidences favoring the above argument highlighting presence of a long-term equilibrium relationship between stock prices and macroeconomic variables such as interest rates, inflation and industrial production.

Studies on crude include Park and Ratti (2008) and Sadorsky (2014)**.** They document the significant impact of crude prices on stock returns, whereas, Nandha and Faff (2008) document negative consequences. Study by Maysami and Koh (2000) document positive relation between money supply innovation and stock market returns in Singapore. Mukherjee and Naka (1995) also confirm positive relationship between money supply and stock returns. Humpe and Macmillan (2009) use the narrow money supply (M1) as a proxy for the money supply. Chen *et al.* (1986) argue that the impact of money supply on stock returns is uncertain because of its impact on the inflationary expectations and real economic activity. Kwon and Shin (1999) found positive relationship between money supply and stock returns in Korean market. Cheung and Ng (1998), Ferson and Harvey (1993), Chen *et al.* (1986) find significance of oil prices on stock market indices in international markets.

Nasseh and Strauss (2000) document significant long-run relationship between stock prices and economic activity in European markets. They use short-term interest rates. Humpe and Macmillan (2009) use only long-term i.e. yield on 10-year government security. Mukherjee and Naka (1995), Chen *et al.* (1986) all use interest rates as input variables for examining long-run relationships between macroeconomic variables and the stock market benchmark index. The impact of short-term interest rates are discussed in Nasseh and Strauss (2000), Mukherjee and Naka (1995), and Chen *et al.* (1986). In few studies in place of Treasury bill rates the call money rates or interbank rates are considered as proxy for risk-free interest rates. Using T-Bills as proxy for interest rates is consistent with several asset pricing theories such as the Capital Asset Pricing Model (CAPM) and Black-Scholes option pricing model.

Brooks and Tsolacos (1999) define interest rate spreads as the yield curve measured as the difference between long-term Treasury bonds and 91-days Treasury Bill rate and similarly construct the term-structure variable. Chen *et al.* (1986) argue that interest rate spreads are also likely to influence stock returns and Fama and French (1989) demonstrate similar result. Chaudhuri and Smiles (2004) claim that due to lowering of interest rates investors exit their investments in debt securities and enter the stock market. This theory is also consistent with the theory of portfolio diversification. Since a very high degree of correlation exists between the long-term and short-term interest rates, therefore using both variables concurrently in VAR estimation poses the risk of multi-collinearity.

However a closer analysis of relationship between short-term and long-term interest rates do not reveal any forecast-able pattern and the term structure of interest rates keep switching between upward sloping and downward sloping. Fama and French (1992) considered spread between long and short rates, the term structure or the yield curve. Estrella and Hardouvelis (1991) argued that the yield curve has an extra predictive power beyond that contained in the short-term interest rates, but we exclude term structure variable as it alternates between positive and negative rendering log transformation impossible.

Some studies relating consumer prices and stock market performance include Nasseh and Strauss (2000). Investment in stocks is considered as a hedge against inflation because the claims of the shareholders are tied to real assets unlike interest bearing securities. In the Indian context this finding was documented in early nineties (see Barua *et al.* 1994, Bhole 1995).

Since most of the time series variables are often found to be non-stationary in their level form i.e. integrated of order one I (1), the usual ordinary least squares approach results in spurious regression (Stock & Watson, 2011). To circumvent the problem of spurious regression usually the first-difference of the non-stationary are considered for analysis. Almost all time series variables are believed to be integrated of order one and taking their first-difference converts them into stationary variables, but, this transformation comes at cost and information on any long-run equilibrium relationship among variables is lost (Brooks, 2008). Engle and Granger (1987) in their seminal paper found that several economic variables shared a long-run equilibrium relationship, if their linear combinations in the level form produced stationary residuals. Such variables are said to be cointegrated.

Two variables are *cointegrated* if they are both I (1) but their linear combination is stationary i.e. I (0) process. This relationship is useful in establishing long-run equilibrium relationships between co-integrating variables since such variables have potential to influence each other over time. Since macroeconomic variables are found to be cointegrated and the stock market of a country is also affected by economic fundamentals, several researchers have attempted to investigate this long-run association between the macroeconomic variables and stock market prices. However, an overwhelming majority of such studies have focused on the relevance of information about the long-run relationship between the macroeconomic variables and the stock market for predicting stock returns, in this thesis the emphasis is on whether such a long-run relationship can be used to predict stock market volatility. An appealing feature of the long-run analysis is that it can be studied both in bivariate and multivariate setting.

Mukherjee and Naka (1995) and Maysami and Koh (2000) perform long-run equilibrium analysis on the exchange rate and stock market. Other studies in international markets include Wu and Su (1998), Gerritis and Yuce (1999), and Taylor and Tonks (1989). Arshanapalli and Doukas (1993) argue that international diversification turns into an effective portfolio hedging strategy if foreign markets lack interdependence with the domestic market. However, studies such as Jaffe and Westerfield (1985) and Eun and Shim (1989) provide evidence of significant linkages among global stock markets (also see Maysami *et al.*, 2004). Abdullah and Hayworth (1993) show that macroeconomic variables Granger cause stock market return and find that inflation positively influences the stock returns while the long-term interest rates have a negative impacts. Studies by Duca (2007) and Sukruoglu and Nalin (2014) involving co-integration analysis using Granger causality approach on international stock markets find evidence supporting the influence of the stock market on economic activity but not vice-versa. Hasan and Javed (2009) using Granger causality and Johansen's co-integration framework find a significant long-run relationship between monetary variables and prices of speculative assets in Pakistan.

Research studies show that money supply may both positively impact the stock returns by its positive effects on real economic activity or negatively as it pushes inflation upwards. Portfolio theory suggests the flight of investors from interest-bearing securities to stocks as money supply increases which lower the interest rates (Chaudhuri and Smiles, 2004). Since variables such as dividends yield and earnings yield are specific to individual stocks and not essentially macroeconomic in nature, we do not include these variables. Studies concerning the impact of these variables on stock market returns are available in Harvey *et al.* (1994), Fama and French (1989) and Schwert (1990). Gan *et al.*(2006) also document that increase in oil prices should affect stock returns negatively for those countries which are a net importer of oil. Emerging stock markets are typically characterized by high volatility, and this fact is confirmed by several researchers (Claessens, Dasgupta, & Glen, 1995; Harvey, 2015). Darrat and Mukherjee (1986) studied the impact of macroeconomic variables on the Indian market. Other studies on the impact of macroeconomic variables in foreign markets include Oyama (1997), Bailey and Chung (1996), Patra and Poshakwale (2006), Leigh (1997), Gunasekarage *et al.* (2004), Kwon and Shin (1999), Fung and Lie (1990), and Gjerde and Sættem (1999) in the Norwegian market provide sufficient evidences on the influence of macroeconomic variables on the stock market returns. A majority of the research studies have focused on modeling the expected stock market return using set of macroeconomic variables in foreign markets and such evidences on Indian stock markets are limited.

Since GARCH models requires a large number of observations fitting quarterly data was not feasible unless alternative approaches such as ARDL models were considered (see Joshi and Giri 2015). Research studies on time-varying relation between macroeconomic variables and Indian stock market returns have shown that the Indian stock market returns are well explained by macroeconomic variables. Further, the evidence on the usefulness of such macroeconomic variables in predicting volatility of Indian stock returns is yet to be explored. The limited studies on explanatory power of macroeconomic variables in explaining stock returns in the Indian context provide evidence of presence of co-integration between the macroeconomic variables and the Indian benchmark stock index. Few studies in the Indian context that document presence of long-run association between macroeconomic variables and stock market returns include Bhunia (2013), Naik, (2013), Patel (2012), Pal and Mittal (2011), Sharma and Mahendru (2010), Srivastava (2010), and Ahmad (2008). The choice of variables in these studies varies as discussed in the literature review above and most of the studies analyze the interlink-ages between economic fundamentals and stock market follow studies in developed and other emerging market for selecting candidate variables. In a recent study, Tripathi and Chaudhary (2016) perform a comparative analysis of volatility between the Chinese and the Indian stock market and note that the evidences on the behavior of conditional volatility from developing markets are rather scarce.

The econometric approaches considered in these studies for identifying long-run relationship include vector auto-regression, ARDL-bounds test, Granger-causality tests, Johansen's co-integration test and vector error correction model. Since, this thesis attempts to utilize the information on long-run association between the economic and stock market variables for predicting the stock market volatility, the vector error correction model (VECM) estimation is considered for identifying the short-run adjustments to long-run equilibrium. Few studies in the global context have attempted to explain the stock return volatility using the information content of the error correction term; these models are popularly known as GARCH-X model where the X term is the augmented error correction term in the conditional variance specification.

Other econometric techniques such as forecast error variance decomposition and impulse response functions are also employed by researchers in examining the presence of structural linkage between macroeconomic variables and the stock market volatility. Léon (2008) documents that interest rates positively impact the conditional volatility of the market however the relationship is found to be insignificant. Rahman and Ashraf (2008) use money supply (M2) and crude oil prices to analyze the impact on volatility and found an inverse relation between money supply and stock market volatility in US market. In an earlier study, Abdullah (1998) showed that macroeconomic variables have an explanatory power in predicting stock market volatility. Majority of these studies find that the macroeconomic variables do contain explanatory power for predicting the stock market returns and hence, to extend this empirical regularity, the predictive ability of macroeconomic variables for explaining stock market volatility is an empirical question undertaken in this study.

2.9 Summary of Literature Review

Table 2.1 provides a brief summary of the papers reviewed in this chapter. The purpose of this table is to summarize the focus areas of research studies covered in each-subsection and to identify research gaps from these studies.

Section	**Focus areas and gaps**	**Influential studies**	**Number of studies referred**
2.2 - ARCH model	ARCH models outperform ARMA models as ARCH models provide estimation approach for time-varying conditional variance whereas ARMA models assume homoscedasticity. Several studies indicate relationship between asset returns and its volatility are related but asymmetrically. Studies also document presence of ARCH effect in the time-series data.	Sharpe (1964) Merton (1973, 1980) Engle (1982) Poon and Granger (2003)	7

2.3 - Variants of the ARCH model	Bollerslev (1986) improves the ARCH model by introducing the GARCH model. Research studies indicate that GARCH (1, 1) outperforms other models of stochastic volatility. Research studies indicate that GARCH models have the ability to capture the statistical properties of time series data. Models of asymmetric volatility such as EGARCH and TARCH are discussed.	Bollerslev (1986) Nelson (1991) Glosten et al. (1993) Zakoian (1994) Select review studies include (Bollerslev et al., 1992, 1994; Poon and Granger, 2003; Hansen and Lunde, 2005; Brownlees *et al.*, 2011)	6
2.4 - Comparative analysis of volatility forecasting models	Several studies attempt to empirically analyze the performance of ARCH-type models compared to conventional models and implied volatility in option prices. Predictive ability of both symmetric and asymmetric GARCH models is studied. Studies encompass different developed markets as well as other asset classes such as foreign exchange rate and oil prices. The studies are largely confined to developed stock markets. The results of several empirical studies do not indicate the universal superiority of any model. It appears from the literature that the non-linear volatility models compete with each other and outperform one another in different time periods and on different asset classes.	French, Schwert and Stambaugh (1987) Akgiray (1989) Pagan and Schwert (1990) Frances and Van Dijk (2000) Balaban (2004) Hansen and Lunde (2005)	30
2.5 Conditional volatility in Indian and other emerging markets	Performance of several conditional volatility models in estimating the volatility hidden in stock price movement indicate that both symmetric and asymmetric volatility models are able to capture important statistical properties of time-series data. Emerging stock markets are more volatile compared to developed markets. Studies also conclude that emerging markets share low correlation with the developed markets and are therefore desirable investment avenues for reducing the diversifiable risk. Empirical studies indicate lack of depth and coverage of studies on return-volatility relationship in the context of emerging markets and in particular the Indian stock market. Empirical studies on volatility forecasting in Indian stock markets ignore comparing the out-of-sample forecasting ability of such models and the results are confined to only within-sample analysis. One parallel that can be drawn from the studies done on developed as well as the emerging markets is that conflicting evidences repeatedly emerge with regard to the choice of the best model. The studies also ignore the fact that considering a long-term data set may contain intermittent structural breaks in the volatility process	Bekaert and Harvey (1997) Aggarwal et al. (1999) Bekaert and Wu (2000) Goudarzi and Ramanarayanan (2011) Chand et al. (2012) Tah (2013)	27

	resulting in misspecification of models or unreliable predictions. Studies also do not consider breaking up the data set into smaller sub-samples to assess the performance of the volatility models across different sample periods. Several studies indicate that high volatility in the emerging markets is attributable more to the local factors.		
2.6 Studies on the properties of conditional volatility	Literature review focuses on studies done on statistical properties observed in time-series data such as persistence and mean reversion of volatility, clustering of volatility, and leverage effects. Persistence in time-series data is high in developed markets. Studies focus on alternative formulations such as Markov switching models to permit for regime changes in the sample period. Many authors argue that presence of structural breaks in the data series artificially results in overestimation of the persistence resulting in wrong inferences about the predictability of the models. Knowledge of statistical properties aid in using financial time-series for making reliable predictions. Studies on asymmetric property of the volatility provide conclusive evidences of presence of asymmetry in volatility in the many international markets as well as Indian stock market. However, no conclusive evidence is reached whether asymmetric models consistently outperform the symmetric models across different sample periods and asset classes. Studies on developed markets comprehensively study the statistical properties of conditional volatility observed in stock returns, however such studies are lacking in emerging markets. Moreover, research studies in Indian context have largely ignored statistical modeling of these properties prior to considering the utility of such time-series data in forecasting returns. From the literature review one potential area of research that emerges is modeling the time-varying nature of the persistence of the volatility. It is well recognized that persistence of typical time-series data is high and in this study we verify this common property by demonstrating how this persistence property evolves overtime as more information is utilized for the estimation models of conditional heteroscedasticity. A significant research gap that we find in the	Mandelbrot (1963) Fama (1965) Black (1976) Poterba & Summers (1986) Lamoureux and Lastrapes (1990) Figlewski (1997) Engle & Patton (2001) Starica (2003) Teräsvirta (2009) Studies in emerging markets and Indian context include: Poshakwale (2002) De Gooijer and Hyndman (2006) Karmakar (2007) Ewing and Malik (2010) Goudarzi and Ramanarayanan (2011)	67

	study of literature on GARCH models is that the statistical properties of volatility are usually modelled considering a very large data set. Many research studies argue that structural breaks that manifest themselves mainly because of local events tend to overstate the persistence of the time-series data and this may result in improper conclusions with regards to the long memory property inherent in the data. To circumvent this misspecification, in addition to the complete data series, smaller sized samples are also considered to assess the behavior of common statistical properties in the sub-samples. Moreover, these samples are not completely arbitrarily sampled and both the local and global factors are considered before deciding the cut-off dates for sub-samples.		
2.7 Impact of market reforms on Indian stock market volatility	Studies attempt to correlate the impact of major financial market reforms that were directed toward increasing foreign market participation or enhancing the regulatory robustness of the Indian capital markets. To empirically verify impact of the financial sector reforms on the Indian markets, studies largely focus on measuring the impact of volatility of markets subsequent to announcements of reforms. Empirical studies have not considered applying conditional volatility models such as GARCH or EGARCH to analyse the volatility in the pre-and-the-post-market-reform periods. Conflicting results emerge from the review of several studies on stock market reforms and their impact on the volatility of the Indian stock market. Research studies are divided and no conclusive evidence supports or rejects the hypothesis that stock market reforms have any impact on the volatility of the Indian stock market.	Kaminsky and Schmukler (2001) Miles (2002) Varma (2002)	25
2.8 Macroeconomic variables and stock market volatility	Several macroeconomic variables are found to have an explanatory power in predicting the stock market returns. Several macroeconomic variables also share a long-run equilibrium relationship with the stock market movement. Studies on macroeconomic variables have used econometric techniques such as vector auto-regression, ARDL approach, Johansen's co-integration and vector error correction mechanism. To the best of the author's knowledge no Indian study has considered modeling the market volatility using the information on long-run association between the macroeconomic variables and the stock market. Individual macroeconomic variables or their linear combinations with other macroeconomic	Ross(1976) Cheung and Ng (1992) Mukherjee and Naka (1995) Welch and Goyal (2008) Humpe and Macmillan (2009)	71

	variables may be useful for predicting the stock market volatility and therefore the study on volatility prediction using information contained in variability in macroeconomic variables has its relevance.		

Table 2.1 Summary of literature review

2.10 Gaps in the Literature

This chapter on the literature review covers relevant aspects related to volatility modeling and forecasting such as types of ARCH models, estimation and forecasting related issues, statistical properties of time-series data, long-run relationship between macroeconomic variables and stock market volatility. These studies were earlier confined to developed markets. In the last two decades, research in the emerging markets are increasingly focusing to model the time-varying volatility of stock markets and have attempted to draw parallels with the results obtained in the developed markets. Common empirical properties or the salient features of time-series data are well studied; however, evidence on time-varying nature of these properties in the context of an emerging market such as India are mixed and not adequate.

Earlier studies have carried out analysis on the market volatility considering a large sample size covering several years. This approach encounters a problem by overlooking possible structural breaks or regime changes in the return generating process and therefore the validity of the results of studies covering a long period is questionable. It is a well-known fact that the volatility in the stock market is sensitive to news arrival, macroeconomic fundamentals, and capital market reforms. These variables have potential to influence the stock market volatility and therefore bringing together these aspects is likely to provide a clearer picture of the nature of conditional volatility in the context of the Indian stock market.

Levels of volatility is reportedly high in emerging markets (Aggarwal & Goodell, 2008; Çağlı, Mandacı, & Kahyaoğlu, 2011; Karmakar, 2007; Lim & Sek, 2013; Srinivasan, 2011; Vijayalakshmi & Gaur, 2013; Wang, 2011) and in this context the studies exclusively on Indian stock market data are relatively fewer (Karmakar, 2005; Kaur, 2004). The results reported in these studies indicate that research studies on modeling volatility of Indian stock returns are inconsistent and vary across data samples and equity markets. The standard GARCH models under the assumption of normal distribution in the error term perform poorly in the presence of extreme observations which a normal distribution fails to predict. Since agents respond asymmetrically to good and bad news and because of the leverage effect have preference for positive returns. Frequent occurrences of large positive and negative movements in the financial markets suggest the use of non-normal densities such as student-t distribution and the generalized error distribution as more appropriate compared to a normal distribution.

To summarize from the review of literature, it emerges from that for a long time it was thought that the stock prices have unpredictable nature and follow a random behavior. Gradually few econometric approaches appeared aiming at describing the underlying process behind stock returns and finally models capable of explaining the variance process gained prominence. It is now generally believed that stock returns and volatility are manifestations of their own lagged values and hence are predictable to some extent (Sullivan, Timmermann, & White, 1999). Stock price data share statistical similarities with common macroeconomic variables such as inflation and interest rates and some firm-specific variables such as dividend yield and price-earnings multiple.

Volatility estimation and forecasting has some very useful applications (Sullivan *et al.* 1999; Marquering and Verbeek 2004). Study by Fleming *et al.* (2001) document superior performance of volatility timing strategies for portfolio management by exploiting the predictability of the conditional second moments. Since the value of a financial instrument is positively related to its volatility any valuation model requires an estimate of volatility to accurately price that asset. Forecast of volatility is good starting point for assessing investment risk since all asset pricing models are based on the assumption of risk-aversion and are therefore representable as function of risk. Application of volatility from option pricing to value-at-risk estimation for position hedging is well-known.

What makes the estimation and forecasting of volatility a challenging task is its elusive nature, and it, therefore, requires a model that is capable of producing reliable estimates of this time-varying stochastic process. In practice volatility estimates based on historical data are popular since they are easy to predict and are considered reliable for short horizons. Standard deviation in spite of being a sample statistic is predominantly referred to situations where risk assessment is needed. Moving averages and exponential moving averages methods also use historical data and centers around forming an estimate of standard deviation as a measure of volatility.

Since, volatility is a stochastic process, one need to get a forecast of volatility considering continuously evolving volatility which is estimated using more sophisticated models such as ARMA. The Box and Jenkins' approach of modeling volatility considering data generating process to be stochastic in nature has unarguably the corner stone of time series data analysis. However, all these linear models based on historical data fail to capture the stylized facts about volatility. Non-negative constraints and lack of a formal procedure to estimate lag lengths continue as prominent reasons for its criticism. ARCH's extension to GARCH addresses many of the shortcomings of the parent model and its ability to allow for modeling of conditional volatility gives it a supreme advantage over many other competing models of volatility. In spite of its unprecedented success, this model suffers from two significant shortcomings. First is the assumption of constant volatility regime and second is the assumption of symmetric nature of volatility. Nelson's EGARCH and GJR-GARCH models confirm the presence of volatility asymmetry and propose models to incorporate so-called leverage effects for estimating volatility.

Becker *et al.* (2007) find that VIX does not contain any additional information relevant to providing more accurate volatility forecasts over GARCH family models. Randolph (1991) also stresses several implications of short-term forecasts of volatility and its impact touch the sensitive nature of macroeconomic variables as well (Chauvet *et al.* 2015; Paye 2012) to study financial crisis (Choudhry & Jayasekera 2015; Rastogi 2014), and to study market integration (Almohaimeed & Harrathi 2013; Arouri & Foulquier 2012). The GARCH model has long been popular in modeling financial time series data, and is proven to be useful in handling the data with high volatility Gourieroux *et al.* (1997). The principal objective of all forms of time series models is to understand the distributional properties of a sequence of observations generated over time.

Hence, to avoid any possible anomaly in the Indian stock market return series, it must be subjected under a thorough diagnosis for the presence of common statistical properties discussed above. Studies in the Indian context do not provide a comprehensive analysis of the time varying nature of such time series properties, and therefore a separate chapter is devoted to studying such stylized facts to ensure that Indian stock market data is suitable for time-series analysis under the GARCH framework. Though substantial evidence exists favoring the assumption of persistence property in stock returns data on developed market, however, studies involving the nature and evolution of volatility persistence inherent in the Indian stocks lacks depth and therefore an exhaustive analysis of the persistence of conditional volatility and other parameters of the GARCH model are discussed in chapter 4.

Thus, the major gaps that emerge from the review of literature are as follows:

a) Lack of comprehensive coverage in empirical studies on the statistical properties of stock returns data, in particular, the persistence and the asymmetry property.

b) Research studies on conditional volatility estimation in the Indian context have not considered stock market reforms and global events before concluding on the comparative performance of volatility forecasting models suitable for the Indian stock market. Though there are no specific criteria to create sub-samples from a large sample size, however, instances of prominent domestic and global events may provide useful but subjective clues for creating sub-samples based on these factors. Empirical studies on performance of volatility forecasting models usually consider a very large sample spanning across decades and conclude on the best fitting model. However, since GARCH parameters are sensitive to the sample size, conclusions drawn from such studies are questionable unless comparisons across smaller samples are also drawn.

c) The evidence on long-run relationship between macroeconomic variables and the Indian stock market volatility is very limited and has largely been left unexplored. The research studies in the Indian context do not provide a concrete evidence on the utility of macroeconomic variables in estimating and forecasting volatility of stock returns.

It is expected that filling these research gaps will enrich the existing body of knowledge on the time varying properties of volatility and usefulness of macroeconomic variables in predicting the stock market volatility. This will enable better identification of GARCH models with appropriate conditional mean and variance specification.

2.11 Research Objectives

Following research objectives are undertaken in this study to address above mentioned gaps identified from literature review:

i. **To estimate the conditional volatility of conventional GARCH-type models using data from the Indian stock market.**
ii. **To perform a comparative analysis of the GARCH models based on the out-of-sample forecasting ability of each model.**
iii. **To model the conditional volatility by augmenting the GARCH models with the long-run equilibrium relationship between the macroeconomic variables and Indian stock market.**

Chapter 3 Research Design and Methodology

3.1 Introduction

Empirical research on volatility forecasting models suggests several prominent factors in explaining the stock market volatility. This thesis concerns explaining three distinct but not independent lines of arguments in describing the stock market volatility. The first two are the importance of historical price behavior and their statistical properties, and the market events that may provide explanation for this time-varying nature of the stock return volatility. The second aspect is the role of quantifiable exogenous factors such as domestic macroeconomic variables in explaining stock price patterns. To meet this objective we perform an exhaustive empirical analysis of time-series data spanning over three decades covering episodes of major financial sector reforms and phases including the global turmoil and euphoria in the stock market.

There exists a comprehensive body of work on predictive ability of conditional volatility models and their statistical properties. As discussed in the literature, forecasting volatility using GARCH model is done in virtually every stock market around the world. However, for GARCH models to adequately predict asset return volatility; the time series data under consideration must be free from any statistical anomaly. Statistical features such as instances of fat-tails in the distributions of returns, clustering of volatility, and higher order serial dependence in returns can be conveniently examined using conventional data diagnostics. However, the other two properties i.e. persistence of volatility and asymmetric response of volatility to news arrival require careful examination of the sign and significance of the coefficient estimates from the GARCH-type models. A detailed analysis of the persistence property is followed by evaluation of symmetric versus asymmetric GARCH models to argue that the Indian stock market data does not suffer from any statistical anomaly and conventional time-series models can be applied for data analysis both on large and small samples.

Research studies on the impact of local and global events on market volatility suggest that the stock market volatility is impacted both by local as well as global events. The financial sector reforms initiated in the Indian capital markets were intended to establish the faith and confidence of investors, both local as well as global. Over the years, these reforms have led to an increase in number of foreign portfolio funds investing in the Indian markets. However, external events, especially periods of global economic crisis, do trigger volatility in domestic markets, and an increased integration with the global market further aggravates the negative impact of global triggers on the domestic stock market. Since GARCH model estimates are sensitive to the sample size, the entire sample period is resized into smaller sub-samples depending on the volatility regime, global factors, and stock market reforms. This sub-division of entire sample period into smaller samples is done to assess whether the out-of-sample forecasting ability of the conditional volatility models improve as compared with model fitted on the entire sample period.

Research studies have documented information content of the macroeconomic variables in forecasting stock market return and found these variables to have economic value in predicting stock market returns. In this thesis we attempt to study a higher order structural integration between macroeconomic variables and the Indian stock market by investigating long-run equilibrium relationship between the macroeconomic variables and the Indian benchmark index.

As discussed in the literature review the studies on modeling volatility have analyzed volatility in the Indian stock market either by applying GARCH models or have studied the impact of stock market reforms and market microstructure factors on the volatility of the Indian stock market. Few studies have investigated the long-run and short-run impact of macroeconomic variables on India's stock market returns but have not studied their relationship with the stock market volatility. To address these research gaps this thesis undertakes comprehensive empirical analysis of the properties of conditional volatility models, impact of market reforms on stock returns volatility and information content of macroeconomic variables in explaining stock market volatility.

3.2 Research Design

The persistence of volatility and asymmetric response of volatility to news arrival are two key properties of volatility that demand comprehensive analysis for drawing reliable forecasts from the GARCH models. Thus the primary objective of this thesis is to address these research gaps by undertaking exhaustive empirical analysis on the persistence property of the volatility, the performance of symmetric versus asymmetric volatility models, and the influence of long-run equilibrium relationship between the macroeconomic variables and Indian stock market volatility.

For accomplishing the research agenda an integrated approach involving an in-depth analysis of the statistical properties and influence of macroeconomic variables is implemented. First, the analysis of the persistence property of the conditional volatility is carried out followed by fitting the symmetric and asymmetric GARCH models on daily stock market returns to identify the optimal model speciation. Two important stylized facts the persistence property and the asymmetric nature of the volatility that are crucial for time series data analysis using GARCH models are discussed in the following chapters. However, the presence of fat-tails in asset returns are better captured by the student's-t distribution and the generalized error distribution and therefore the comparative analysis of the GARCH models also consider these non-normal distributions and document any improvement in volatility prediction.

Fitting the GARCH models on any time series requires that the data is free from any statistical anomaly. Anomalies such as low persistence of volatility, no leverage effect and homoscedasticity in asset returns should be investigated before reliable forecasts can be constructed after fitting the conditional volatility models. Also, the economic value of GARCH specification is realized only when the process under consideration exhibits evidence of the presence of conditional heteroscedasticity. To test this hypothesis we construct continuously compounded return series and divide it across different samples consistent with significant local and global events. Statistical procedures of analyzing the time series data are employed to investigate whether the data suffers from any statistical anomaly. To compare volatility models the squared returns in all sampling frequencies are taken as proxy for volatility. This exercise ensures whether standard volatility forecasting models, mostly developed in western markets, can be applied and be interpreted reliably in Indian context. For example, theory and empirical evidences on asymmetric volatility states that leverage effects do cause volatility to be influenced more by negative returns than by positive ones and hence the asymmetric models of conditional volatility are more suitable for estimating variance of returns.

Reliable forecast of return and volatility requires a proper specification of the conditional moments of first two moments. For adequate specification of the conditional mean equation, research studies largely suggest modeling the return process as a random walk model or auto-regressive moving average model and subsequently establish linear dependency in the data using tests of auto-correlation. Though an overwhelming majority of empirical studies finds such specifications suitable for modeling the conditional first moment of the return process, however, one limitation of this strategy is that it excludes the impact of any contemporaneous variables on the variance of such a process.

As noted in the literature review section, many studies on impact of macroeconomic variables on stock market find significant influence of several macroeconomic variables on the predictability of stock returns and many studies provide empirical evidence on the presence of co-integration between macroeconomic variables and stock prices. And therefore, in addition to the specification of the conditional mean, this study also includes the macroeconomic variables as exogenous regressors for modeling the conditional second moment. The econometric methodology adopted for this purpose is described in chapter 5. Since no exogenous variables are considered in conditional mean specification, it is free from any possible model misspecification and therefore conventional tests of diagnosis of model misspecification are not required.

To accomplish the above mentioned research objectives the analysis is divided into chapters four and five. Chapter four provides a comprehensive analysis on the persistence of conditional volatility by using daily stock market returns on a benchmark stock, Nifty. To study the presence of leverage hypothesis symmetric and asymmetric GARCH models are covered on equal sized sub-sample of five years each spanning from 1985 to 2014. Other statistical properties of Indian stock market data such as statistical dependence, serial correlation, zero mean processes, presence of fat-tails in return series, heteroscedasticity, stationarity of the log differenced returns series, etc. are done on the overall sample size beginning year 1985 to 2016-mid. Hence, the sample period consists of the most volatile phase in the recent history of the Indian stock market early years of 1990s as well as the most volatility phase globally which was the sub-prime crisis that began in the year 2008.

An in-depth analysis of the common statistical properties of time-series data is presented in chapter four. For standard econometric models to work and give reliable results it is required that the time-series is free from any statistical anomaly and therefore the discussions undertaken in chapter four are essential before GARCH models are fitted on the data series. The characteristics of daily stock return patterns including the time-series properties are discussed along with a detailed analysis of the persistence and asymmetry property of volatility observed in the Indian context.

As discussed in the introductory chapter, the Indian stock market witnessed wild swings during 1990-1993 due to number of stock market scams and economic reforms. The stock market has been particularly volatile in the early 1990s with within-year movements witnessing per cent rise and fall to the tune of 250 per cent positive in one year then falling by 50 per cent in another year and subsequently rising by 135 per cent to close at 4,588 points (Sensex) by August 1994, these variations cannot be explained by economic fundamentals of a country. Hence, the period prior to 1994 is clearly not a desirable sample period to be included for analyzing long-term volatility in the Indian stock market as it might potentially impact the estimation results; however, when we adopt period specific study this period is considered to illuminate the findings specific to that period.

The revival in the Indian stock market following the announcement of the economic reforms was not immediate as investors remained sceptical about the economic fundamentals. These phases are also marked by very important stock market reforms such as launch of financial derivatives trading on the Indian stock market, creation of SEBI, NSE and dematerialization of physical shares of the companies. The time periods also overlap with events of marked significance for stock market volatility such as bursting of the dotcom bubble and the sub-prime mortgage crisis.

Starting year 1991, when the economic reforms were initiated the following two years remained highly volatile which remains inexplicable. Therefore, the sampling period undertaken to study the impact of stock market reforms and global events begin from January 1994. This phase overlaps with creation of National Stock Exchange, hailed as a very significant development in Indian capital markets that permanently changed securities trading and settlement mechanism. The first phase runs from January 1994 to December 1997. The second phase ranges from January 1998 - December 2002 and include significant local and global factors such as the Russian ruble crisis and bursting of the dotcom bubble. The third phase covers the bull-phase starting year 2003 till the beginning of the sub-prime crisis, mid-2007. The fourth phase considers the two year period covering the sub-prime crisis and the subsequent recovery. The sixth and the final phase considers the post-recovery phase starting year 2010 to 2013.

GARCH models champion in capturing salient features of financial time-series and a significant amount of attention is given to study whether there are any prominent aberrations when data from Indian stock market is considered. An intriguing challenge facing volatility forecasting is limitations of these models in generalizing the forecasting performance as forecast horizons vary. We, therefore, in addition to identifying the best performing model across competing models also test the forecasting ability of these models on different forecast horizons considering varying sampling frequency. The analysis of forecasting ability of GARCH models is done on the out-of-sample data for each sub-sample. Standard (symmetric) loss functions are used to evaluate the performance of the competing models. Two loss functions are considered that are the mean absolute error and the root mean squared error. The out of sample periods are constructed by considering a non-overlapping full calendar year beginning immediately after the end of in-sample period. The entire sample from 1994 to 2013 is also use for GARCH estimations and out of sample forecasts for this period range from January 2014 to May 2016.

Impact of macroeconomic variables on the volatility of stock market provides direction as to whether these macroeconomic variables are suitable for capturing the time varying nature of the stock market volatility from a professional fund management point of view. Literature studies in Indian context reveal that several macroeconomic variables cause stock market returns, we extend this finding by augmenting the GARCH type models with exogenous macroeconomic factors to estimate the individual and collective influence of macroeconomic variables on the Indian stock market. We investigate and provide empirical evidences on whether the macroeconomic variables share long-run association with the Indian stock market returns. The dynamic relationships between the macroeconomic variables along with their long-run association with the stock index are analyzed to predict stock market volatility.

3.2.1 Data and Sampling

The analysis requires data on a proxy of Indian stock market returns and select macroeconomic variables. The data on stock market returns and the macroeconomic variables is purchased from tradingeconomic.com. The proxy for Indian stock market is taken as two prominent benchmark indices i.e. BSE Sensex and S&P CNX Nifty. The sampling frequency and resizing of samples for creating sub-samples for data analysis are discussed in the relevant chapters.

The analysis of persistence property and asymmetry property is done on a daily sampled data. To ensure that the results are not sensitive to the choice of benchmark index, the study considers both Sensex and Nifty. First, the persistence property is examined on daily returns on S&P CNX Nifty from 1997 to 2012. NSE was recognized as a stock exchange in the year 1993 and the trading and settlement of dematerialized stocks commenced in the year 1996 on NSE and therefore the sample period we have considered begins from 1997. Properties of the conditional volatility estimated using GARCH model require a large sample size. The study on the persistence property attempts to provide empirical evidence on the number of observations that are required for obtaining reliable estimates from fitting the GARCH model. Studies on the volatility in the Indian stock market have usually considered a sample size ranging from 2 years to 20 years. The analysis of persistence property considers a sixteen year sample period from January 1997 to December 2012 which is much larger than the average sample size found in the empirical studies.

For analysis of long-run association between the Indian stock market and the macroeconomic variables five different proxies of macroeconomic factors are considered. The factors that are considered include the long-term interest rate, inflation, foreign exchange rate, crude prices, domestic output, and liquidity. The variable that are taken as proxy for these factors include yield on 10 Year GOI, nominal consumer price index, nominal effective exchange rate (NEER), nominal West Texas Intermediate (WTI) crude prices, nominal exports, and nominal broad money supply (M3). Since, one of the objectives of this thesis is to analyze whether long-run dynamic association between macroeconomic variables and stock market contains any incremental information in predicting volatility of the Indian stock market, the conditional volatility is modelled by augmenting GARCH models augmented with monthly sampled macroeconomic variables.

All econometric analysis in this thesis is done on the statistical package Econometric Views 9.0.

3.2.2 Econometric Tools & Techniques

This empirical research work considers the alternative formulations of the GARCH-type models under the assumption of normality of the error terms. This distribution assumption is later relaxed, and other non-normal distributions like student-*t* and generalized error distribution (GED) are also considered for model estimations. Non-symmetric GARCH based models including the exponential GARCH (EGARCH) model (Daniel B Nelson, 1991) and the threshold GARCH (TARCH) model (Glosten et al., 1993; Zakoian, 1994) under the normal and non-normal error distributions are considered. For improving the volatility predictability, the higher order ARMA specifications are also incorporated in the GARCH framework. In all above estimations, residuals from higher order ARMA specifications of the conditional mean equation are obtained for fitting GARCH conditional variance equation. Three model selection criteria *viz.* Akaike Information Criterion (AIC), Schwarz Criteria (SC) and Hannan-Quinn criterion (HQ) are used for selecting models that better fit the data. Thereupon, the selected models are analyzed for their out-of-sample forecasting ability by comparing results of loss functions such as Mean Squared Error (MSE) and Mean Absolute Error (MAE). Forecasting ability of any model is a key criterion on which model selection depends on, and hence the most suitable models for Indian stock market are identified by selecting the models with minimum value of the loss functions in the out-of-sample study.

Economic theory suggests that several macroeconomic variables share a long-run equilibrium relationship between them. Macroeconomic variables such as money supply, inflation, interest rates, and return on a benchmark stock index etc. have a contemporaneous influence on each other. Our strategy in this analysis is to establish whether macroeconomic variables share any long-run relationship with the Indian stock market, and then, to utilize the information on the long-run dependence for modeling the conditional variance of the process. To this end, the Johansen's co-integration is considered followed by the application of the error correction mechanism for extracting the error correction component. Finally, the GARCH conditional variance estimation is augmented by considering individual macroeconomic variables, combined impact of these macroeconomic variables and finally to test whether the error correction component has any significant impact on the conditional heteroscedasticity. The conclusions on the research hypothesis will not only allow us to accept or reject the efficient market hypothesis, in its weak-form, but will also provide directions for further research on the elusive relationship between macroeconomic variables and stock market volatility.

3.3 Research Questions

The major body of this work is therefore concerned with three areas of research in volatility forecasting namely –

- The dynamic nature of the evolution of volatility of Indian stock markets in the post-liberalization period.
- The asymmetric response of volatility to news arrival.
- The influence of macroeconomic variables on stock market fluctuations in India.

For meeting the research objectives four broad research questions (RQ) are examined.

RQ 1: Does the conditional volatility of returns on an Indian stock market index exhibits strong long-memory effects?

RQ 2: Does the conditional volatility in the Indian stock market respond asymmetrically to news arrival?

RQ 3: Does the Indian stock market share long-run equilibrium relationship with the macroeconomic variables?

RQ 4: Does the inclusion of macroeconomic variables have informational content in explaining the stock index volatility?

3.4 Summary

This thesis primarily focuses on few key issues for meeting its research objectives. The first is volatility properties and its impact on ARCH model estimation and forecast. The second research problem is to investigate the asymmetric nature of volatility, and the third issue deals with the consequences of macroeconomic variables on stock return volatility.

Chapter four carries out the comparative analysis of symmetric and asymmetric volatility models using daily stock market returns. Alternative GARCH models are estimated for modeling the intertemporal behavior of asset return volatility with an objective to identify volatility models with superior forecasting ability. Chapter five accomplishes the second research objective by investigating the role of macroeconomic variables in explaining the conditional volatility of asset returns. First, a long-run relationship between macroeconomic variables and stock prices is identified, thereafter, the GARCH-*type* models are augmented to obtain GARCH variance forecasts considering the long-run associations and comparisons are drawn. Empirical evidences on whether information contained in the macroeconomic variables can be utilized to outperform volatility forecasts from conventional GARCH-type models are presented. An elaborate discussion on these research problems is presented in chapter four and five.

Chapter 4 Properties of Conditional Volatility and its Forecasting

4.1 Introduction

To answer the first two research questions posed in the previous chapter, this chapter carries out an extensive empirical analysis to examine the persistence and asymmetry property of stock return volatility in the Indian stock market. The persistence property is important from the perspective of examining the stationarity of the volatility process and the asymmetry property yields information on whether the forecasting ability of symmetric GARCH models outperforms the asymmetric models or vice versa.

As discussed in the literature review chapter, research studies have attempted to examine the forecasting ability of GARCH models for practical risk management purpose. The interpretation of the estimates of the GARCH models and their out-of-sample forecasting accuracy requires that the statistical properties of the time-series data under consideration do not suffer from any statistical anomaly. The persistence of volatility is one such key statistical property and a thorough empirical investigation on the nature of the persistence of GARCH estimates is carried out in this chapter to examine the time-varying persistence property.

The GARCH model does not impose any restrictions on the value of coefficients and hence the coefficients are allowed to take any finite real value. However, if the individual coefficients of the GARCH model or their sum take a value greater than unity then a practical problem arises with regard to the utility of such coefficients for forecasting volatility. A stationary GARCH model requires the coefficients in all estimations to be less than one else the conditional volatility process becomes explosive and approaches infinity as forecast horizon increases.

This is a common concern that needs careful examination before the GARCH estimates are used for forecasting volatility for the next *k*-steps. The time-varying evolution of the persistence parameter using iterative model estimation of the GARCH (1, 1) model is illustrated, which enables the inquiry into the relationship between the GARCH parameters. This study analyzes the time-nature of the stationarity of volatility as new information is sequentially updated for model estimation. The intertemporal evolution of the constant term, the ARCH term and the GARCH term in the GARCH model allows drawing inferences on the stationarity and the long-memory property of the GARCH parameters. Both the stationarity and long-memory property have implications for performing out-of-sample forecasting. Since, the persistence of GARCH model is sensitive to sampling frequency and number of observations in the sample, the stock market returns based on the daily closing value is considered for this analysis. The daily return series is constructed by taking the log-difference of subsequent closing prices of Nifty index.

Subsequent to the examination of the persistence property, this chapter discusses the utility of GARCH models in forecasting volatility by performing an exhaustive comparative analysis of volatility forecasting models. Using the daily returns data on Sensex, both the symmetric and asymmetric GARCH models under normal and non-normal probability distribution assumptions are considered.

To add flavour to this inconsistency in the existing empirical studies the data is divided into smaller sub-samples, both arbitrarily as well as coinciding with significant events in the global financial markets. Subsequently, the GARCH parameters estimated from sub-samples and the overall sample period are utilized for constructing the out-of-sample forecast of the conditional volatility. Two loss functions viz. the root mean squared error (RMSE) and the mean absolute error (MAE) are used for evaluating the out-of-sample forecasting accuracy by comparing the GARCH conditional volatility with a proxy of realized stock market volatility.

4.2 Properties of Volatility

Common statistical properties of stock returns that emerge from empirical studies on asset returns are asymmetric response of stock return volatility to positive and negative returns (Glosten et al., 1993; Daniel B Nelson, 1991), clustering in asset returns (Daal et al., 2007; Fama, 1965; Zivot, 2009) and persistence in volatility (Charles & Darné, 2014; Chou, 1988; Poterba & Summers, 1986).

Various studies (French, Schwert, & Stambaugh, 1987; Nelson, 1989) argue that stock market volatility increases subsequent to fall in prices. Poterba & Summers (1986) also confirm that rise in volatility causes stock prices to fall as the discount factor governing the present value of future cash flows increases. Though in GARCH (p, q) model many possible values of p and q can be considered, studies find GARCH (1, 1) formulation as very satisfactory (P. R. Hansen & Lunde, 2005). Other extensions to GARCH models include the models of asymmetric volatility and GARCH-in-mean specification.

A large number of studies concerning the performance of GARCH models in modeling and forecasting volatility exist in literature. West and Cho (1995) document superiority of GARCH model in forecasting dollar exchange rate volatility. Superiority of conditional heteroscedasticity models over exponentially weighted moving average and historical mean models for forecasting monthly US index stock volatility is demonstrated in Akgiray (1989). Brailsford & Faff (1996) find GJR-GARCH model superior to other models in predicting Australian stock index volatility. Similar results appear in Balaban et al. (2001); they include GARCH effects in the conditional mean equation to investigate the impact of variance on asset returns. Balaban (2004) compares symmetric and asymmetric volatility models and finds exponential GARCH (EGARCH), introduced by Nelson (1991) as the best model. Their results document poor performance of GJR-GARCH models in forecasting volatility. Loudon, Watt, & Yadav (2000) study several parametric GARCH models and claim that optimal choice of model is inconsistent and specific to sample periods. Studies comparing linear and non-linear GARCH models (Franses & Van Dijk, 2000) conclude that non-linear GARCH models are unable to outperform standard GARCH models. Pagan & Schwert (1990), study over ninety-year sample period and compare the performance of non-parametric modeling techniques with GARCH-type models and conclude that in the out-of-sample forecasting the non-parametric models fare worse than the parametric ones.

Levels of volatility are reportedly high in emerging markets (Aggarwal & Goodell, 2008; Çağlı, Mandacı, & Kahyaoğlu, 2011; Karmakar, 2007; Lim & Sek, 2013; Srinivasan, 2011; Vijayalakshmi & Gaur, 2013; Wang, 2011) and in this context the studies exclusively on Indian stock market data are relatively fewer (Karmakar, 2005; Kaur, 2004). The results reported in these studies indicate that research studies on modeling volatility of Indian stock returns are inconsistent and vary across data samples and stock markets.

Econometricians have attempted to model several statistical properties of asset returns and many such properties are considered in developing the ARCH model and its various extensions (see: Poon and Granger, 2003; Bollerslev et al., 1994; Bollerslev et al., 1992, for excellent reviews on advances in volatility forecasting literature). Statistical aspects such as specification of the conditional mean and the conditional variance equation, probability density assumptions of the innovation terms, nature of time-varying persistence in GARCH parameters, and debates on the symmetric behavior of volatility process have encouraged researchers to propose alternative approaches that can better explain the underlying data generating process.

A key characteristic of conditional volatility is its persistence, that is, its ability to carry the impact of significant news on asset volatility to future periods. If persistence is high, a shock in the volatility process temporarily increases the variance of expected returns before it reverts towards its long-term mean. The tendency of volatility to persist over time is widely studied by Bollerslev et al., (1992), Pagan and Schwert (1990), Schwert (1989), Chou (1988), and Engle and Bollerslev (1986). Seminal works by Mandelbrot (1963) and Fama (1965) identified latent properties of asset returns such as clustering of returns and lack of statistical dependence structure. For example, Fama (1965) concluded absence of serial correlation in asset returns and argued that asset returns are statistically independent and the return generating process is representable as a pure martingale process. Mandelbrot (1963b), however, noticed serial dependence in stock returns and identified the presence of volatility clustering in asset returns and this statistical property provides a useful interpretation the analysis of time series data. Earlier works, (e.g. Poterba and Summers, 1986), rejected the hypothesis of non-stationarity in the volatility process and suggested that shock to volatility does not persist for long. Officer (1973), on the other hand, noticed high persistence and high volatility during periods of Great Depression.

Lamoureux and Lastrapes (1990) indicate an increase in the persistence of GARCH coefficients under the presence of structural breaks. Hamilton (1989) considers permitting sudden and discrete changes in the GARCH model to account for structural breaks in volatility. Several authors (Klaassen, 2002; Cai, 1994; Hamilton and Susmel, 1994; Brunner, 1991) use Markov switching model to permit regime switches within the volatility forecasting framework for obtaining reliable forecasts. Chou (1988) studies the persistence of GARCH parameter estimates and its impact on volatility forecasting using stock returns. The majority of studies on volatility and its properties in context of developed markets and relatively fewer studies document such properties in emerging markets.

Review of literature on volatility forecasting suggests that conditional volatility estimates of a GARCH process exhibit high persistence. It also indicates an upward bias in volatility persistence when regime changes or structural breaks are ignored while modeling the conditional volatility. The Iterated Cumulative Sums of Squares (ICSS) algorithm of Inclán and Tiao (1994) is used extensively for detection of structural breaks in the volatility process. Emerging markets are typically characterized by high levels of volatility and empirical results confirm this fact (Aggarwal et al., 1999; Bekaert & Harvey, 1997). Studies conducted on crude prices by Kang et al. (2009), Ewing and Malik (2010) and Ozdemir et al., (2013) also provides evidence on high association between persistence in the volatility of returns in crude prices and structural breaks in the variance. As pointed out by Poon and Granger (2005) the auto-correlation of variances remains significantly above zero beyond 1000 lags, suggesting strong long memory effect

Malik (2003) studies sudden changes in variance and persistence in currency movements and documents positive relation between persistence of volatility and structural breaks in the underlying series. Various studies on stock returns in emerging markets, developed markets and domestic market provide evidences correlating presence of structural breaks and overestimation of persistence (Kumar and Maheswaran, 2012; Wang and Moore, 2009; Hammoudeh and Li, 2008; Malik et al., 2005). Studies in emerging markets indicate that the persistence of volatility reduces if the models are augmented with the structural breaks or regime switches, however none of the studies offer any theoretical explanation behind this phenomenon.

Several studies also suggest significant influence of domestic macroeconomic events causing permanent change in the variance structure (Aggarwal et al., 1999). As the period of study and the nature of capital markets differ across these empirical findings, it is unlikely that similar generalizations will qualify for all markets. Choudhry (1996) demonstrates change in ARCH parameter before and after the crash of 1987 and points out that changes are not uniform across markets. This uncertainty is further heightened in the wake of dramatic globalization in the last decade-and-half, and the 2008 global financial crisis affirms volatility spill-over from developed markets to emerging markets. However, the impact of sub-prime crisis on volatility of emerging markets is mixed and both symmetric and asymmetric models provide reliable estimates for conditional volatility (Rastogi, 2014). Thus, it is doubtful that presence of structural breaks in return series will continue to be largely driven by local factors. These studies on volatility persistence have largely focused on structural breaks and regime switches to estimate long memory property of stock returns and augment GARCH models to accommodate structural breaks for achieving stable estimates.

To draw reliable forecasts from volatility models, it is crucial that the persistence of the GARCH estimates are stationary. The next section briefly discusses the GARCH models that are considered for analysis in this thesis. The subsequent section proceeds with the inspection of the persistence property and time-varying nature of GARCH coefficients using data from the Indian stock market.

4.3 GARCH-family Models

This thesis carries out an extensive study on GARCH and its various extensions. This section briefly describes the GARCH model specification under alternative distributional assumptions that are used for volatility estimations in this study. The following section discusses the econometric specification and stability conditions required for a GARCH process under alternative assumptions for the conditional error density function.

Models of conditional heteroscedasticity are used to estimate the second order moments conditional on past information. Hence, the assumption of homoscedastic errors no longer holds. The ability of GARCH models in capturing salient properties of volatility makes it a desirable choice for analyzing inter temporal patterns in volatility and this fact combined with the assumption of heteroscedasticity in the innovations qualifies it as a suitable approach for dealing with changing variances in financial data. Bollerslev (1986) generalized the ARCH (q) model by including a GARCH term in the conditional variance equation. However, it is possible to specify a common equation for the conditional mean both for ARCH and GARCH, specification of the variance equation differentiates the choice of the model. GARCH model and its various extensions permit an infinite lag-order of ARCH terms and are therefore a representation that is more parsimonious and flexible and allows higher degrees of freedom. Hence, for analysis purpose this study focuses on GARCH and its extensions and considers the popular ARCH-LM test to detect heteroscedasticity in the regression residuals.

For modeling a GARCH (1, 1) process specification of the conditional mean equation is required. To model the conditional volatility of the Indian stock market this study considers two specifications for the mean equation i.e. pure white noise and ARMA (p, q) processes. Review of studies suggest that first order ARMA specification is desirable for financial time series data but we consider lag orders for p and q up to two lags. The residuals from the mean equation are used for estimating the conditional variance equation.

Brief discussion on the ARCH (q) and GARCH (p, q) models and constraints required for their stability follow.

Let r_t be the continuously compounded daily returns calculated as the first difference of the natural log of price, P_t at time t with its lagged value, P_{t-1}, and then the random variable r_t is modelled as

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad 4.1$$

The simplest conditional mean equation describes the return generating function as a process dependent on the long-term average and is expressed as

$$r_t = c + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma_t^2) \qquad 4.2$$

Several linear and non-linear specifications for the random variable r_t are plausible. The ε_t term is the innovation term in the conditional mean equation. Equation 4.2 models daily returns as a white noise process. The specification can take various forms such as the auto-regressive (AR) process, the moving average (MA) process and as the auto-regressive moving average (ARMA) process of first order as well as higher orders. For modeling a GARCH (1, 1) process, first a specification of the conditional mean equation is essential. As discussed above, in addition to pure white noise process for the mean equation, this study also considers higher order ARMA specifications to obtain the residuals from the conditional mean equation.

The conditional variance estimate from a GARCH model is weighted average of unconditional variance, the news surprise in the preceding period and lagged period conditional variance. GARCH specification simultaneously allows estimation of conditional mean as well as conditional variance. As is evident from the above discussion, various formulations of conditional mean equation are possible and it is the choice usually left to the researcher. Since, GARCH approach models the conditional variance depending on the residual from the conditional mean equation, a variety of formulations based on lagged AR and GARCH-M terms in the conditional mean equation allows for range of model specifications.

From the literature, it is evident that GARCH (1, 1) usually is the most preferred model and delivers superior results. Hence, since the GARCH (1, 1) is adequate in most empirical studies we consider only one lag for both ARCH and GARCH terms for specifying the variance equation, under the assumption that higher order models will not outperform GARCH (1, 1). The residuals obtained from the mean equation can be expressed in terms of a pure white noise process v_t and time-varying standard deviation σ_t as

$$\varepsilon_t = v_t \sigma_t \tag{4.3}$$

$$v_t \sim N(0, 1) \tag{4.4}$$

This distinguishes ARCH models from traditional ordinary least squares model since the assumption of homoscedastic error variance is no longer required. The time-varying conditional variance in an ARCH (q) model is specified as

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} (a_i \varepsilon_{t-i}^2) \tag{4.5}$$

Here σ_t^2 is the time varying variance of the underlying data generating process dependent on lagged squared residuals. Stability of the estimated variance requires that $a_0 > 0$, $a_i \geq 0$, for $i = 1, \dots, q$. For brevity, often the above model is represented in terms of lag operator as,

$$\sigma_t^2 = a_0 + A(L)\varepsilon_t^2 \tag{4.6}$$

Here L denotes the lag operator and $A(L) = (a_1 L + a_2 L^2 \dots + a_q L^q)$.

Defining, $u_t = \varepsilon_t^2 - \sigma_t^2$, the model for conditional volatility can be expressed as:

$$\varepsilon_t^2 = a_0 + A(L)\varepsilon_{t-1}^2 + u_t \qquad 4.7$$

By definition, u_t is serially uncorrelated with $E_{t-1}(u_t) = 0$ but neither independently nor identically distributed. The process is covariance stationary, if and only if all the roots of $\sum_{i=1}^{q}(a_i L^i) = 1$ lie outside the unit circle. If the process is covariance stationary, its unconditional variance becomes:

$$V(\varepsilon_t) \equiv \sigma^2 = a_0(1 - \sum_{i=1}^{q}(a_i))^{-1}) \qquad 4.8$$

Bollerslev (1986) generalized the ARCH process by including lagged conditional variance. The GARCH (*p*, *q*) model is given by:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q}(a_i\varepsilon_{t-i}^2) + \sum_{\mathrm{j}=1}^{p}(b_j\sigma_{t-j}^2) \qquad 4.9$$

Equation 4.9 can also be written using lag operator as

$$\sigma_t^2 = a_0 + A(L)\varepsilon_t^2 + B(L)\sigma_t^2 \qquad 4.10$$

Stability conditions for this model require that$a_0 > 0, a_i \geq 0, i = 1, \dots, q \; and \; b_j \geq 0, j = 1, \dots, p$. The unconditional variance of ε_t for this process is constant and is given by

$$V(\varepsilon_t) \equiv \sigma^2 = a_0\big(1 - \sum_{i=1}^{q}(a_i\big) - \sum_{j=1}^{p}(b_j))^{-1} \qquad 4.11$$

The model is covariance stationary if all the roots of $A(L) + B(L) = 1$ lie outside the unit circle, or equivalently if $\sum_{i=1}^{q}(a_i) + \sum_{j=1}^{p}\big(b_j\big) \leq 1$.

In equation 4.9, a_i measures the impact of previous period's disturbance on current period conditional volatility and are called the ARCH effect, b_j measures the GARCH effect, and ω is long-run variance. For GARCH variance to be stationary, the persistence of GARCH model defined as sum of ARCH and GARCH coefficients $(a_i + b_j)$ should be less than unity. The value of persistence closer to one indicates slow decay of volatility shocks.

Values of p and q determine the order of the GARCH process. When p=0, and q=1 the model becomes ARCH (1). The GARCH model allows flexibility in choosing the lag length and alternative formulations considering higher orders of p and q are also plausible. Though lag-order higher than one of ARMA terms is considered in this thesis for specifying the conditional mean equation, the lag orders higher than one are not considered for the conditional variance because in majority of empirical studies the first lag-order is found to be adequate for estimating the conditional variance (Bera & Higgins, 1993; P. R. Hansen & Lunde, 2005).

The GARCH model with normally distributed innovations fails to adequately model the occurrences of fat-tails and leptokurtosis in return distribution and to address this issue the conditional volatility is estimated under two other probability distributions.

The estimation of conditional volatility of asset returns based on positive and negative news arrival involves estimating an asymmetric volatility models such as the threshold GARCH (TARCH), which is also referred as GJR-GARCH, and the exponential GARCH (EGARCH).

The variants of GARCH model include the Threshold GARCH, or TARCH (1, 1) model specified as

$$\sigma_t^2 = \omega + a\varepsilon_{t-1}^2 + b\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}. \qquad 4.12$$

Where, $I_{t-1} = 1\ if\, \varepsilon_{t-1} < 0;\ I_{t-1} = 0\ otherwise$, γ measures the asymmetric impact of returns on index volatility.

The variance equation of the Exponential GARCH or EGARCH model is specified as

$$\sigma_t^2 = \omega + b\log\sigma_{t-1}^2 + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + a\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \frac{2}{\pi}\right] \qquad 4.13$$

The asymmetric impact of index returns on volatility is measured by γ.

The models discussed above require the disturbance term in the conditional mean equation to follow normal distribution. However, other conditional distributions such as generalized error distribution and student's t distribution are also considered in research studies. Since asset returns very often exhibit thick-tails, the non-normal conditional densities fit the data better.

4.4 Persistence of Volatility

Most studies on persistence of volatility work on large data sets and apply algorithms for identifying breaks in the time series. This study attempts to explain the nature of volatility persistence without hypothesizing or testing the presence of structural change and therefore the data is not divided into periods as per volatility regimes. Rather the approach considered in this study is to demonstrate and discuss time-varying patterns observed in the persistence of variance of returns, and its evolution over a long-term horizon. Using an iterative estimation procedure, the GARCH (1, 1) is repeatedly estimated over the sample period and the coefficients obtained are analyzed to study the inter-temporal behavior of GARCH coefficients. This simple empirical strategy enables us to analyze the progression and consistency of parameter estimates and their influence on the stock market volatility.

4.4.1 Data and Sampling

The sample period is from 01 Jan 1997 to 31 Dec 2012 and contains 3994 observations, excluding weekends and public holidays. Data is obtained from the official website of National Stock Exchange (nseindia.com). Standard time series diagnostic tests for stationarity, normality and conditional heteroscedasticity rule out any anomaly in the return series and we find that the data suffers from conditional heteroscedasticity. The sample period includes both stock market crashes and periods of euphoria spanning over these sixteen years. The inclusion of both the sub-prime crisis and the recovery period post crisis allows analysis of the evolution and nature of conditional volatility simultaneously in bear market and bull markets. For obtaining consistent and reliable estimation results under smaller sub-samples the entire sample is divided into annual, biennial and four-year sample periods.

Since, the GARCH parameters estimates are sensitive to the sample size; examination of GARCH parameters under different sample size will be more meaningful to draw conclusion on the persistence property. In the research studies, the choice of the size of sample is arbitrary and to address this issue of arbitrariness several sample resizing is considered. The overall sample size spans over a sixteen year period and in addition to the entire sample, the samples are sub-divided into samples of four years, two years, annual, and daily.

However, in a single study, it is implausible to perform the investigation on host of statistical features of the time series data, under all sub-divisions, and therefore the descriptive statistics and statistical properties of stock market returns are discussed for only the four year sub-samples and the entire sample period. In the subsequent sections, we illustrate that the analysis of the time-series properties of stock market returns using fewer observations does not yield reliable results. Since, one of the primary motivations of this chapter is to model the persistence property of stock returns, all the sample sub-divisions are considered for arriving at the conclusion on the dynamic nature of volatility persistence.

4.5 Descriptive Statistics and Diagnostics

It is a well-known fact that the stock prices in their level form are integrated of order one (refer to Fig. 4-1). Before proceeding with time series estimation, it is essential that the data is transformed from their daily price level to returns using first-order log difference of prices. This transformation makes the data stationary and suitable for time series diagnostics and modeling. Before performing the iterative estimation using daily observations, the data is first divided into non-overlapping sub-samples of four years each to examine the descriptive statistics and stationarity of stock market returns. The comparison of GARCH coefficients obtained from these samples is made with the model estimates of the whole sixteen-year sample. Estimates of persistence in these five samples provide details on time-varying nature of persistence of volatility.

Table 4.1 contains descriptive statistics of daily return series in all samples. Since the mean of daily returns is not significantly different from zero in all samples, the conditional mean equation is specified as a process fluctuating randomly around a mean value of zero with a strong mean-reverting tendency. The value of kurtosis across all samples is higher than three suggesting fat-tailed distribution in daily return series. Jarque-Bera statistic also rejects the null hypothesis of normality in all the samples. Fig. 4-2 presents the Quantile-Quantile (Q-Q) plot of the whole period, which also confirms returns to be non-normally distributed. Skewness is negative in all the periods other than 2009-2012 which suggests that instances of negative returns in the daily return series out number positive returns. This bias in the investor’s behavior appears to be related to information arrival on account of which the market tends to overreact to bad news compared to good news. However, these observations are not significantly different from studies conducted earlier.

The maximum and minimum values of daily returns also indicate presence of high volatility in the Indian stock market. The range of extreme values in all samples is very high compared to the average daily returns, which is close to zero. In the all samples, the difference between the range, which is defined as the difference between the absolute value of maximum and minimum daily returns exceed fifteen percent.

Period	***Mean***	***Maximum***	***Minimum***	***Skewness***	***Kurtosis***	***Jarque-Bera***
1997-2000	0.0003	0.099	-0.088	-0.04	5.99	372.04
2001– 2004	0.0005	0.080	-0.131	-1.04	12.19	3723
2005-2008	0.0004	0.068	-0.130	-0.59	7.12	763.07
2009-2012	0.0007	0.163	-0.064	1.35	20.01	12274.92
1997-2012	0.0005	0.163	-0.131	-0.19	9.65	7372.16

Table 4.1 Descriptive statistics of daily returns on Nifty index

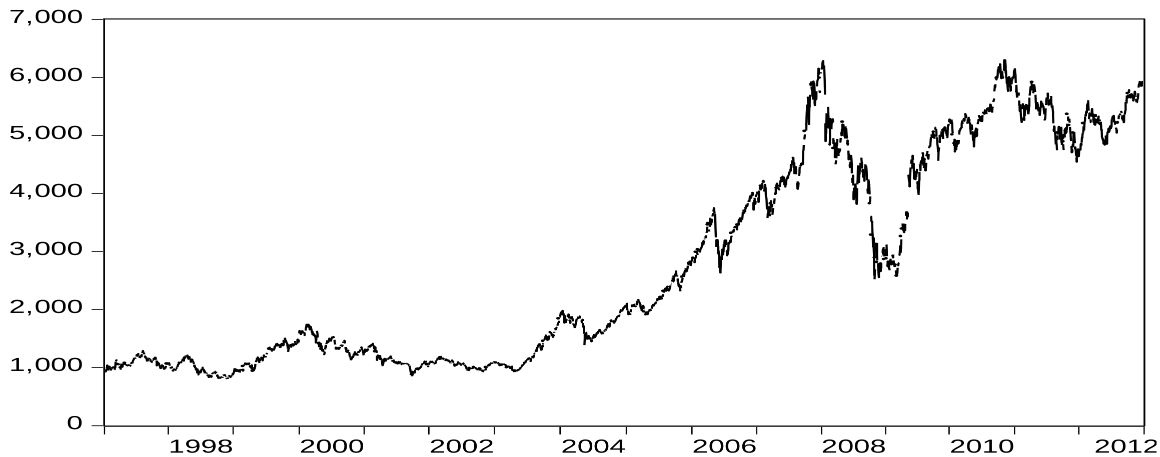


Fig. 4-1 Daily closing level of Nifty index from 1997 to 2012

The high level of volatility in the Indian stock market is also evident from the above figure. The daily closing of Nifty indicates abnormally high volatility overlapping with the sub-prime crisis of year 2008 and the bursting of the dotcom bubble in year 2000.

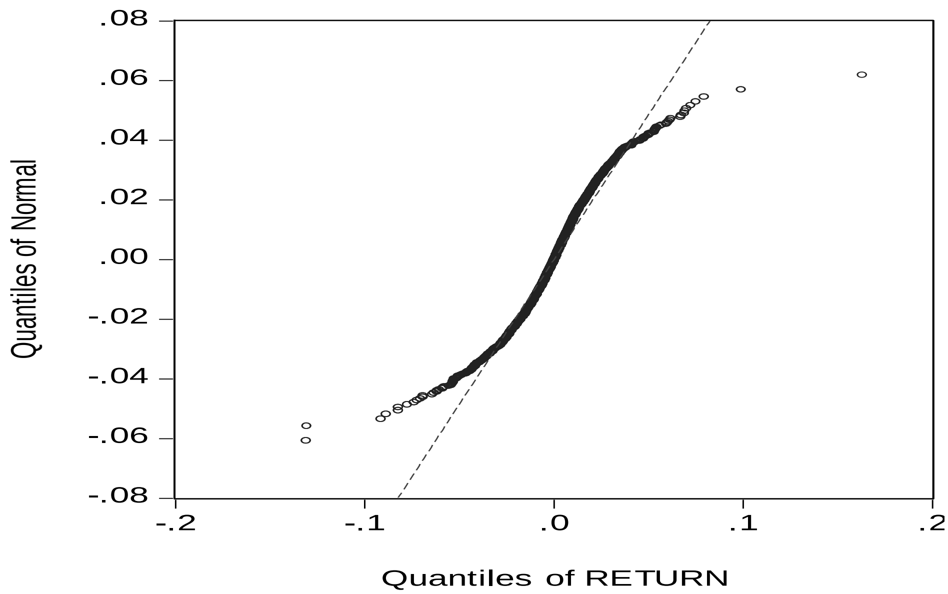


Fig. 4-2 Q-Q plot of daily returns on Nifty from 1997 to 2012

The plot of daily returns (Fig. 4-3) suggests two useful statistical aspects. First, the presence of volatility clustering in the daily return series is evident. In financial time series data analysis, a frequent observation is that periods of high and low volatility tend to cluster together and separate from each other (Mandelbrot, 1963). This phenomenon is known as volatility clustering. Second aspect is the random fluctuations of daily returns around the mean level of zero. These two properties allow us to model the conditional return as a mean reverting process and motivate us to test for the presence of ARCH effects in the daily return series.

The Augmented Dickey-Fuller test and Phillips-Perron test strongly reject the presence of unit root in the return series in all samples. The ARCH test for the presence of conditional heteroscedasticity confirms inter-temporal variation in the squared returns.

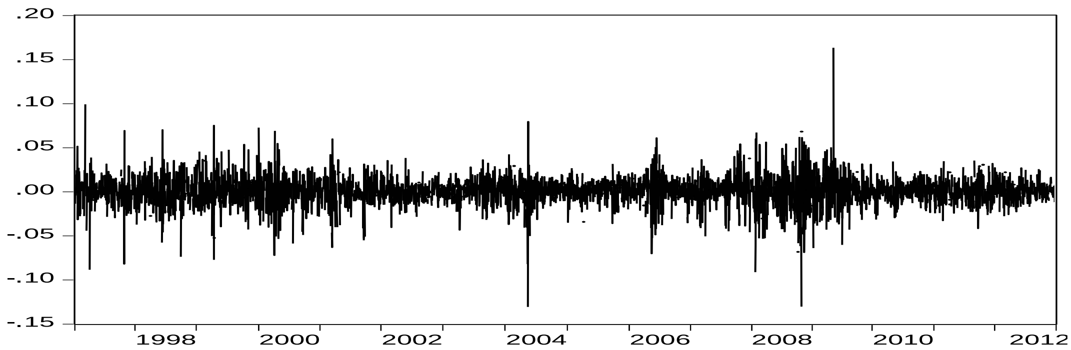


Fig. 4-3 Nifty daily returns from 1997 to 2012

To test the presence of ARCH effects the conditional mean equation is modelled as a pure white noise process and as an auto-regressive process of order one i.e. AR (1). The ARCH-LM (Lagrange Multiplier) test performed on all conditional mean equations rejects the null hypothesis of no ARCH effects at 5% significance in all samples. Thus, heteroscedasticity in the mean equation suggests modeling the return and its variance as a GARCH process for obtaining estimates of the asset's risk and return.

In the following analysis only the estimation output from GARCH (1, 1) model is discussed. Conditional volatility graph (Fig. 4-1) modelled by GARCH (1, 1) shows presence of volatility clustering in return innovations. ARCH models champion in capturing this statistical property and that enhances precision in forecasting volatility. Descriptive statistics on residuals obtained by fitting GARCH (1, 1) on the entire sample is given in Fig. 4-5. The residuals are non-normally distributed and excess kurtosis in residuals is evident. The standard deviation of residuals is high, considering mean reverting process in conditional mean specification. Tests of conditional heteroscedasticity rule out presence of ARCH effects in all the estimations.

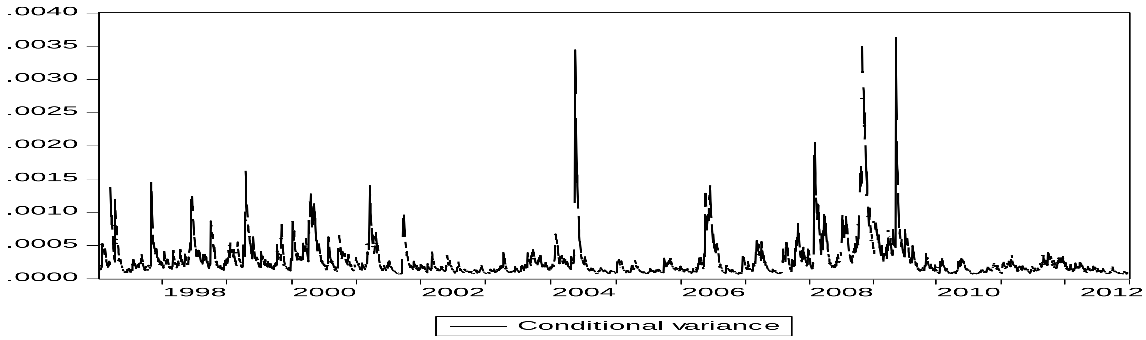


Fig. 4-4 GARCH conditional volatility Nifty from 1997 to 2012

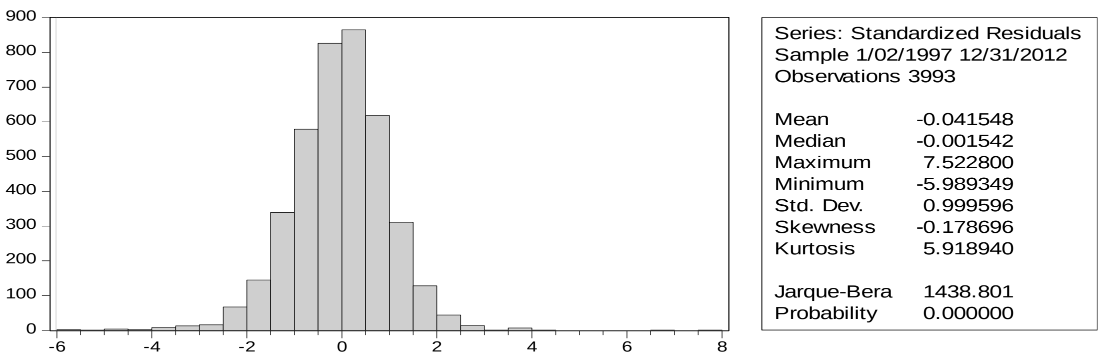


Fig. 4-5 Descriptive statistics of GARCH (1, 1) errors from 1997 to 2012

Maximum Likelihood estimates of GARCH (1, 1) for all sample periods assuming normal distribution, student-*t* distribution and generalized error distribution are given in Table 4.2, Table 4.3, and Table 4.4 respectively. Volatility persistence is high and very close to one, in all samples. Estimates across all the three distributions are not significantly different from each other. However, under all distributional assumptions the coefficients vary across samples, indicating time varying nature of volatility.

Period	Constant	ARCH Term	GARCH Term	Persistence	Count	Unconditional Variance
1997-2000	0.00005	0.0823	0.7854	0.8677	997	0.00035
2001-2004	0.00001	0.1821	0.7496	0.9317	1,007	0.00020
2005-2008	0.00001	0.156	0.8219	0.9779	996	0.00040
2009-2012	0.00000	0.0515	0.9426	0.9941	993	0.00016
1997-2012	0.00001	0.1225	0.8624	0.9849	3,993	0.00040

Table 4.2 Comparison of GARCH (1,1) estimates (normal distribution)

Period	Constant	ARCH Term	GARCH Term	Persistence	Count	Unconditional Variance
1997-2000	0.00004	0.0975	0.7974	0.8949	997	0.00035
2001-2004	0.00001	0.1608	0.7762	0.937	1,007	0.00020
2005-2008	0.00001	0.1565	0.8342	0.9907	996	0.00068
2009-2012	0.00000	0.0445	0.9433	0.9878	993	0.00013
1997-2012	0.00001	0.1142	0.8663	0.9805	3,993	0.00032

Table 4.3 Comparison of GARCH (1,1) estimates (student's-t distribution)

Period	Constant	ARCH Term	GARCH Term	Persistence	Count	Unconditional Variance
1997-2000	0.00004	0.0873	0.7983	0.8856	997	0.00034
2001-2004	0.00001	0.1705	0.7621	0.9326	1,007	0.00020
2005-2008	0.00001	0.1537	0.8292	0.9829	996	0.00044
2009-2012	0.00000	0.0489	0.942	0.9909	993	0.00015
1997-2012	0.00001	0.1159	0.8655	0.9814	3,993	0.00033

Table 4.4 Comparison of GARCH (1, 1) estimates (generalized error distribution)

As compared to other samples, in the sample periods 2001 to 2004 and 1997 to 2000, we observe low (but statistically significant) values of GARCH coefficients, indicating smaller impact of past conditional volatility on current period volatility in these periods. The GARCH parameters are not sensitive to choice of probability distribution, and under various distributional assumptions the coefficient estimates of GARCH (1, 1) are similar. All further estimations for modeling the persistence property are done considering normal distribution in residuals.

4.6 Examination of the Persistence Property

This section contains detailed analysis on the behavior of the GARCH parameters obtained by iteratively estimating GARCH (1, 1). The results enable us to draw inferences regarding time varying nature of volatility and its persistence. As discussed above, persistence in conditional volatility is measured as the sum of the coefficients of ARCH and GARCH terms. For the model to successfully capture conditional volatility the persistence must be significantly greater than zero. Stability conditions require the value of persistence to be less than or equal to one, else the volatility process is explosive and non-stationary.

Table 4.5 presents the cumulative persistence of volatility that is obtained by fitting GARCH (1, 1) on daily returns. GARCH (1, 1) is first estimated on daily returns for the first year and the process is then repeated by sequentially adding subsequent years' data while retaining existing observations. This process gradually incorporates new information on asset returns and enables in detecting changes in conditional volatility when modelled as a function of information set. This procedure provides useful insights because stock returns vary across time and hence the conditional volatility estimate displays dynamic behavior. As discussed above, the conditional variance in GARCH (1, 1) is modelled as function of lagged squared residual of the conditional mean and the past period estimate of conditional variance, the latter is called GARCH effect. Higher GARCH effects generally lead to higher persistence in the conditional volatility and are of practical interest. Results indicate that as estimation window inflates, the value of persistence becomes larger and subsequently stabilizes. The maximum value of persistence is for the sample period 1997 to 2012. This shows that the persistence of GARCH coefficients is sensitive to number of observations and persistence in conditional volatility gradually stabilizes, as more observations are included in estimation. For the year 1997, the value of persistence is mere 0.027, which is alarmingly low. Lower value of persistence may be due to unusually low stock market volatility throughout the year or due to absence of volatility clustering. Refer to Fig. 4-6 on daily stock market returns pattern for the year 1997. It is evident that for a substantial number of trading sessions throughout the year, the variation in returns is low which might be a cause behind low values of GARCH parameters.

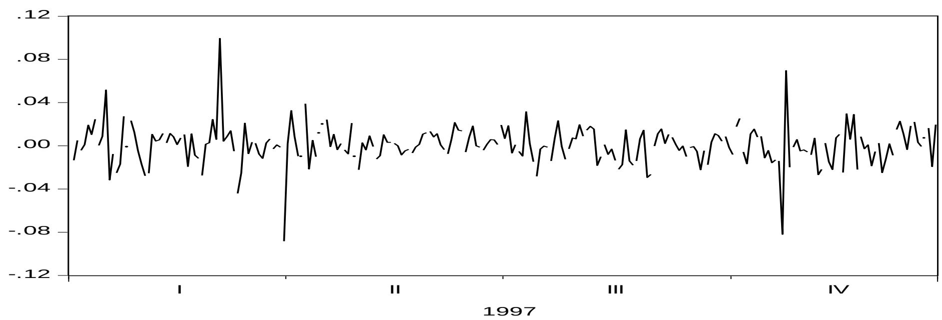


Fig. 4-6 Daily returns on Nifty for the year 1997

On the other extreme is the year 2009, where persistence is very close to 1 and Fig. 4-7 illustrates that the daily returns throughout the year fluctuate widely and the clustering is more prominent, which contributes to increase in the conditional volatility.

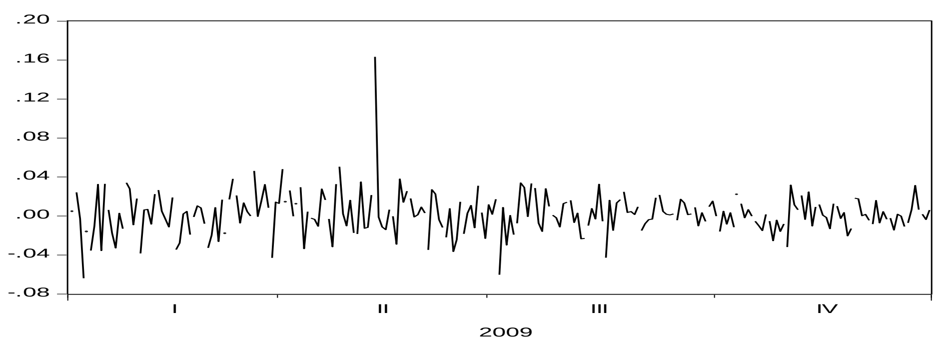


Fig. 4-7 Daily returns on Nifty for the year 2009

Much of the persistence is explained by the GARCH coefficient. Table 4.6 and Table 4.7 present the estimation output of annual and biennial persistence respectively. The results indicate presence of high persistence, and the persistence has a tendency to increase, as more observations are included in the estimation. The behavior of GARCH coefficients during 2008 sub-prime crisis is consistent with other periods, which ensures reliability of performance of GARCH model even in periods of high volatility.

Period	**Constant**	**ARCH Term**	**GARCH Term**	**Persistence**	**Observ-ations**	**Unconditional Variance**
1997	0.00025	0.081	0.126	0.207	243	0.00031
1997-1998	0.00008	0.075	0.677	0.752	493	0.00032
1997-1999	0.00007	0.085	0.697	0.782	747	0.00032
1997-2000	0.00005	0.082	0.785	0.868	997	0.00035
1997-2001	0.00003	0.110	0.791	0.901	1245	0.00034
1997-2002	0.00002	0.112	0.841	0.953	1496	0.00033
1997-2003	0.00001	0.111	0.852	0.964	1750	0.00031
1997-2004	0.00001	0.132	0.837	0.969	2004	0.00035
1997-2005	0.00001	0.127	0.842	0.969	2255	0.00032
1997-2006	0.00001	0.135	0.835	0.970	2505	0.00032
1997-2007	0.00001	0.130	0.838	0.968	2754	0.00031
1997-2008	0.00001	0.141	0.834	0.974	3000	0.00038
1997-2009	0.00001	0.135	0.847	0.982	3243	0.00046
1997-2010	0.00001	0.135	0.850	0.984	3495	0.00046
1997-2011	0.00001	0.128	0.855	0.983	3742	0.00041
1997-2012	0.00001	0.123	0.862	0.985	3993	0.00040

Table 4.5 Cumulative time varying persistence (1997 to 2012)

Persistence is also high in the periods of recovery post-financial crisis indicating consistent performance of symmetric GARCH (1, 1) across all sub-sample periods. Next section investigates evolution of volatility persistence by adopting a dynamic updating strategy by incorporating news arrival on a daily basis.

Period	Constant	ARCH Term	GARCH Term	Persistence	Observ-ations	Unconditional Variance
1997	0.00025	0.081	0.126	0.207	243	0.00031
1998	0.00005	0.104	0.745	0.848	250	0.0003
1999	0.00006	0.107	0.725	0.832	254	0.0003
2000	0.00005	0.121	0.743	0.864	250	0.0004
2001	0.00003	0.360	0.542	0.902	248	0.0003
2002	0.00003	0.091	0.614	0.705	251	0.0001
2003	0.00001	0.064	0.892	0.957	254	0.0002
2004	0.00001	0.214	0.781	0.995	254	0.0012
2005	0.00001	0.047	0.859	0.905	251	0.0001
2006	0.00002	0.259	0.682	0.940	250	0.0003
2007	0.00001	0.089	0.868	0.957	249	0.0003
2008	0.00004	0.186	0.781	0.967	246	0.0011
2009	0.00000	0.066	0.933	0.999	243	0.0015
2010	0.00001	0.117	0.804	0.921	252	0.0001
2011	0.00001	0.032	0.936	0.968	247	0.0002
2012	0.00000	-0.035	1.025	0.989	251	0.0000

Table 4.6 Modeling persistence of annual GARCH (1, 1) parameters

Period	Constant	ARCH Term	GARCH Term	Persistence	Observ-ations	Unconditional Variance
1997-1998	0.00025	0.081	0.126	0.207	243	0.00031
1998-1999	0.00005	0.104	0.745	0.848	250	0.0003
1999-2000	0.00006	0.107	0.725	0.832	254	0.0003
2000-2001	0.00005	0.121	0.743	0.864	250	0.0004
2001-2002	0.00003	0.360	0.542	0.902	248	0.0003
2002-2003	0.00003	0.091	0.614	0.705	251	0.0001
2003-2004	0.00001	0.064	0.892	0.957	254	0.0002
2004-2005	0.00001	0.214	0.781	0.995	254	0.0012
2005-2006	0.00001	0.047	0.859	0.905	251	0.0001
2006-2007	0.00002	0.259	0.682	0.940	250	0.0003
2007-2008	0.00001	0.089	0.868	0.957	249	0.0003
2008-2009	0.00004	0.186	0.781	0.967	246	0.0011
2009-2010	0.00000	0.066	0.933	0.999	243	0.0015
2010-2011	0.00001	0.117	0.804	0.921	252	0.0001
2011-2012	0.00001	0.032	0.936	0.968	247	0.0002

Table 4.7 Persistence of biennial GARCH estimates

For modeling the persistence of volatility we use GARCH (1, 1) model to estimate daily persistence to identify the minimum number of observations that are required for fitting a GARCH model. Iterative estimations by updating subsequent information enable us to check dynamic behavior of GARCH parameters as one-step ahead information is updated. From 01 January 1997 to 31 December 2012, a total of 3990 regressions are estimated using an iterative procedure in which the subsequent day's returns are continuously updated to obtain estimates of conditional volatility on daily basis. The procedure is repeated until all the observations in the sample period are incorporated. Fig. 4-8 contains the graph of time varying persistence. Comparison between the constant term and the unconditional volatility is shown in Fig. 4-9. Long-run average volatility is expected to remain stable and no significant departure from long-run mean is observed, except for minor increase in period 2009-2010 and 2011-2012. These two periods are particularly important to our analysis. Post sub-prime crisis Indian stock market witnessed a dramatic recovery in the year 2009 and 2010 and investors became more cautious in subsequent years, halting the euphoria in year 2011-2012 due to global factors such as concerns regarding European economy.

The reason for this unexpected increase in unconditional volatility is particularly because of high persistence in both sample periods. This provides an explanation behind reasons for preferring models of symmetric volatility to asymmetric ones, since uniform increase in GARCH coefficients during stock market crash as well as periods of bull-run is noticeable.

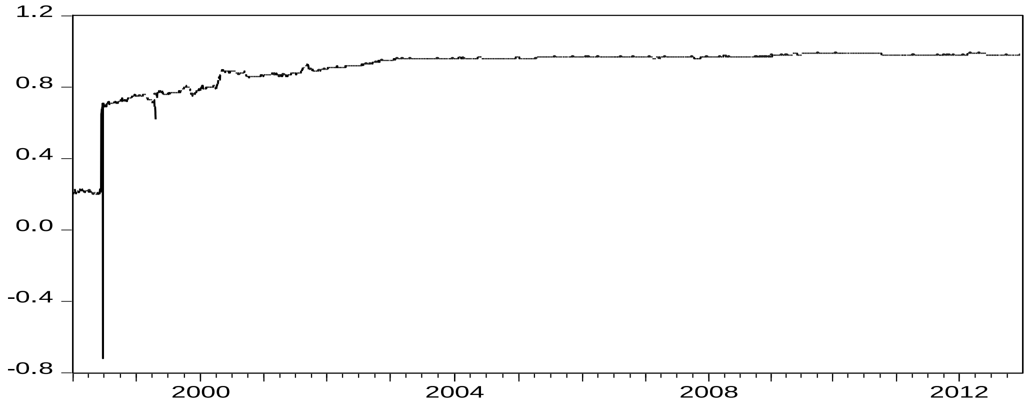


Fig. 4-8 Plot of time varying persistence from 1997 to 2012

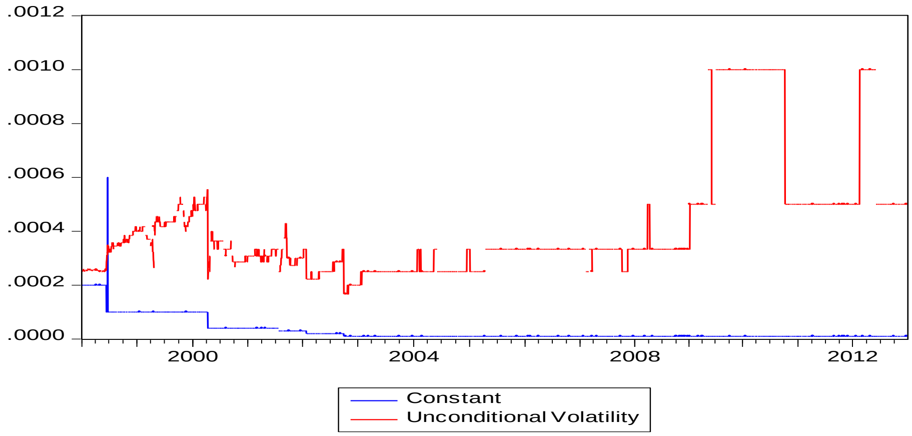


Fig. 4-9 Plot of time varying unconditional volatility and constant from 1997 to 2012

However, a thorough comparative analysis between symmetric and asymmetric models to reach such a conclusion is more desirable and is left for future research. Fig. 4-10 shows a strong positive relation between persistence and GARCH coefficients and they consistently move together as estimation window expands.

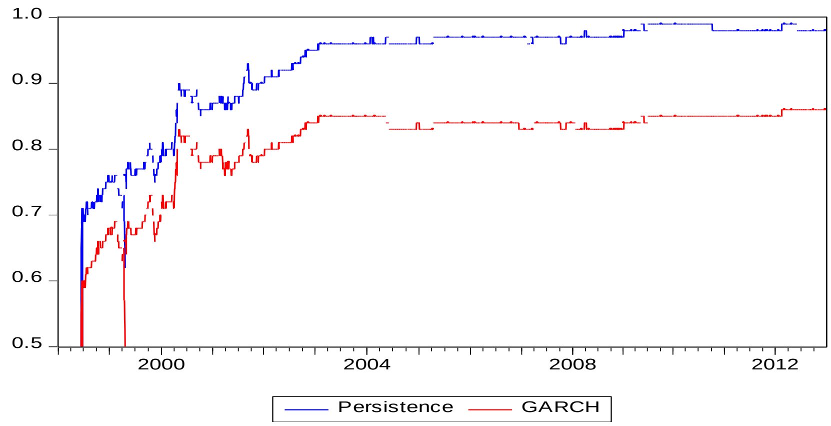


Fig. 4-10 Plot of time-varying persistence and GARCH coefficient from 1997 to 2012

The GARCH coefficients are non-stationary and fluctuate widely for smaller estimation windows. Fig. 4-11 describes plots of ARCH and GARCH coefficients and the daily estimates of GARCH parameters are volatile and frequently violate stationarity conditions for almost first 300 observations. However, the persistence value stabilizes over time and gradually approaches unity, as more observations are included in the estimation. GARCH coefficients are consistently higher than ARCH coefficients; hence its usefulness in forecasting time-varying volatility, over ARCH models is noteworthy.

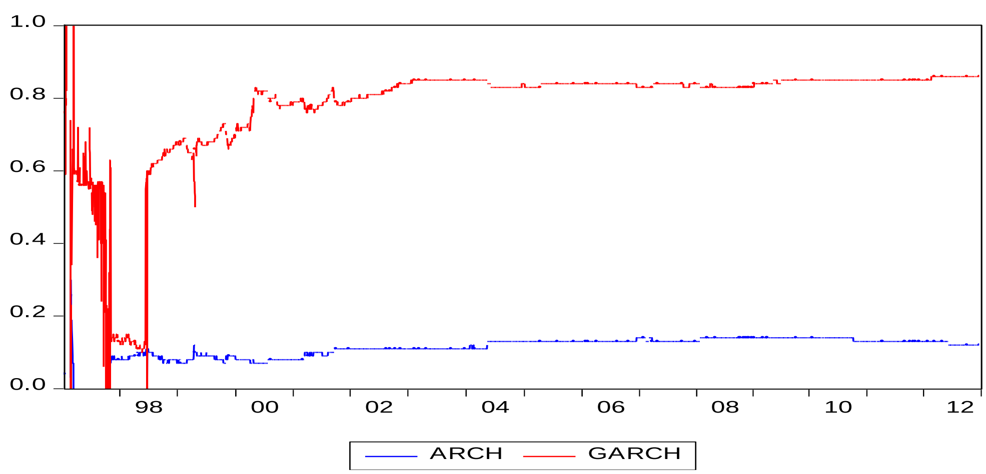


Fig. 4-11 Time varying ARCH and GARCH coefficients from 1997 to 2012

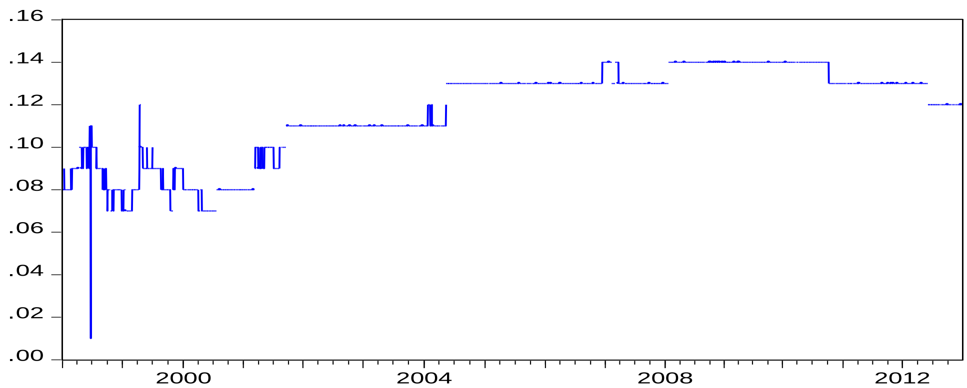


Fig. 4-12 Time varying pattern of the ARCH term from 1997 to 2012

The analysis of the persistence property suggests that the conditional volatility in the Indian stock market is highly persistent which suggests that any significant news arrival impacts the future volatility for several periods. The result of evolution of GARCH estimates indicate that in the context of the Indian stock market the stock returns do not usually suffer from any anomaly and therefore we can proceed with the comparative analysis of symmetric and asymmetric GARCH models using data from Indian stock exchanges.

4.7 Asymmetry in Conditional Volatility

As discussed above, the asymmetry property implies that the conditional volatility is sensitive to the sign of new arrival in the preceding period. If the conditional volatility is asymmetric in nature then the market volatility is more sensitive to negative news as compared to positive news. This phenomenon is popularly known as the leverage effect which claims that as the market value of a firm falls its debt to equity ratio increases resulting in an increase in the risk premium demanded by the investors. The higher risk premium causes the stock price to decline subsequently.

The daily closing prices of the BSE Sensex from 03 Jan 1985 to 31 Dec 2014 is considered for the analysis. BSE Sensex is a free-float market capitalization index of a fully diversified portfolio containing 30 largest stocks, by market capitalization, listed on Bombay Stock Exchange. It is a benchmark index referred to analyze performance of stocks trading on Indian stock exchanges. To analyze the time-varying patterns in volatility we divide data into samples of five years each and perform econometric analysis on all the six sub-samples and the overall sample period. This division of data into sub-samples permits modeling and analysis of time series properties and estimates of conditional volatility for different time-periods that includes phases of stock market rise and decline. The sample period includes several important global and domestic events like the recent sub-prime crisis, the dot-com bubble, Russian government's debt default, and liberalization of Indian economy etc. The data source on daily closing values of BSE Sensex is www.tradingeconomics.com.

4.8 Descriptive Statistics

Research (Brooks, 2008) suggests that macroeconomic variables in their level form contain unit root which paralyses inferential statistics adopting standard time series approaches and therefore testing the unit root hypothesis in the series is of paramount importance. Stock prices in their level form are non-stationary as these asset prices tend to move in trends.

Fig. 4-13 plots the log price series for the entire sample and it shows an upward trend in the series spanning over sample period. First difference of log prices, defined as $r_t = \ln(P_t/P_{t-1})$, usually converts the series to stationary.

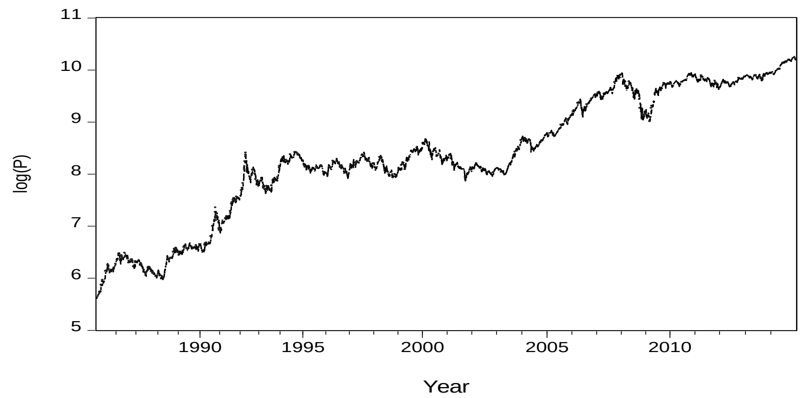


Fig. 4-13 Sensex daily closing from 1985 to 2014

The graph of daily returns r_t (Fig. 4-14) fluctuates around a long-term average value and displays tendency to frequently revert to this average. Interestingly, the long-term arithmetic mean of daily returns is very close to zero. There is no evidence of trend in this series, which suggests stock prices in their level form might be integrated of order one, i.e. I (1).

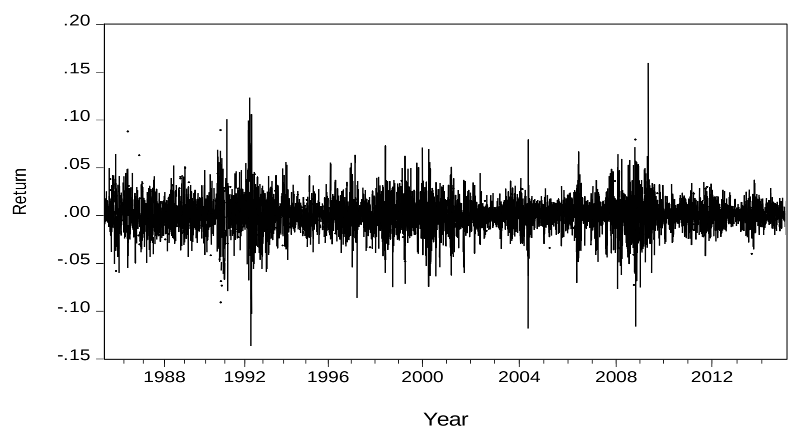


Fig. 4-14 Sensex daily returns from 1985 to 2014

Formal tests of stationarity echoes the above observation and rejects presence of unit root in the return series. To account for impact of a single large break in the return series on its stationarity the Break Point test suggested by Perron (1989) is also performed. Studies on relationship between a structural change and the stationarity of macroeconomic variable suggest testing for unit root in presence of a highly persistent single large break (B. E. Hansen, 2001;

Perron, 2006). All tests deny the possibility of non-zero drift in return series by strongly rejecting the null hypothesis of unit root in the series Table 4.8.

Sample	ADF test-statistic	*p-value*	PP test-statistic	*p-value*	Unit root with break	*p-value*
1985-89	-27.92	0.0000	-27.69	0.0000	-7.79	<0.01
1990-94	-29.10	0.0000	-29.12	0.0000	-6.76	<0.01
1995-99	-31.83	0.0000	-31.85	0.0000	-10.77	<0.01
2000-04	-33.28	0.0000	-32.24	0.0000	-7.54	<0.01
2005-09	-32.51	0.0000	-32.47	0.0000	-8.38	<0.01
2010-14	-33.84	0.0000	-33.84	0.0000	-8.81	<0.01
1985-2014	-76.59	0.0001	-76.68	0.0001	-14.83	<0.01
Note: To test stationarity, the Augmented Dickey Fuller (ADF), Ng-Perron, and unit root with break tests are conducted on daily return series. Test statistics for the null hypothesis of unit root and corresponding p-values are given.						

Table 4.8 Stationarity tests of Sensex daily returns

Table 4.9 provides summary statistics on Sensex daily returns for all samples. The log-differenced series fluctuates around a mean value close to zero.[18] In all samples, the value of kurtosis is in excess of three and returns distribution exhibit fat-tails and peaks, centered at mean, higher than the normal distribution. The Jarque-Bera statistic significantly rejects the null hypothesis of normality in daily returns. The presence of fat-tails is also a property of a non-normal distribution and the value of kurtosis, which is significantly greater than three, also confirm the non-normality in daily returns.

[18] Test statistic to test the null hypothesis of zero mean against a two-sided alternative is rejected in all sample periods. However, overall sample mean is .00065, which is not large for constructing successful trading rules.

Statistic	1985-89	1990-94	1995-99	2000-04	2005-09	2010-14	1985-2014
Standard Deviation	0.0169	0.0228	0.0165	0.016	0.0196	0.0103	0.0172
Average	0.001	0.0016	0.0002	0.0002	0.0008	0.0004	0.0007
Maximum	0.0874	0.1234	0.0731	0.0793	0.1599	0.0370	0.1599
Minimum	-0.0600	-0.1366	-0.0862	-0.1181	-0.1160	-0.0421	-0.1366
Range	0.1474	0.26	0.1594	0.1974	0.2759	0.0792	0.2965
Skewness	0.24	-0.03	0.05	-0.7	0.07	-0.01	-0.02
Kurtosis	4.32	7.342	5.07	7.53	8.811	3.97	8.292
No. of Obs.	1048	1037	1206	1256	1238	1277	7062
Jarque-Bera (J-B) stat ***p-values in brackets***	86 (*0.0000*)	815 (*0.0000*)	217 (*0.0000*)	1178 (*0.0000*)	1744 (*0.0000*)	51 (*0.0000*)	8248 (*0.0000*)
Note: Average returns are calculated by taking arithmetic mean of continuously compounded daily returns.							

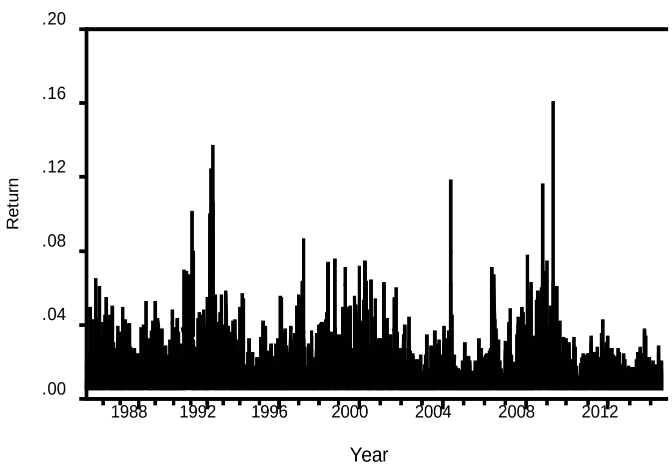
Table 4.9 Descriptive statistics of daily Sensex returns

Interpretation of standard deviation as a risk of random variable is only meaningful, if the random variable is distributed under a known probability distribution (Poon & Granger, 2003); in this study, the assumption of normality is considered. Across sample periods, the daily standard deviation of returns varies from 1.03% to 2.28% suggesting wide inter-sample variation in returns from one period to another. The wide variation increases the likelihood of errors being heteroscedastic when returns are modeled as function of exogenous variables. Large variation in standard deviation between samples leaves us questioning whether sample standard deviation influences its conditional volatility. If standard deviation is a measure of volatility then the conditional variance estimates of GARCH models must also be large in those sub-samples.

Sample skewness in stock returns is negative in overall sample that partially suggests larger impact of negative news on actions of investors. However, the sign of skewness of returns alternates in consecutive samples. Similar findings on sample kurtosis and skewness are documented by Hagerman (1978) and Kim and Kon (1994). Average daily returns are very close to zero, which allows us to model the conditional mean equation as a function of long-term average. The absolute range of index returns is as much as 29.65% in one sample, which is extremely high considering the returns are sampled on daily frequency. However, like standard deviation, the range of daily returns also varies from a minimum of 14.74% to 29.65%. Standard deviation and range of returns are not same in all sample periods and rather vary widely. These empirical facts are indication of time varying volatility in Sensex daily returns.

4.9 Analysis of Daily Return Series

The daily return series contains phases of high and low volatility. The large (small) returns tend to follow large (small) returns of either sign, first documented in (Mandelbrot, 1963). This is a strong indication of serial correlations in daily returns. Fig. 4-15 shows plots of squared and absolute daily returns and similar to daily returns the graph on absolute and squared returns shows that daily index return series exhibits alternating episodes of high volatility followed by low volatility. These phases, however, appear as realizations of a random process.



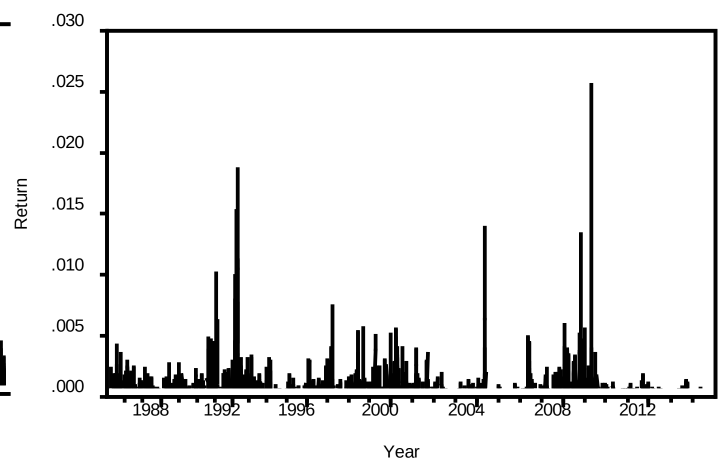


Fig. 4-15 Sensex squared and absolute returns from 1985 to 2014

Table 4.10 contains the auto-correlations in daily, absolute and squared returns for up to ten lags and these correlation coefficients reveal the dependence structure in daily returns. The auto-correlations in daily index returns indicate dependence at lag one. However, the correlation estimate is very small in magnitude as opposed to the auto-correlation coefficients of absolute returns and squared returns, which are highly significant up to more than ten lags and much larger in comparison to auto-correlations of daily returns. Engle (2004) mentions that high correlation in daily returns indicates predictability in returns, whereas, high correlation in squared or absolute returns suggest presence of higher order dependence. Our findings provide evidence from Indian stock market that degree of predictability is negligible in daily returns. From these empirical findings, the higher order dependence in returns is very likely, which challenges the assumption of independence in returns.

Lags	**Daily Returns***	**Absolute Returns**	**Squared Returns**
1	0.093	0.261	0.245
2	(0.026)*	0.230	0.169
3	0.002*	0.241	0.215
4	(0.001)*	0.234	0.208
5	(0.017)*	0.225	0.160
6	(0.023)*	0.215	0.167
7	0.007*	0.212	0.183
8	0.040*	0.182	0.126
9	0.024*	0.185	0.148
10	0.017*	0.211	0.180
***Note: Negative numbers are given within parentheses*[19]. * indicates significance at 5% level.			

Table 4.10 Lung Box Q statistics

An important implication of this result immediately follows – rejection of the weak-form random walk hypothesis. Random walk hypothesis in its weak form assumes the underlying return-generating dynamics as a pure-martingale process. It contends that past information about prices cannot be exploited for generating abnormal profits and rejects presence of statistical

[19] The first-lag correlation is statistically significant and much larger than correlation at higher lags. Analysis of descriptive statistics indicates that daily returns are non-Gaussian and therefore the statistical significance of auto-correlation coefficients will likely further reduce (Akgiray, 1989).

dependence in returns. The Wald-Wolfowitz runs test on the entire sample period to test the null hypothesis of randomness in returns. It is a simple non-parametric test performed on a two-valued data sequence and is a suitable approach here because of non-normal distribution of returns. The number of runs in the series is significantly higher than expected and the corresponding value of Z-statistic rejects the null hypothesis of independence in returns (Table 4.11).

Number of runs	**3222**
p-value	.0000
Z-score	7.73

Table 4.11 Wolf-Wolfowitz test on Sensex returns

These evidences concerning statistical properties allow us to proceed with modeling second moments of daily return series by employing several models of conditional heteroscedasticity.

4.9.1 Analysis of Results

Coefficient estimates and their statistical significance describe the symmetric and asymmetric nature of volatility in different sample periods. For the entire period, the daily returns modelled as an AR (1) process gives superior results in both symmetric and asymmetric variance models. The conditional mean coefficients of GARCH-M approach are insignificant in majority of models compared to the GARCH and AR-GARCH specification. Results of our study confirm that AR (1) specification for conditional mean is a better approximation than GARCH-M model. In comparing all estimations, no single model outperforms the other as per information criteria, and the findings suggest that estimates of conditional mean and the conditional variance improve in the asymmetric EGARCH and TARCH models than the symmetric GARCH model. In the evaluation of variance, all GARCH coefficients are statistically significant and large in magnitude, which explains high influence of past volatility on future volatility. All coefficients of asymmetric volatility, in EGARCH and TARCH models, are also statistically significant. Our results suggest that modeling daily returns using past conditional volatility gives poor results. Hence, GARCH-M models are not suitable for modeling return volatility of Indian stock markets. This result is consistent with the results reported in Karmakar (2007).

The sample specific performance of models and selection of best models according to the AIC (Akaike Information Criteria) and SIC (Schwarz Information Criteria) criteria are given in Table 4.12. We look independently at both AIC and SIC values and the model having minimum information criteria values are considered superior. It is possible that more than one model qualify considering AIC and SIC criteria and in such cases the models with both minimum AIC and SIC values simultaneously get preference over others. In all sample periods only the AR (1) specification for the conditional mean appears as a desirable choice, with an exception of 2010-2014 sample period. Both the symmetric and asymmetric models of volatility perform well in estimating conditional volatility. On an overall comparison among all model the estimation results reveal that the lowest value for AIC and SIC is obtained in the sample period 2010-2014 on the asymmetric models.

This period is also important because it is considered as the recovery period post sub-prime financial crisis of 2007-2008. The volatility is highly persistent across all sample periods (i.e. in excess of 0.90), which suggests long memory of conditional volatility in influencing future volatility. In the individual samples, however, the results vary and no superior model emerges as the preferred choice. This suggests that performance of GARCH models also depend on the period chosen for analysis. For the whole sample period, six different conditional volatility specifications are chosen by AIC and SIC criteria.

Sample	AIC	SIC
1985-89	AR-GARCH(1,1)	AR-GARCH(1,1)
1990-94	AR-EGARCH(1,1)	AR-EGARCH(1,1)
1995-99	AR-GARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)	AR-GARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)
2000-04	AR-TARCH(1,1)	AR-TARCH(1,1)
2005-09	AR-EGARCH(1,1)	AR-EGARCH(1,1)
2010-14	EGARCH(1,1) TARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)	EGARCH(1,1) TARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)
1985-2014	AR-GARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)	AR-GARCH(1,1) AR-EGARCH(1,1) AR-TARCH(1,1)

Table 4.12 Model selection based on information criteria

The period 2005-2009 includes the sub-prime mortgage crisis that caused significant slowdown in the global economy. The asymmetry volatility (EGARCH) model outperforms all other specifications in this period. This suggests higher reaction of volatility to negative returns as compared to positive returns on a larger data sample. The period 1990-94 is considered as one of the landmark periods for Indian economy as several reforms on the economic front were unleashed during this period, which also includes capital market reforms. The AR-EGARCH (1, 1) model performs better than other models in this period. Similarly, another model of asymmetric volatility, TARCH (1, 1), outperforms all other models in the period 2000-04, which overlaps with the dotcom bubble and subsequent fall in stock prices. Our results indicate that, in general, models of asymmetric models are better approximations of conditional volatility than the symmetric ones. However, the preceding analysis compares volatility forecasting model by fitting daily returns data on equal sized samples without taking into consideration significant domestic and global factors. As discussed in the literature review chapter factors such as economic reforms influence volatility in the stock market and hence in the next discussions we have considered the impact of local and global factors for conditional volatility estimation.

4.10 Local, Global Factors and Inter-temporal Volatility

Through the results of the previous section, we identified that the choice of a better forecasting model depends on factors such as the sample period under consideration, conditional probability distribution, and model evaluation criteria. In this section we elaborate more on these aspects by resizing the sub-sample periods depending on key local and global events that overlapped during those periods. As mentioned in the chapter 1 and 2 of this thesis, the Indian financial system has undergone a complete overhaul following the launch of economic reforms of 1991. Empirical studies have documented both the positive and negative influence of capital market reforms and trade openness on the country's domestic stock market returns. Bekaert and Harvey (1997) and DeSantis and Imrohoroğlu (1997) provide empirical evidences highlighting fall in stock market volatility following capital market reforms, whereas Huang and Yang (2000) detect increase in unconditional volatility following liberalization. In the context of Indian markets Debasish (2008) documents no significant change in volatility of spot segment following introduction of

Nifty index futures. Most of these studies have focused on the impact of these reforms on stock market returns and very few (Varma, 2002b) have considered the impact of market reforms on the stock market volatility. Due to increased market integration over the past two decades the global triggers such as the Dotcom bubble and the recent financial crisis of 2008 also play a significant role in influencing the volatility of India's stock market.

The choice of a superior volatility forecasting model is sensitive to aspects such as the forecast horizon and sampling frequency. Also as mentioned in Brownlees *et al.* (2011) fitting a GARCH model on a very large dataset may give unreliable results because of loss of information on parameter variation and hence prefer to estimate volatility using a small sized window period. Poon and Granger (2003) emphasize on the utility of out-of-sample forecasting over in-sample forecasting and recommend model selection based on loss functions used for evaluating out-of-sample forecasting accuracy.

To identify the model that best fits the Indian stock market volatility all the above mentioned aspect are taken into consideration and models are ranked based on the performance of the loss function statistic. Two loss functions namely root mean squared error (RMSE) and mean absolute error (MAE) are considered.

In few cases the window of sample size was straightforward to determine such as sub-prime crisis, the bull phase of 2003-2007 and bursting of the dotcom bubble. As discussed above, due to excessive market movement between the years 1990 to 1993 the sample period is excluded from this study as it may distort the conclusions due to its idiosyncratic factors and may mislead into wrong model selection. Taking evidences from stock market reforms and instances of global events coinciding with the domestic factors the entire sample is resized.

The sub-sample used for re-estimating the GARCH models are as follow:

Sub-sample 1: 1994 - 1997

Sub-sample 2: 1998 - 2002

Sub-sample 3: 2003 - 2007 (June)

Sub-sample 4: 2007 (July) - 2009

Sub-sample 5: 2010 - 2013

Entire sample period: 1994 - 2016 (May)

Literature review suggests that both the symmetric and asymmetric GARCH models have superior forecasting ability and therefore in this analysis the conditional variance is modelled using GARCH, TARCH and EGARCH models under three different probability distribution. GARCH estimates also depend on the specification of the conditional mean equation and since stock returns exhibit higher order serial correlation the ARMA specification is also considered for the mean equation. To gauge the effect of market risk on the risk premium demanded by the investors the lagged period conditional variance is also included in the mean equation. The independent variables in the conditional mean equation thus include the constant term the auto-regressive term (AR), the moving average (MA) term and the conditional variance of the previous period. The AR and MA terms up to order two are considered along with the combined auto-regressive moving average (ARMA) specification with lag order up to two for both the AR and the MA terms. This result is a total of seven different specifications of the conditional mean equation. The conditional variance equation is modelled under three alternative specifications namely GARCH (1, 1), EGARCH (1, 1), and TARCH (1, 1). As discussed above, the daily returns on stock index exhibit instances of fat-tails and therefore the probability density assumption for the error term also considers student's-t distribution and the generalized error distribution. All combinations of the conditional mean specification and conditional variance specification under three different distributional assumptions allow us to estimate one hundred and twenty six models per sample and a total of seven hundred and fifty six models across all sample periods.

For selecting the best GARCH model for the Indian market a two step strategy is followed. In step one we consider three information criteria i.e. Akaike Information Criteria (AIC), Schwartz Information Criteria (SIC) and the Hannan-Quinn (HQ) criteria. The model with the minimum value of these information criteria is considered to be the best model. However, it is possible that these information criteria give conflicting results and therefore to circumvent the subjectivity aspect, we consider all the models with a corresponding minimum value of the information criteria. Therefore, in every sample and under every distributional assumptions, if the three information criteria give minimum values to three different models, we consider all of them for further analysis.

In the second step we perform the out of sample forecasting of the selected models and use two different loss functions for comparison. The out of sample forecasting is done by constructing one-step ahead static forecasts obtained till time *t*. For every sub-sample, the out of sample window includes the following twelve month period. The forecasted conditional variance is then compared with a proxy of risk. Any reliable proxy may qualify for the comparative analysis and following the usual convention we use the squared returns as proxy of risk. Finally, the model rankings are done on the basis of the least value of the loss functions. The most desirable conditional volatility models, in each sub-sample, chosen as per the loss functions are given in Table 4.13.

The out of sample forecasting results suggest that both the symmetric and asymmetric GARCH models perform well when fitted with the Indian stock market data. The assumption of normal distribution for the GARCH errors is not adequate and the GARCH models perform better under non-normal probability distributions.

Sample period	**RMSE**	**MAE**
1994-1997	MA(1)-GARCH(1,1) Student's-t	MA(1)-EGARCH(1,1) Student's t
1998-2002	AR(1)-GARCH(1,1) Student's-t	AR(1)-GARCH(1,1) Student's-t
2003-2007(mid)	ARMA(2,2)-TARCH(1,1) Student's-t	AR(1)-EGARCH(1,1) GED
2007(mid)-2009	GARCH(1,1) Student's-t	MA(1)-GARCH(1,1) Student's-t
2010-2013	ARMA(1,1)-EGARCH(1,1) Normal	ARMA(1,1)-EGARCH(1,1) Normal
1994-2016(May)	EGARCH(1,1) Student's-t	ARMA(1,1)-GARCH(1,1) GED

Table 4.13 Model selection based on out of sample forecasting results

The GARCH-in-mean models are not ideal specification for the Indian stock market and in all the estimations their coefficients were highly insignificant. Both the first order and higher order ARMA representations give satisfactory results with highly significant coefficients. The forecasts of the Indian stock market volatility improve when the lag period auto-regressive and moving average terms are considered. This suggests that ARMA-type specification for the conditional mean corrects for higher order serial correlation in asset returns. For modeling the long-run volatility both the symmetric and asymmetric GARCH models outperform which suggests that the estimation results are sensitive to the choice of the loss function. This finding is consistent with the results reported in Brownlees *et al.* (2011).

4.11 Discussion on Results and their Implications

The study confirms high persistence of volatility in the daily return series. The fact that Indian capital markets fall under emerging markets, which are categorized as highly volatile, could be a source of these large GARCH coefficient estimates and their persistent nature. In all sub-samples under different distributional assumptions for the innovation terms, the estimates of GARCH (1, 1) indicate presence of high volatility. In some estimation periods the persistence is very close to being non-stationary i.e. equal to 1, indicating need of cautious approach while modeling stock market returns using GARCH (1, 1) as suggested in Brownlees *et al.,* (2011) that predictive ability of these models is sensitive to sampling frequency, sample period and forecast horizon. This conclusion is also consistent with the arguments of Starica (2003), where the author has raised doubts regarding fitting GARCH model on data covering longer-horizons. GARCH (1, 1) model fail to appropriately capture volatility clustering during episodes of low stock market volatility and hence their usefulness appears to be restricted to periods of high volatility only. Persistence indicates the rate of decay of a volatility shock to future periods. High persistence corresponds to a slow rate of decay of shock in the volatility process suggesting a significant influence of current volatility on future volatility. The agents may utilize this information to adjust the portfolio hedge ratios depending upon expected volatility and knowledge about clustering allows agents to adopt flexible and dynamic trading strategies suitable either for low volatility or high volatility regimes. Another implication of this study could be for traders who price long-term options using standard option pricing models. Options are priced on the basis of the volatility expected to remain over their life and therefore any clues about the degree of persistence of volatility may enable the agents to appropriately price these contingent liabilities.

Our findings are in accord with studies that claim presence of high persistence in the volatility process. The estimates of conditional volatility obtained by fitting GARCH (1, 1) are highly persistent, which provides a strong evidence for the presence of clustering in volatility. The findings, however, do not elaborate on the specific economic causes behind observed dynamic patterns of volatility persistence and it would be of value to characterize the nature of persistence in volatility as realizations of underlying economic theory.

Several alternative specifications of conditional mean and conditional variance equation allow analysis of the inter-sample performance of volatility models. In particular, the specification of conditional mean equation as an AR process suggests improvements in volatility estimates across different samples. It is surprising that the GARCH (1, 1) model fails to dominate other specifications, especially the asymmetric ones, in modeling the conditional second moments of index returns. Since this study spans over 30 years, different phases of stock market including global financial crisis, dot-com bubble, liberalization of Indian economy etc. are taken into consideration. We observe similar performance of conditional volatility models in estimating volatility during stock market rise and decline. In particular, the specification of the conditional mean influences the estimates of the variance and hence important for analyzing the asset return volatility. GARCH-M models fail to improve volatility estimates and in most cases turn out to be insignificant and the results are consistent with those reported in Baillie & DeGennaro (1990). We conclude that both the symmetric and asymmetric models of conditional volatility, with conditional mean modeled as AR (1) process, emerge as the ideal choice for model specification. However, it remains to be seen if similar results appear and whether choice of conditional mean specification plays significant role in estimating volatility for individual stocks, commodities and foreign currency.

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Chapter 5 Modeling Volatility with Macroeconomic Variables

5.1 Introduction

The last three decades following the introduction of co-integration theory (Robert F Engle & Granger, 1987; Granger, 1986; Granger & Weiss, 1983) and contributions by Sims (1980) in popularizing the vector auto-regressive (VAR) models, empiricists have relentlessly engaged in examining the dynamic influence of macroeconomic variables on stock prices. The agenda of such large body of research is primarily motivated towards unraveling the latent nature of stock return dynamics and describing the data generating process as function of economic variables. Though substantial evidence favoring the hypothesis of association exists in the finance literature, empirical studies on the causality dynamics between macroeconomic variables and stock market falls short of reaching a consensus due to conflicting evidences. An overwhelming number of studies in this area have confined themselves to developed markets, though in recent years emerging markets have also received academic spotlight.

Asset pricing theorists have advocated the usefulness of discounted cash flows approach for estimating the intrinsic value of an asset. Therefore, it seems plausible that firm's market value in a well functioning stock market with high liquidity, low impact costs and sizeable trading volumes, appropriately reflects the agent's expectations of the firm's future cash flows and the risks involved. Conventional asset pricing approach describes the value of an asset as the present value of all future cash flows. The discount rate i.e. the required rate of return explains the risk perceived by the investors. The present value model is given as:

$$P = \sum_{t=1}^{\infty} \frac{CF_t}{(1+k)^t}$$

where,

P is the price of the stock

CF_t is the cash inflow to the firm occurring at time t and

k is the required rate of return on the stock.

The above relationship states that the variables which influence cash flows of the firm and the stock's risk premium are appropriate for forecasting price movements. We demonstrate that these macroeconomic variables not only influence the return generating process of stocks but can also be used to model and forecast the volatility inherent in these assets. Understanding of asset price volatility may not reduce the uncertainties associated with such investments but may nevertheless provide effective measures to limit losses in an unforeseen event. For instance implementation of statistical risk management strategies such as Value-at-Risk and portfolio position hedging using financial options and futures etc. provide considerable reduction in portfolio exposure. Volatility refers to fluctuations in the price of an asset and this chapter analyzes this time-varying nature of volatility by exploring the long-run association between macroeconomic variables and a well diversified benchmark portfolio of Indian stocks.

Modeling the dynamic response of investor sentiments to news arrival is crucial both for long-term investment and short-lived speculative decisions and hence the factors on which the firm's future cash flows are contingent upon and the discounting rate used for arriving at the present value are considered useful for practical asset valuation. The dependence of the stock price on the rate of reinvestment and the expansion plans of the firm are inherent in the demand for capital goods as well as requirement for capital infusion to enhance existing capacity. Much of the firm's financing needs are intricately linked with its market value and thus the maximization of the stock price is consistent with the shareholder's wealth maximization principle. Therefore relevant variables both external and internal to the firm qualify as desirable candidates. These variables can be segregated depending on whether they influence the income/expense of the firm (i.e. expected profitability) or the risk of the firm i.e. the likelihood of the desirable outcome. Income side variables include cost of input factors and prices of output. The revenue of the firm also depends on the demand for its products which may be modelled as a function of real economic activity, inflationary expectations, country's gross domestic product, unemployment rate, disposable personal income, etc. Several such areas lay need for empirical investigation in the context of Indian markets. Earlier studies conducted by Ross (1976) and Fama and French (1992) looked at the aggregates of firm specific variables such as dividend yield, earnings and size of the firm etc. However, in the recent years researchers have also emphasized inclusion of macroeconomic variables in explaining aggregate stock market return and its volatility. In continuation of this spirit the central issue addressed in this chapter deals with analyzing statistical association between macroeconomic variables and a representative index of the Indian stock market.

Albeit the enormous body of research on the inherent interactions between economic variables and stock prices has unravelled interesting results, yet a practical challenge in modeling such a relationship still remains inexplicable is the problem of variable selection. Several variables qualify as potential candidates and economic theories do not provide concrete suggestions regarding the preference of one over the other (Brooks and Tsolacos 1999).

Modern portfolio theory describes the total risk of an investment as combination of two components; the idiosyncratic risk and the systematic risk. These two components of risk add up to total risk inherent in an investment. Portfolio theory also demonstrates that the idiosyncratic risk component declines non-linearly as more stocks are included in the portfolio and this component of risk can be totally eliminated in a well diversified portfolio. Hence, the only relevant risk that remains in a well-diversified portfolio is the systematic or the market risk of the portfolio and consequently the required return commensurate to that level of risk adjusts itself. The aggregate risk of a portfolio is estimated by its beta which is calculated as the linear combination of weighted betas of *all* stocks in the portfolio. The diminishing effect on the benefits of diversification restricts inclusion of securities in a portfolio beyond a certain number and therefore substituting a benchmark portfolio as a proxy for stock market has its economic significance. A benchmark representative index adequately reflects the risk-return characteristics of the domestic stock market. An empirical question that remains is concerning the factors that influence the level of the stock index.

The balance sheet of a firm provides details on capital mobilization, capital investment, and capital utilization. Variables influencing risk premium include financial leverage (debt/equity) ratio, gross non-performing assets, rate of interest, the security's risk premium (as measured by the firm's beta), the risk free rate of interest which is dominated by aggregate money supply and inflation. Several other factors like management's competence, short-term and long-term strategic decisions, competition for market share, geographical location, credit rating, size of the firm and its age are specific to a firm. However, portfolio diversification theory suggests that all these idiosyncratic factors tend to nullify each other and the only relevant risk of the portfolio is the market risk or in other words the macroeconomic risk. It is implausible to explain the entire market risk but review of literature suggests that to an extent suitable proxies of market risk such as the macroeconomic variables may be considered to identify dynamic interactions between these variables and the aggregate stock market performance. This chapter attempts to draw a structural interlink between macroeconomic variables and a benchmark stock exchange with an objective to investigate whether the GARCH models augmented with the macroeconomic variables provide a better estimate of Indian stock market volatility.

5.2 Review of Selected Studies

Numerous studies have documented the impact of macroeconomic variables on stock market returns. Most frequently occurring variables in literature are proxies for consumer price index, foreign exchange rates, money supply, interest rates, dividend yields, price-to-earnings ratios, book-to-market value ratios, industrial production, oil price, exports, business confidence index and gross domestic product. An earlier discussion on the impact of the exogenous variables on stock returns are available in Ross (1976) arbitrage pricing theory (APT) and by Fama and French (1989). These studies on individual stocks are also further extended in the context of broader stock market index (Chaudhuri & Smiles, 2004; Cheung & Ng, 1998; Gan et al., 2006; Humpe & Macmillan, 2009; Mukherjee & Naka, 1995). Since, these variables in their level form are found to be integrated of order one i.e. I (1), the usual ordinary least squares approach results in spurious regression (Stock & Watson, 2011) which also results in an estimation result having R^2 value greater than the Durbin-Watson statistic.

Gan *et al.* (2006) employed the Johansen co-integration test in the VECM and found evidence of co-integration between New Zealand stock market and seven macroeconomic variables. Other empirical studies concerning long-run association between macroeconomic variables and stock market include Patra and Poshakwale (2006) on the Athens stock exchange, Maysami and Koh (2000) carry out similar analysis in the Singaporean market with five macroeconomic variables. Gan *et al.* (2006) mention that there does not appear to be a unified theory regarding the selection of these macroeconomic variables and in most of the studies the approach is guided by researcher's perspective and analytical outcomes of his study. Other studies on emerging markets include Patra and Poshakwale (2006), Gunasekarage *et al.* (2004). Large number of studies on influence of macroeconomic variables on stock returns has focused on developed markets. Studies by Cheung and Ng (1998) for example provide useful references to studies conducted in Japanese market. Mukherjee and Naka (1995) find presence of three long-term equilibrium relationships among macroeconomic variables and stock market. It is often argued that macroeconomic variables such as inflation rate, rate of interest, and foreign exchange rates influence the movement in stock markets. Chen *et al.* (1986) provide empirical evidences favoring the above argument highlighting presence of a long-term equilibrium relationship between stock prices and macroeconomic variables such as interest rates, inflation and industrial production. Studies on crude include Park and Ratti (2008) and Sadorsky (2014) . They document significant impact of crude prices on stock returns, whereas, Nandha and Faff (2008) document negative impact. In this study we consider WTI crude as proxy for crude prices to assess its impact on the Indian stock market volatility. Maysami and Koh (2000) document positive relation between money supply innovation and stock market returns in Singapore. Mukherjee and Naka (1995) confirm positive relationship between money supply and stock returns. Humpe and Macmillan (2009) use M1 as proxy for money supply. Chen *et al.* (1986) argue that the impact of money supply on stock returns is uncertain because of its impact on the inflationary expectations and real economic activity. Kwon and Shin (1999) found positive relationship between money supply and stock returns in Korean market. Chen *et al.* (1986), Ferson and Harvey (1993), Cheung and Ng (1998) find significance of oil prices on stock market indices in international markets. Nasseh and Strauss (2000) document significant long-run relationship between stock prices, economic activity and short-term interest rates in the European markets. Humpe and Macmillan (2009) use only long-term i.e. yield on 10-year government security. Chen *et al.* (1986) and Mukherjee and Naka (1995) use interest rates as input variables for examining long-run relationships between macroeconomic variables and the stock market benchmark index. Impact of short-term interest rates are discussed in Chen *et al.* (1986), Mukherjee and Naka (1995), and Nasseh and Strauss (2000). In few studies in place of Treasury bill rates the call money rates or interbank rates are considered as proxy for risk-free interest rates. Brooks and Tsolacos (1999) define term-interest rate spreads as the yield curve measured as the difference between long-term Treasury bonds and 91-days Treasury Bill rate and similarly the term-structure variable is constructed. Chen *et al.* (1986) argue that interest rate spreads are also likely to influence stock returns and Fama and French (1989) demonstrate similar result. Chaudhuri and Smiles (2004) argue that due to lowering of interest rates investors exit their investments in debt securities and enter the stock market. This theory is also consistent with the theory of portfolio diversification. In the context of Indian markets, a closer analysis of the relationship between short-term and long-term interest rates do not reveal any forecast-able pattern and the term structure of interest rates keep switching between upward sloping and downward sloping. Fama and French (1992) considered spread between long and short rates, the term structure or the yield curve. Estrella and Hardouvelis (1991) argued that the yield curve has extra predictive power beyond that contained in the short-term interest rates but we exclude term structure variable as it alternates between positive and negative rendering log transformation impossible. In the present study, the yield on 10 year government bond is used as a proxy of interest rate. Some studies relating to consumer prices and stock market performance include Nasseh and Strauss (2000). Investment in stocks is considered as a hedge against inflation because the claims of the shareholders are tied to real assets unlike interest bearing securities. In the Indian context this finding was documented in early nineties Barua *et al.* (1994). In another study, Rao and Bhole (1990) mention that the stock market investment provides only a partial hedge against inflation. Mukherjee and Naka (1995) and Maysami and Koh (2000) perform long-run equilibrium analysis on exchange rate. Other studies on long-run relationship between stock market and macroeconomic variables in the developed as well as developing markets include Kwon and Shin (1999), Leigh (1997), Fung and Lie (1990) in Taiwan and Gjerde and Sættem (1999) Norway. Their study covers South Korea, Singapore, Taiwan and Norway respectively. Other studies in international markets include Wu and Su (1998) and Gerritis and Yuce (1999), Taylor and Tonks (1989). Arshanapalli and Doukas (1993) argue that international diversification turns into an effective portfolio hedging strategy, if foreign markets lack interdependence with the domestic market. However, studies such as Jaffe and Westerfield (1985) and Eun and Shim (1989) provide evidence of significant linkages among global stock markets; also see Maysami *et al.* (2004). Abdullah and Hayworth (1993) show that macroeconomic variables Granger cause stock market return and find that inflation positively influences the stock returns and the long-term interest rates negatively impacts the interest rates. Another study Duca (2007) involving co-integration analysis using Granger causality approach on international stock markets finds evidence supporting influence of stock market on economic activity but not vice-versa. Hasan and Javed (2009) using Granger causality and Johansen's co-integration framework find significant long-run relationship between monetary variables and prices of speculative assets in Pakistan.

Money supply may impact positively the stock returns by its positive effects on real economic activity or negatively as it pushes inflation upwards. Portfolio theory suggests flight of investors from interest bearing securities to stocks as money supply increases which lowers the interest rates (Chaudhuri & Smiles, 2004). Since variables such as dividends yield and earnings yield may be stationary at level such variables are not included in this analysis. Studies concerning impact of these variables on stock market returns are available in Fama and French (1989), Schwert (1990), Harvey *et al.* 2002. The emerging stock markets usually exhibit high volatility and this fact is confirmed by several researchers (see for example: Claessens *et al.* 1995, Bekaert and Harvey 2003). Darrat and Mukherjee (1986) studied the impact of macroeconomic variables on Indian market. Oyama (1997) studies the Zimbabwe market, Bailey and Chung (1996) study the Philippines stock market from macroeconomic variables perspective. Other studies include Patra and Poshakwale (2006) on Athens market, Leigh (1997) in Singapore market, Gunasekarage *et al.* (2004) in Srilanka, Kwon and Shin (1999) in Korea, Fung and Lie (1990) in Taiwan and Gjerde and Sættem (1999) in Norway market. Mukherjee and Naka (1995) confirmed positive relationship between depreciating domestic currency and increase in exports in Japan. They also concluded that stock returns respond negatively to changes in interest rate and inflation but positively to economic activity.

5.3 Data and Sampling

As evident from the review of literature, there is no consistent economic theory that directs the selection of the variables for modeling the long-run relationship between the stock index and economic variates. The time period chosen for this study begins from April 1994. There are three reasons for choosing April 1994 as the sample starting period. First reason is that early years of the 1990 decade was marked by several stock market scams and structural weakness in the Indian economy. Therefore including such time period may include potential structural changes that followed the launch of economic reforms. Also as discussed in the literature, this period was characterized with an abnormal level of volatility and contained wild swings in the stock market that are not clearly attributable to either domestic factors or any global phenomena. Second, a large number of landmark economic and financial market reforms were launched during 1991-1993. As discussed above, many researchers make a curious observation that volatility in the financial markets tend to increase following economic liberalization and in the context of the Indian stock market a marked increase in the volatility during 1990-1993 is evident. The third reason was the availability of the data on macroeconomic variables. Considering the above factors and along with the review of literature, the variables that were chosen for investigating the presence of long-run equilibrium relationship using a system based regression framework were the benchmark BSE Sensitive Index (Sensex), 10 Yr GOI bond yield (Long), consumer price index (CPI), West Texas Intermediate (WTI) as proxy for crude prices (Crude), broad money supply (M3), nominal effective exchange rate (NEER), and exports.

The data on macroeconomic variables and stock index are sampled at monthly frequency. The entire sample period begins from April 1994 and ends at Apr 2014, containing a total of 241 observations. Data window period from May 2014 to Apr 2016 is kept separate for the purpose of out of sample forecasting. A monthly sampled series is constructed using the end-of-month values for the variables. The monthly time-series values are log-transformed by taking their natural logarithms. A useful implication of log-transformation is that the first difference of the log-transformed series gives the continuously compounded monthly returns of the variables which later aids in the interpretation of performance of these variables on a monthly basis. Since the monthly interest rates yield is already in the percentage form the first difference of the series provides monthly variation in the long-term interest rates.

The data for these variables are obtained from www.tradingeconomics.com. Studies on co-integration in time series do not advocate data smoothing such as de-trending of the time series however while dealing with monthly or lower frequency data such as quarterly series it is recommended to correct the data for any seasonality. Therefore, except the long-term yield all other variables in their log form are seasonally adjusted to remove the seasonal component of the time series data. The seasonal adjustment on Sensex, CPI, WTI, Exports, M3 and NEER is done using the standard x-13ARIMA-SEATS seasonal adjustment procedure. The beginning of the sample period is taken as the common base year for all variables except the long-term interest rates.

In this thesis we have considered the nominal value of variables. Research study such as Naka, Mukherjee, & Tufte (1998) has used a similar approach. In the literature, we found that the variables that are usually converted in their real terms are industrial production and the gross domestic product. From literature review, it is observed that the macroeconomic variables such as money supply, exchange rates, and crude prices are included either in their real terms (Chaudhuri & Smiles, 2004) or in their nominal terms (Naka et al., 1998) and there is no clear guideline either as per economic theory or from empirical studies.

5.4 Descriptive Statistics

Graphs of the data series at level indicate presence of non-stationarity and the first differenced series of all variables appears to be stationary. A stationary series is defined as one with a constant mean, constant variance, and constant auto-covariances for each given lag and for stationary series the shocks to the system gradually die away making forecasting possible.

Table 5.1 provides the descriptive statistics of these variables at level. All variables except the long-term interest rate are log transformed. The Jarque-Bera statistic confirms that the series is not normally distributed and all variables except the NEER exhibit positive skewness and kurtosis less than three. Analysis of descriptive statistics on all variables, at level, indicate that the Indian benchmark index, broad money supply (M3), and exports experience wider fluctuations compared to long-term interest rates, consumer price index and exchange rate. It is usually observed in the Indian context that the long-term interest on government securities rates do not experience very high volatility and therefore it is not surprising to note that that standard deviation of historical long-term interest rates is very close to zero. As discussed in the literature, the Indian debt market has historically experienced very high interest rates regimes but in the past decade and half both the long-term interest rates and foreign exchange rates have not exhibited abnormally high levels of volatility. This is partly attributed to the increasing participation of foreign investors that have swelled the foreign exchange reserves and a proactive role adopted by the Reserve Bank of India in operationalising monetary policy including prioritizing the control on the inflation rates. The low interest rates also reduce the borrowing costs thereby encouraging households and firms to borrow more for personal and capital expenditures. Though the interest rates in India are usually high compared to the developed countries, primarily because of high inflation rate, they have, in recent years, become more stable. Except, the exchange rate variable, all variables have positive skewness, indicating frequent instances of observations greater than the long-term average value. In their level values, the long-term interest rate has the highest positive skewness, which signifies a higher than the average interest rate in the domestic market. The skewness of the NEER is negative. The NEER is the weighted average of a currency against a basket of foreign currencies and the skewness indicates the relative strength or weakness of the domestic currency against the foreign currency basket. A negative skewness indicates that a greater degree of weakness in the Indian currency is experienced in the sample period.

The correlation matrix (Table 5.2) indicates presence of linear association among the variables in their level form. Except for the variables Long and NEER the Sensex shares a positive and very high degree of correlation indicating presence of inherent long-run association. Sensex shares particularly high correlation with CPI, crude, M3 and exports which is also suggested by the graphs of these variables in their level form (refer to Fig. 5-1). However, since the cross-correlation between these variables is for the whole sample period, we cannot premise upon whether similar short-run associations exist between these variables and therefore further analysis on these variables in their first difference is warranted.

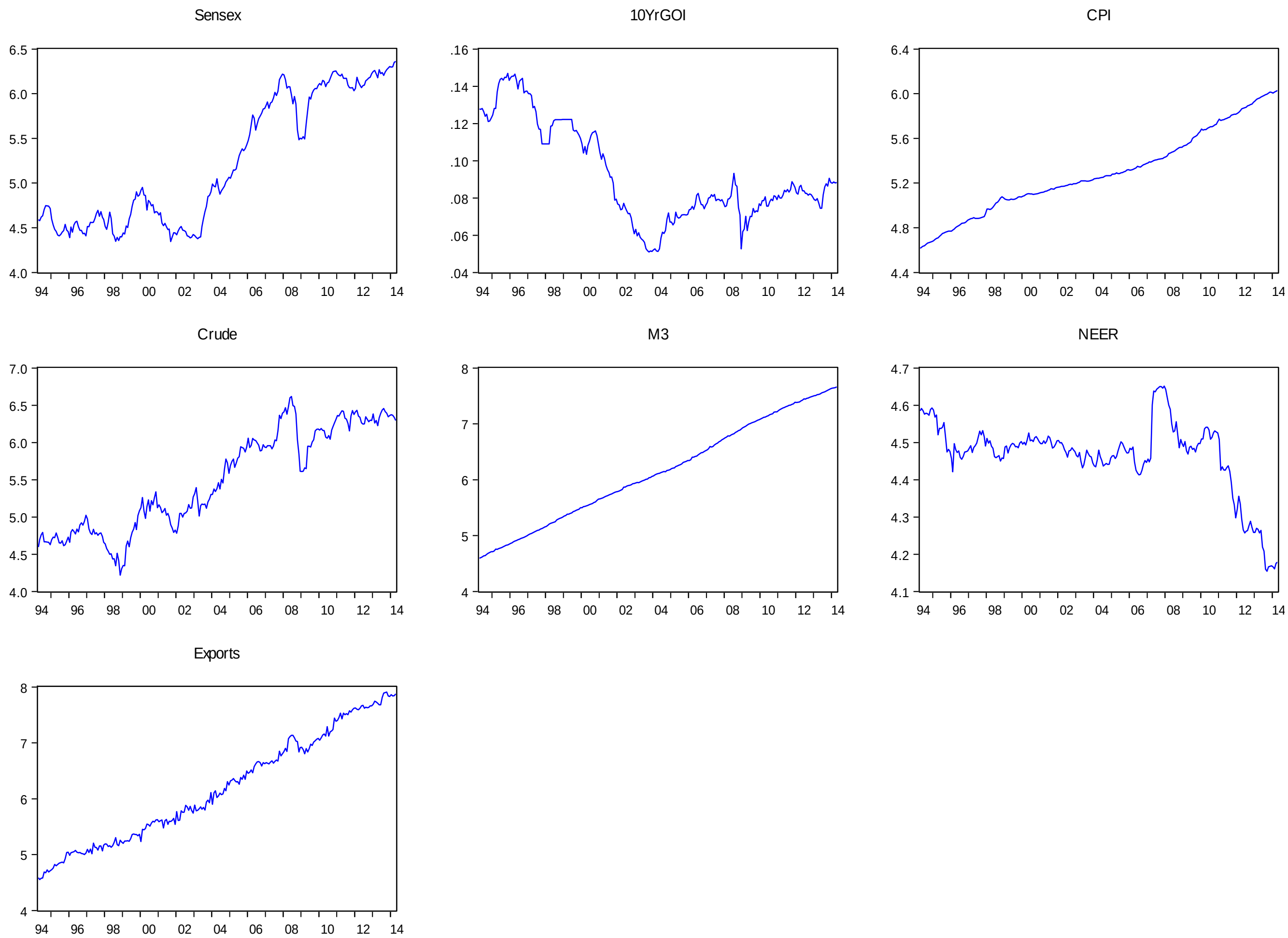
	Sensex	**Long**	**CPI**	**Crude**	**M3**	**NEER**	**Exports**
Mean	5.23	0.09	5.30	5.49	6.14	4.46	6.18
Median	4.95	0.08	5.24	5.38	6.11	4.48	6.09
Maximum	6.36	0.15	6.03	6.62	7.66	4.65	7.91
Minimum	4.35	0.05	4.62	4.22	4.59	4.15	4.55
Std. Dev	0.72	0.03	0.37	0.67	0.91	0.10	0.98
Skewness	0.26	0.55	0.25	0.01	0.03	-1.31	0.18
Kurtosis	1.36	2.17	2.22	1.53	1.78	5.14	1.75
Jarque-Bera	29.78	18.99	8.65	21.73	14.87	115.11	17.07
Probability	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Obs.	241	241	241	241	241	241	241

Table 5.1 Monthly Descriptive statistics at level

	Sensex	Long	CPI	Crude	M3	NEER	Exports
Sensex	1						
Long	-0.49	1					
CPI	0.89	-0.63	1				
Crude	0.94	-0.62	0.89	1			
M3	0.91	-0.70	0.99	0.93	1		
NEER	-0.37	0.19	-0.61	-0.38	-0.53	1	
Exports	0.93	-0.65	0.98	0.95	0.99	-0.55	1

Table 5.2 Cross correlation at level

The graphical analysis of the series in their level form is given in Fig. 5-1. The graphs shows time varying trend in the in-sample values of these variables. The graphs indicates that few time series variables follow a deterministic trend and few have stochastic trends i.e. random walk with drift, however none of the variables in their level form display white noise behavior. All time-series variables share long-term trends in their level form which suggests presence of time varying mean and variance in these variables. The monthly data on Sensex, consumer price index, crude price, money supply and exports exhibit long-term upward sloping trends whereas the interest rate and the nominal effective exchange rate variable share downward trends. In-spite of this difference in the slope patterns, these variables may have long-run association with each other which indicates statistical dependence among them.



Note: In the graphical presentation the long-term interest rates are labelled as 10YrGOI.
Elsewhere the legend used for this variable is referred to as 'Long'.

Fig. 5-1 Time-varying pattern of the macroeconomic variables in their level form

According to the co-integration theory only the variables integrated of the same order can be cointegrated. For the analysis on the presence of co-integrating relationship between Sensex and other macroeconomic variables the Johansen and Juselius approach require that all variables are non-stationary in their level form and become stationary after first differencing, i.e. all variables I(1). We use the Johansen (1991) and (Søren Johansen & Juselius, 2009) multivariate co-integration analysis to determine whether the variables are cointegrated. If the variables are found to be cointegrated the analysis proceeds with estimating the Johansen's vector error correction model (VECM) to detect whether the self-adjusting long-run equilibrium relationship exists between these variables. Impulse response and variance decomposition analysis is considered for examining the time-varying relationship between the Indian stock market and macroeconomic variables. Further details on these tests and discussion on results follow in the subsequent sections.

Graphical analysis of the first difference of all variables appears in Fig. 5-2.

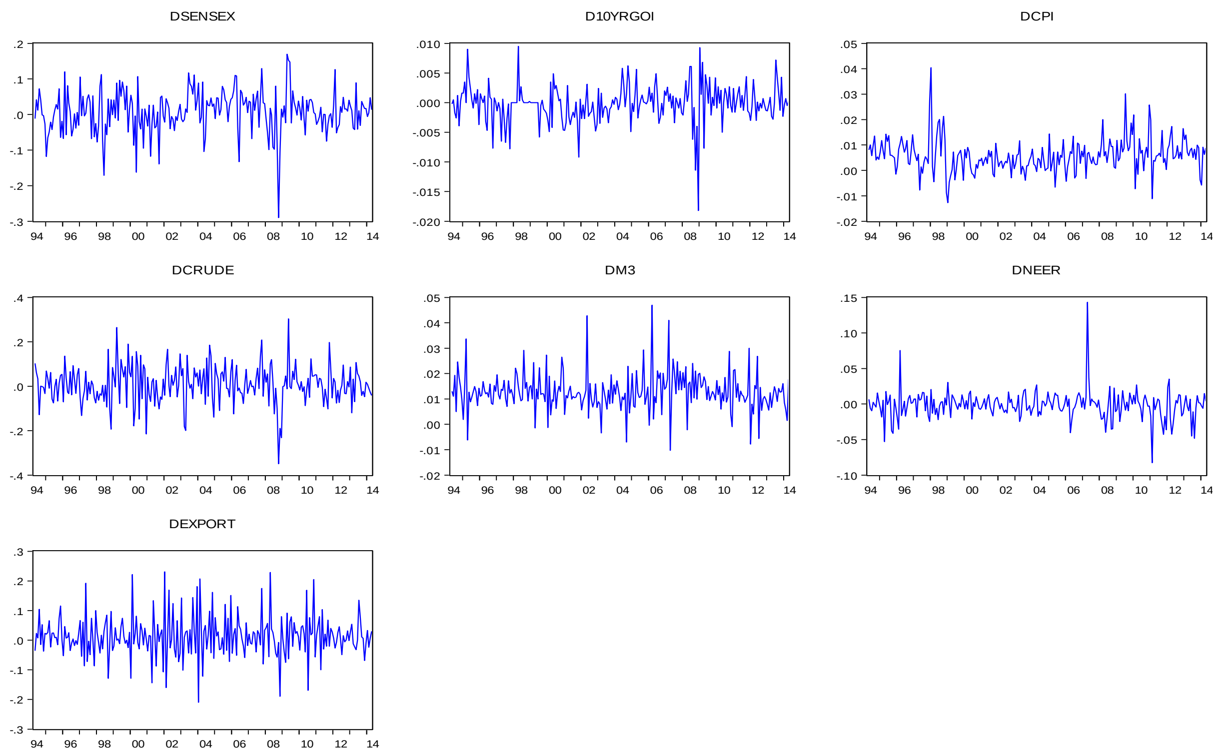


Fig. 5-2 Graphical presentation of all variables in their first-differenced form

The time varying evolution of the first differenced series appears to be oscillating within a narrow band and does not depart permanently from its mean value in other words all series exhibit a very strong tendency to revert to their long-term mean. This is a very strong indication that the first difference of the log-transformed variables is stationary.

Table 5.3 contains the descriptive statistics of first differenced variables and cross-correlation of all variables with each-other are given in Table 5.4.

	ΔSensex	**ΔLong**	**ΔCPI**	**ΔCrude**	**ΔM3**	**ΔNEER**	**ΔExports**
Mean	0.007	-0.000	0.006	0.007	0.013	-0.002	0.014
Median	0.011	0.000	0.005	0.004	0.012	0.000	0.011
Maximum	0.169	0.01	0.040	0.304	0.047	0.143	0.231
Minimum	-0.290	-0.018	-0.013	-0.349	-0.01	-0.083	-0.209
Std. Dev	0.059	0.003	0.007	0.085	0.007	0.019	0.069
Skewness	-0.644	-0.74	1.00	-0.181	0.711	1.411	0.361
Kurtosis	5.64	7.97	7.06	4.67	6.57	17.92	4.55
Jarque-Bera	86.32	269.26	204.55	29.24	147.67	2306	29.28
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	240	240	240	240	240	240	240

Table 5.3 Monthly Descriptive statistics - first difference

The descriptive statistics on the first difference of all variables indicate that the average values of these variables is close to zero and the first difference graph of these variables indicate a strong tendency of these variables to fluctuate around the mean value. The long-term interest and NEER have a negative average monthly change indicating that these variables experience more frequently a fall compared to the previous month. However, the average monthly change in long-term interest rates and NEER are very small and share similarity with the behavior observed in other variables. A low value of monthly average change in these variables compared to the standard deviation indicates a high degree of volatility inherent in these variables. The standard deviation of these variables relative to the monthly return is high in Sensex, crude, and exports which suggests a high relative riskiness of these variables compared to other macroeconomic variables. The kurtosis value in all the variables is significantly greater than one which suggests that all these variables exhibit significant departure from normality. The Jarque-Bera statistic also confirms the non-normality in the monthly returns on these variables.

	ΔSensex	**ΔLong**	**ΔCPI**	**ΔCrude**	**ΔM3**	**ΔNEER**	**ΔExport**
ΔSensex	1						
ΔLong	-0.11	1					
ΔCPI	-0.15	0.09	1				
ΔCrude	0.30	0.19	-0.16	1			
ΔM3	0.05	-0.05	-0.07	-0.03	1		
ΔNEER	0.19	-0.13	-0.04	0.02	-0.15	1	
ΔExports	0.01	0.01	-0.04	0.05	-0.02	-0.07	1

Table 5.4 Cross correlation between first difference variables

The cross correlation of the first-difference in Sensex with macroeconomic variables suggests that monthly returns are positively correlated with change in crude prices, money supply, NEER and exports. However, monthly Sensex returns share very low correlation with money supply and exports. Sensex returns are negatively correlated with changes in long-term interest rates and the consumer price index suggesting a negative linear association of long-term interest rates and consumer price index on Sensex. The stock market's contemporaneous response on account of changes in interest rates and inflation is usually negative because of flight of investors from stock market to debt-market and increase in risk premium. Nevertheless, the correlation between variables just signifies presence of linear association and not necessarily causation and therefore the study proceeds with cause-and-effect analysis of these macroeconomic variables on the return and volatility of the Indian stock market by investigating presence of log-run co-integrating relationship between macroeconomic variables and the stock market index. To that end, the first step is to determine the order of integration in these variables and then apply tests of co-integration to establish presence of long-run equilibrium relationship between the variables.

5.5 Tests for Stationarity

A variable is said to be integrated if its current value is representable as sum of lagged period innovations. The unit root tests including both the intercept and the time trend. Testing of the order of integration in these series is done using the Augmented Dickey Fuller (ADF), Ng-Perron, and *Kwiatkowski–Phillips–Schmidt–Shin* (*KPSS*) tests both including the intercept and intercept and trend because several variables exhibit time trends.

The most common test of stationarity is Augmented Dickey Fuller test. A test applied to higher order model to test for the presence of serial correlation in the data. The ADF test on variable Y_t is generally applied on the data generating process considering an intercept and trend and intercept. The test equations are given below:

$\Delta Y_t = \mu + \beta Y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta Y_{t-i} + \varepsilon_t$

$\Delta Y_t = \mu + \alpha t + \beta Y_{t-1} + \sum_{i=1}^{k} \gamma_i \Delta Y_{t-i} + \varepsilon_t$

Y_t is the time series, μ is the constant term capturing the drift component in the data, t is the time-trend, k is the number of lags, and Δ is the difference operator. The null hypothesis (H_0) of presence of unit root tests whether $\beta = 0$ versus the alternative hypothesis ($\beta < 0$).

Two other tests (KPSS and Ng-Perron) are also employed to test whether the series in level is stationarity or not. The results of the ADF and KPSS tests on variables in their level form and in their first differenced form are presented in Table 5.5 and Table 5.6 respectively.

	Intercept					Trend and Intercept				
	ADF-stat.	*p-value*	Lag Length	KPSS stat.	*crit-value*	ADF-stat.	*p-value*	Lag Length	KPSS stat.	*crit-value*
Sensex	-0.21	0.93	1	1.74*	0.46	-2.17	0.50	1	0.27*	0.15
Long	-1.43	0.57	0	1.20*	0.46	-0.91	0.95	0	0.41*	0.15
CPI	0.62	0.99	1	1.89*	0.46	-0.63	0.98	1	0.32*	0.15
Crude	-1.07	0.73	0	1.83*	0.46	-2.27	0.25	0	0.151*	0.146
M3	-0.70	0.84	1	1.96*	0.46	-1.08	0.93	1	0.19*	0.15
NEER	-0.75	0.83	1	0.71*	0.46	-1.37	0.87	1	0.23*	0.15
Exports	-0.11	0.95	2	1.95*	0.46	-2.57	0.29	2	0.33*	0.15
Lag length for each variable chosen that minimizes the value of SIC. * denotes rejection of Null hypothesis at 5% level.										

Table 5.5 Results of Unit Root test at level under intercept and trend and intercept

	Intercept					Trend and Intercept				
	ADF-stat.	*p-value*	Lag Length	KPSSstat.	*crit-value*	ADF-stat.	*p-value*	Lag Length	KPSS stat.	*crit-value*
ΔSensex	-12.84*	0.00	0	0.12	0.46	-12.86	0.00	0	0.07	0.15
ΔLong	-8.87*	0.00	1	0.19	0.46	-14.76	0.00	0	0.08	0.15
ΔCPI	-11.16*	0.00	0	0.38	0.46	-11.17	0.00	0	0.30	0.15
ΔCrude	-14.95*	0.00	0	0.04	0.46	-14.91	0.00	0	0.04	0.15
ΔM3	-19.85*	0.00	0	0.17	0.46	-19.83	0.00	0	0.16	0.146
ΔNEER	-13.47*	0.00	0	0.18	0.46	-13.49	0.00	0	0.09	0.15
ΔExports	-15.84*	0.00	1	0.06	0.46	-15.80	0.00	1	0.04	0.15
Lag length for each variable chosen that minimizes the value of SIC. * denotes rejection of Null hypothesis at 5% level.										

Table 5.6 Results of Unit Root test of first differenced variables under intercept and trend and intercept

5.6 Econometric methodology

5.6.1 Vector Auto-regression (VAR) and Vector Error Correction Model (VECM)

The primary motivation behind implementing a VAR (Sims, 1980) or VECM (Johansen and Juselius 1990, Johansen, 1991) strategy is to simultaneously model all variables as endogenous variables and assess their causal interrelationship. Time series data that are non-stationary result in spurious regressions and the usual estimates of ordinary least squares lose their economic value. A plausible econometric estimation of such variables is possible with sensible interpretation only if the residuals of the linear regression are stationary and in such cases the variables are said to be cointegrated. If the residuals of a linear regression containing non-stationary variables are found to be integrated of order zero a plausible long-run association between the variables may exist which can be exploited because this inherent structural association between the variables does not allow them to drift and permanently depart from each other.

More formally, if the time series data Y_t and X_t are integrated of order one or I (1) then Engle and Granger (1987) and Granger (1986) suggest that in case the linear combination of these non-stationary variables, given by, $\hat{\varepsilon}_t = Y_t - \hat{\beta}_t X_t$, turns out to be stationary i.e. $\hat{\varepsilon}_t \sim I(0)$, the variables are said to be cointegrated and in such cases an error correction term exists in the system that drives both the x and y variables to their long-run equilibrium. In such a scenario the use of co-integration technique for modeling long-run equilibrium relationship between these variables is more appropriate.

A popular strategy for estimating such relationships is VECM. In VAR framework the dynamic response of the dependent variable is modelled as function of the lagged independent variables which may also include the auto-regressive and moving average terms. In the VAR framework a system of regression models are dynamically estimated considering all other variables as independent but endogenous. Since, all the variables are endogenous; the contemporaneous terms of the independent variables are not included, the only exception being unless exogenous variables are explicitly included in the regression. The VAR specification also requires the variables to be stationary and therefore all variables entering the estimation must be integrated of order zero. This stationarity requirement is considered to be a major shortcoming of the VAR system because differencing the variables removes information on the long-run relationship between the variables. Brooks (2008) suggests that when we take first difference of the log transformed variables any long-run equilibrium information is lost. First differencing purges vital information regarding long-run equilibrium and is therefore not desirable approach in analyzing long-run relationships (Arshanapalli and Doukas 1993). Therefore the conventional approach to take the first difference of the log of the variables to make the variables stationary is not desirable if inherent in the presence of potential log-run association between variables.

However, if the variables are cointegrated i.e. the residuals of their linear combinations are stationary then the multivariate Vector Error Correction Mechanism (VECM) approach is used to examine the long-run relationships between the variables. The VECM technique is more general case of the standard VAR model. The analysis proceeds by first determining the appropriate lag length p, for the dynamic terms i.e. lagged variables in the first difference form, the number of co-integrating vectors and the structural co-integrating vectors of the VECM. If an appropriate lag-length is chosen for model estimation then the residuals of the error correction model are free from serial correlation Lütkepohl (2005). Five criteria are usually available for selecting the lag-length i.e. sequential modified LR test statistic, final prediction error (FPE), Akaike information criteria (AIC), Schwarz information criteria (SIC), Hannan-Quinn information criteria (HQ).

Since the data are monthly sampled the maximum lag-length for VECM lag selection is taken as twelve. Many authors have argued the appropriate lag-length to be chosen based on the sampling frequency.

Table 5.7 contain the results of all lag-length selection criteria considered in this analysis.

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	1454.609	NA	7.62e-15	-12.64287	-12.53791	-12.60053
1	4167.883	5236.976	5.98e-25	-35.91165	-35.07196*	-35.57289*
2	4237.427	129.9760	5.00e-25*	-36.09106*	-34.51665	-35.45590
3	4274.185	66.45440	5.58e-25	-35.98415	-33.67501	-35.05259
4	4310.935	64.19177	6.25e-25	-35.87716	-32.83329	-34.64919
5	4347.248	61.20956	7.04e-25	-35.76636	-31.98777	-34.24198
6	4379.661	52.65226	8.24e-25	-35.62149	-31.10817	-33.80071
7	4420.583	63.97428	9.01e-25	-35.55094	-30.30290	-33.43375
8	4464.969	66.67656	9.62e-25	-35.51065	-29.52788	-33.09705
9	4494.497	42.55109	1.18e-24	-35.34059	-28.62309	-32.63058
10	4534.097	54.64419	1.33e-24	-35.25849	-27.80626	-32.25207
11	4595.617	81.13146	1.26e-24	-35.36783	-27.18088	-32.06501
12	4663.904	85.88031*	1.13e-24	-35.53628	-26.61460	-31.93705
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Table 5.7 VAR Lag order selection criteria

The sequential modified LR test statistic also suggests optimal lag length of twelve for VECM estimation and therefore the error correction model estimation proceeds with twelve lags. Table 5.8 contains the test of null hypothesis of no serial correlation in the VAR (12) model selected according to the LR statistic criteria. Econometric theory suggests p+1 lag specification for examining the VAR (p) residuals for the presence of serial correlation. According to the LM statistic we fail to reject the null hypothesis of no serial correlation and hence the lag order selection for VECM estimation is optimal.

Lags	LM-Stat	Prob
1	53.83035	0.2947
2	49.79593	0.4415
3	50.30343	0.4216
4	32.68238	0.9647
5	41.26739	0.7758
6	56.29592	0.2207
7	41.63114	0.7633
8	59.40194	0.1467
9	49.99739	0.4335
10	51.78155	0.3658
11	42.71960	0.7243
12	32.00326	0.9712
13	51.38718	0.3804

Table 5.8 Residual serial correlation LM Test for VAR (12) model

5.6.2 Johansen-Juselius Co-integration Test

For performing the Johansen (1991) co-integration test following steps are performed. First, examine the order of integration of all the variables in the model. Determine the optimal lag length for the VAR model to verify that estimated residuals are not autocorrelated. And finally, estimate the restricted VAR model to construct the co-integration vectors to determine order of integration. If the variables are cointegrated they share long-run relationship and in the presence of co-integrating vectors the multivariate VECM model is then estimated for constructing the co-integrating vectors. The Vector Error Correction Model is a restricted VAR and is used with non-stationary time series that are known to be cointegrated. The Granger representation theorem states that if there exists a dynamic linear model with stationary disturbances and the variables are integrated of the order one, then the variables must be cointegrated.

Johansen's co-integration approach uses trace statistics and maximum eigenvalue which are sensitive to lag-length used in estimation. It is important to recognize that the trace and maximum eigenvalue statistics may indicate different number of co-integrating vectors and appropriate lag-length selection is a precondition for obtaining reliable results. In the presence of more than one co-integrating vector (Søren Johansen & Juselius, 2009) suggest the first eigenvector to be the most appropriate.

Before proceeding with the VECM estimation we need to check for the presence of co-integration in the variables. At least one co-integrating vector must exist in order to perform the VECM estimation. Since all time series contain a stochastic trend, a linear trend in VAR and intercept in co-integrating relationship is considered. Selection of the variables for inclusion in the VAR model is usually taken from the literature as there is no universally set of variables prescribed by economic theories.

There are two likelihood ratio tests in the Johansen's co-integration approach that determine the number of co-integrating vectors (r). The trace statistic and the maximum eigenvalue test statistic tests the null hypothesis for the number of co-integrating vectors. If $r = 0$ then there is no evidence of co-integration and an unrestricted VAR estimation is appropriate. If the number of co-integrating equations is greater than zero then the analysis proceeds with the estimation of vector error correction model.

The test for co-integration among variables in multivariate analysis is done using the Johansen (1991) framework. The Johansen's approach is an extension of vector auto-regression where all the variables are estimated simultaneously using p-lags of all system variables. Mathematically it is expressed as:

$$X_t = \mu + A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \varepsilon_t$$

where X_t is $n \times 1$ vector, containing n variables integrated of order 1. μ is an $n \times 1$ vector of constants, A_p is $n \times n$ matrix of coefficients and ε_t is $n \times 1$ vector of residual terms. Following Enders (2004) the above equation can be written in an error correction form as

$$\Delta X_t = \delta + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-p} + \varepsilon_t$$

where ΔX_t is a $n \times 1$ vector of first-differenced variables and δ is an $n \times 1$ vector of constants.

$$\Gamma_i = \left(A_1 + A_2 + \cdots + A_{p-1} - I\right)$$

explains the short-run dynamics of the model.

$\Pi = \left(A_1 + A_2 + \cdots + A_p - I\right)$ is the error correction mechanism and explains the long-run impact of disequilibrium on stock prices.

An important aspect to note is the rank of the matrix Π which is equal to the number of co-integrating vectors; clearly if rank (Π) = 0 we have a null matrix and the restricted VAR reverts back to unrestricted VAR in its usual form. Π is constituted of two components and can be compactly represented as $\Pi = \alpha\beta'$ where α is an $n \times 1$ column vector representing the speed of short-run adjustment to the long-run equilibrium, and β' is a $1 \times n$ co-integrating vector with the matrix of long-run coefficients; Γ is an $n \times n$ matrix representing the coefficients of the short-run dynamics. Finally ε_t is an $n \times 1$ vector of white noise error terms; and p is the order of auto-regression; this equation has basically two channels of causation one is through lagged exogenous variable's coefficients and the other is the error correction term (ECT) which captures the adjustment of the system towards its long-run equilibrium.

As discussed above determining the rank of matrix Π is of utmost importance for drawing any conclusions regarding presence of co-integration. The rank of matrix Π is determined by considering eigenvalues of Π that are significantly different from zero.

Under the Johansen approach the two test statistics for identification of co-integration among variables are given as

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right)$$

and

$$\lambda_{max}(r, r+1) = -T\, ln(1 - \hat{\lambda}_{r+1})$$

where r specifies the number of co-integrating vectors under the null hypothesis. If r is greater than zero but less than n, it implies presence of stationary linear combinations in the vector process X_t. $\hat{\lambda}_i$ is the *i*th ordered eigenvalue from the Π matrix. Each eigenvalue has a corresponding eigenvector associated with it and a non-zero eigenvalue will have a significant and non-zero eigenvector. Often the results drawn from trace statistic and maximum eigenvalue statistic indicate different number of co-integrating vectors.

Since the VAR methodology simultaneously estimates all n-variables as function of remaining n-1 variables, we can think of all variables entering in estimation as endogenous to the system. In the Johansen's test the decision on number of co-integrating relations is based either on the trace statistic or on the maximum eigenvalue and the inference under the two approaches may differ. The first rejection of the null hypothesis is taken as an estimate of r. The null hypothesis of the trace test tests whether the number of co-integrating vectors i.e. r is less than number of system variables n i.e. r < n. Following Enders (2004) we follow maximum eigenvalue test statistic for concluding the presence of number of co-integrating vectors. The co-integration test results indicate that all the macroeconomic variables considered in this analysis share a long-run relationship. The results of co-integration tests are given in Table 5.9. Co-integration coefficients, of system variables, normalized on the Sensex are given in Table 5.10.

H_0	H_a	Maximum Eigen Stat.	5% critical value	H_o	H_a	Trace Stat.	5% Critical value
r = 0	r = 1	72.47	45.28	r = 0	r > 0	204.96*	124.24
r ≤ 1	r = 2	47.20	39.37	r ≤ 1	r > 1	132.49*	94.15
r ≤ 2	r = 3	40.47	33.46	r ≤ 2	r > 2	85.29	68.52
r ≤ 3	r = 4	22.66	27.07	r ≤ 3	r > 3	44.81	47.21
r ≤ 4	r = 5	11.28	20.97	r ≤ 4	r > 4	22.15	29.68
r ≤ 5	r = 6	9.83	14.07	r ≤ 5	r > 5	10.87	15.41
r ≤ 6		1.03	3.76	r ≤ 6		1.03	3.76
Johansen (unrestricted) co-integration rank test results (Osterwald - Lenum critical values) * denotes rejection of null hypothesis at 5% level. Lag length as per LR statistic. Both maximum eigenvalue statistic and trace statistic suggests 3 co-integrating equations at 5% level.							

Table 5.9 Johansen's test for co-integration

SENSEX(-1)	C	Long(-1)	CPI(-1)	Crude(-1)	M3(-1)	NEER(-1)	Exports(-1)
1.00	-22.29	-25.45*	9.01*	2.13*	-3.87*	-0.32	-2.39*
		(3.65)	(1.86)	(0.38)	(-1.21)	(1.04)	(0.72)
Standard errors are given in parentheses.							

Table 5.10 Normalized co-integrating coefficients of the first co-integrating equation

All the coefficients of the first normalized co-integrating equation are significant except the nominal effective exchange rate. The long-term government bond yield, broad money supply, nominal effective exchange rate and exports have negative coefficients suggesting that these variables share a negative long-run relationship with the Indian stock market. The negative long-run relation between exports and Sensex is surprising but similar observation is documented by Aizenman, Pinto, & Sushko (2013) that financial contraction usually follows the period of high activity in the real sector and therefore drawing consistent conclusions about this lead-lag relationship is not straightforward. The level of consumer price and crude price has a positive long-run association with the stock market index. The interest rates are sensitive to the domestic price levels resulting in a stable real interest rate on debt investment. This could explain the positive long-run relationship between inflation and the stock market index because the investment in stock market is considered by many researchers as a hedge against inflation. Also the flight of investors from risky assets to relatively risk free assets provides an explanation for the negative sign of the long-term interest rate coefficient. This result of a significant and negative long-run association between the stock index and long-term interest rates is consistent with several studies such as Gunasekarage et al., (2004), Humpe & Macmillan (2009), and Mukherjee & Naka (1995). Many researchers have documented conflicting finding with respect to the relation between money supply and the stock market index. Kwon & Shin (1999) document a positive relationship between money supply and the Korean stock market whereas Chen et al., (1986) argue that impact of money supply on the stock market is uncertain because of the inflationary pressure that is created by money supply. Further, as evident from the analysis of the descriptive statistics the fluctuations in the money supply is a remote issue, due to very low coefficient of variation, and therefore it may not have a significant contemporaneous influence on the stock index movement. India is a net importer of oil and increase in crude prices in global markets slows-down the economic activity in the Indian economy by significantly increasing the cost of inventory of oil importing industries. The long-run association between the proxy for crude oil and the Indian stock market is significant and positive which is counterintuitive. However, in a recent study on dependence between crude prices and stock markets, Zhu, Li, & Li (2014), find a strong evidence of weak dependence between crude prices and several Asia-Pacific markets. Another study by Narayan & Narayan (2010) also find oil prices to be positive and statistically significant for Vietnamese stock exchange. The result of co-integration tests provides empirical evidence favoring a positive long-run association between the Indian stock market and crude prices which shares similar findings as mentioned above. Another explanation for this positive relationship could be attributable to the fact that in the past two decades both the domestic stock market and crude prices in the international markets have witnessed a significant rise, and several domestic factors have fuelled growth in stock prices. Since the impact of nominal effective exchange rate in the co-integrating equation is insignificant we drop this variable and re-examine the presence of co-integration between Sensex and the remaining macroeconomic variables.

Table 5.11 contains the results of the Johansen's co-integration test, excluding the nominal effective exchange rate. The normalized co-integrating coefficient of the first co-integrating equation is given in Table 5.12.

H_0	**H_a**	**Maximum Eigen Stat.**	**5% critical value**	**H_o**	**H_a**	**Trace Stat.**	**5% Critical value**
$r = 0$	$r = 1$	62.42*	39.37	$r = 0$	$r > 0$	159.90*	94.15
$r \leq 1$	$r = 2$	42.49*	33.46	$r \leq 1$	$r > 1$	97.48*	68.52
$r \leq 2$	$r = 3$	30.20*	27.07	$r \leq 2$	$r > 2$	55.00*	47.21
$r \leq 3$	$r = 4$	12.99	20.97	$r \leq 3$	$r > 3$	24.80	29.68
$r \leq 4$	$r = 5$	9.67	14.07	$r \leq 4$	$r > 4$	11.82	15.41
$r \leq 5$	$r = 6$	2.15	3.76	$r \leq 5$	$r > 5$	2.15	3.76
Johansen (unrestricted) co-integration rank test results (Osterwald - Lenum critical values) * denotes rejection of null hypothesis at 5% level. Lag length as per LR statistic. Both maximum eigenvalue statistic and trace statistic suggests 3 co-integrating equations at 5% level.							

Table 5.11 Johansen's test for co-integration

The co-integration results indicate that over a long period of twenty years the Indian stock market is significantly impacted by these macroeconomic variables and there exists a long-run equilibrium relationship shared between the macroeconomic variables and the Indian stock index. All the macroeconomic economic variables in the co-integrating equation are statistically significant. None of the variables in the new co-integrating equation exhibit any reversal in the sign compared with that of the previous co-integrating equation suggesting that excluding the insignificant variable does not affect the long-run relationship between the macroeconomic variables and the stock market. Subsequently, the error correction model is estimated for drawing conclusions on the sign and size of the error correction term.

SENSEX(-1)	C	Long(-1)	CPI(-1)	Crude(-1)	M3(-1)	Exports(-1)
1.00	-50.81	-40.18*	18.29*	4.87*	-7.37*	-4.69*
		(6.76)	(2.98)	(0.81)	(1.57)	(1.25)
Standard error are given in parentheses.						

Table 5.12 Normalized co-integrating coefficients of the first co-integrating equation

5.6.3 Error Correction Model

The error correction model is the dynamic model for the short-run response of the cointegrated variables. Since, all variables in the co-integrating equation are significant at 5% level the VECM estimation is performed rather than the Granger causality test. The coefficients of the error correction model provide useful insights and the information on the short-run influence of the independent variables on the dependent variables can be interpreted through the sign of the coefficients as well as the analysis of the impulse response function. However, a more useful interpretation in the error correction term is the sign and magnitude of the coefficient of the error correction term (ECT). If the dynamic self-adjusting long-run equilibrium between the variables exists then the coefficient of the error correction term is negative and statistically significant. In other words, in an error correction term the previous period's error is assumed to influence the short-run disequilibrium to the system and therefore must have a negative sign which suggests that any transitory deviation from the equilibrium i.e. the error in the previous period determines the movement in the dependent variable in the subsequent periods. Further, the magnitude of the coefficient the ECT explains the periodic adjustment of the long-run equilibrium process after every shock that leads to temporary disequilibrium in the long-run relationship.

The coefficients along with their statistical significance on the ECT and the short-run relationship of the VECM appear in Table 5.13.

ECT	**Δ Long**	**Δ CPI**	**Δ Crude**	**Δ M3**	**ΔExports**
-0.023*	0.001*	-0.001	-0.07*	0.002	0.03*
(0.01)	(0.000)	(0.001)	(0.02)	(0.002)	(0.02)
***indicates significance at 5% (standard errors in parentheses)**					

Table 5.13 Result of VECM estimation

The coefficient of the error correction term is significant and negative suggesting that there exists a dynamic and self-adjusting mechanism that ensures long-run stable relationship between the macroeconomic variables and the Indian stock index. In the short-run, the long-term interest rate, crude prices and exports exert their influence on the Indian stock market since these variables are statistically significant in the error correction model. The lagged period long-term interest rate and exports positively influence the Indian stock market suggesting a presence of lead-lag relationship and degree of predictability for the movement in the benchmark index. Past period information available on the consumer price index and money supply are not significant predictor for the Indian stock market.

The coefficient of the error correction term indicates that approximately twenty seven percent of correction in short-run adjustments to long-run equilibrium happens within a year. The error correction parameter is found to be statistically significant indicating its relevance in predicting stock market returns subsequent to shocks in these variables. This finding motivates us to further investigate whether there exists any interrelationship between the macroeconomic variables and Indian stock market volatility. This area is left totally unexplored in the context of Indian stock market.

5.6.4 Innovation Accounting

Innovation accounting expresses the duration for which the influence of innovations exists in the system. Two approaches are considered for describing the innovation impact on the stock returns. The first approach is the impulse response function (IRF), which describes the responses of all variables to one unit shock in one variable in the model. The IRF results indicate that the impulse response of all macroeconomic variables on Sensex is transitory and not non-stationary as the influence dies out quickly Fig. 5-3. The responses are plotted on the Y-axis with periods starting from the first shock on the X-axis.

The forecast error variance decomposition (FEVD), given in Table 5.14, breaks up the proportionate contribution of a one unit variation attributable either to the variable itself or to other system variables.

Variance decomposition provides the contribution of each explanatory variable in determining *h*-step ahead forecast error variance of the dependent variable. The significance of a variable in regulating the movement in the underlying series for the foreseeable future can be quantified based on FEVD analysis. In this thesis the IRF and the FEVD analysis is used to examine the short-run linkages between the stock index and macroeconomic variables. The long-run association is analyzed using the error correction term.

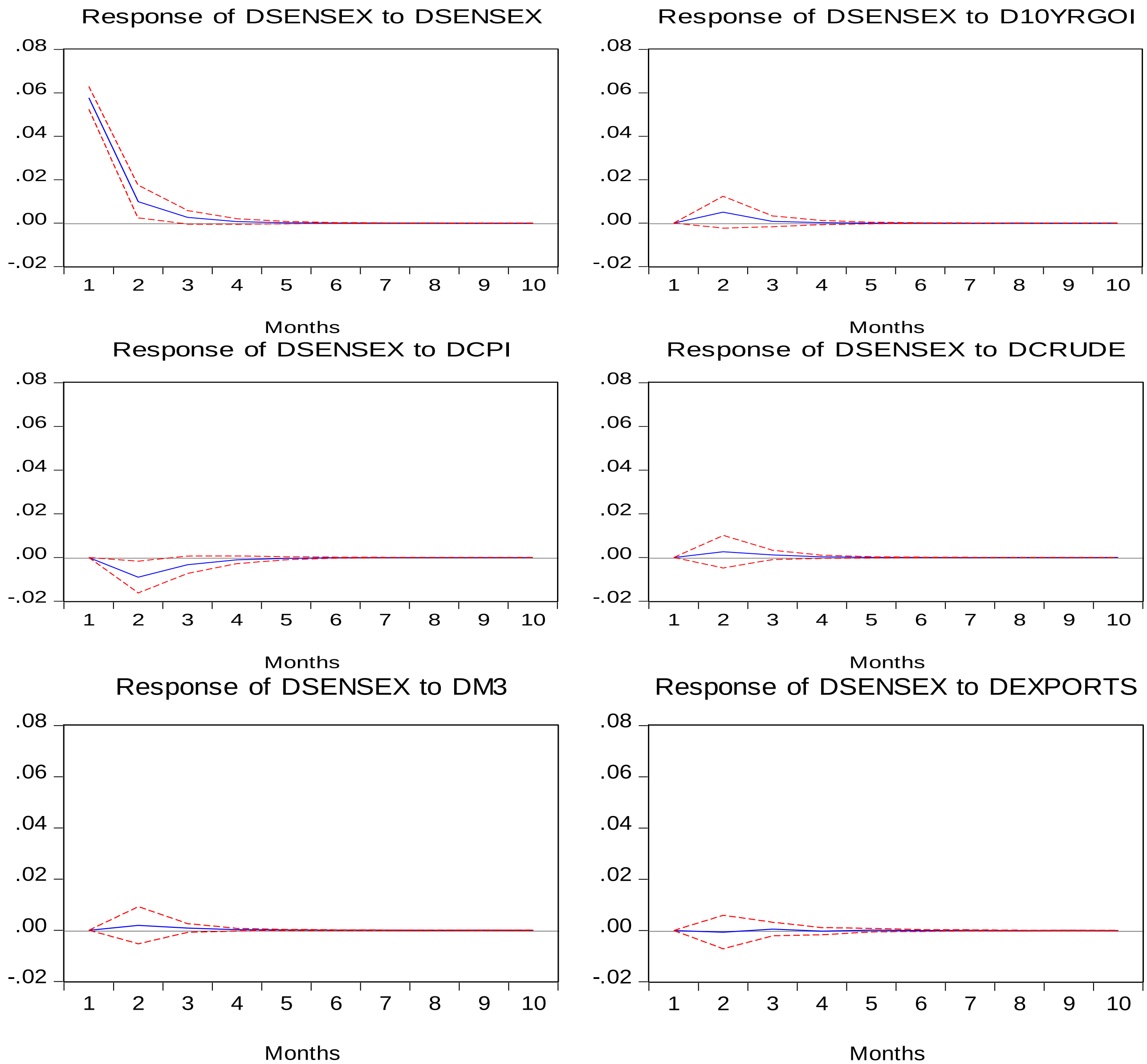


Fig. 5-3 Impulse response of Sensex to Cholesky One S.D. Innovations

As evident from IRF and FEVD, the innovations to the process die down quickly and the error correction mechanism adjusts by approximately twenty seven percent per year.

From the preceding analysis, it is established that the Indian stock market returns share a long-run relationship with the macroeconomic variables and short-run adjustments are prominent that maintain this long-run equilibrium between macroeconomic variables and the Indian stock market index.

Period	S.E.	DSENSEX	DLong	DCPI	DCRUDE	DM3	DEXPORTS
1	0.057682	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.059516	96.67989	0.706015	2.300710	0.195743	0.104834	0.012808
3	0.059691	96.30275	0.718128	2.604475	0.230133	0.123927	0.020585
4	0.059707	96.26394	0.718794	2.637078	0.231994	0.124832	0.023358
5	0.059709	96.25903	0.718753	2.641454	0.231995	0.125086	0.023684
6	0.059709	96.25846	0.718751	2.641850	0.232008	0.125090	0.023844
7	0.059709	96.25838	0.718753	2.641902	0.232009	0.125094	0.023866
8	0.059709	96.25836	0.718752	2.641905	0.232009	0.125094	0.023875
9	0.059709	96.25836	0.718753	2.641905	0.232009	0.125094	0.023876
10	0.059709	96.25836	0.718753	2.641905	0.232009	0.125094	0.023877

Table 5.14 Variance decomposition of Sensex

Presence of this structural association between a set of five macroeconomic variables that include the long-term interest rate, consumer price index, crude price, money supply, and exports with the Indian stock market motivates us to test the predictive ability of such associations on the stock market volatility. Alternative formulations of the GARCH type models are augmented with the macroeconomic variables and error correction term to identify the information content of these variables in explaining the volatility of monthly returns on Sensex. The predictive ability of these augmented GARCH models are discussed in the subsequent section.

5.7 Augmented GARCH Models

As discussed in earlier chapters the usefulness of GARCH models lie in their ability in generating reliable forecasts for volatility. So far all the GARCH models are estimated considering alternative conditional return specifications, different GARCH formulations considering both the symmetric and asymmetric approaches, and under different probabilistic assumptions for the error term. Since it is possible to estimate a GARCH model using exogenous variables; investigating the hypothesis we have set out in this chapter will yield useful insights with regards to whether the inherent structural association between the macroeconomic variables and the benchmark stock index of India are useful for predicting the volatility in the Indian stock market.

Comparative analysis is drawn between the GARCH-type models without any exogenous variable and the GARCH models augmented with the macroeconomic variables. The following augmented GARCH models are estimated for estimating the volatility in BSE Sensex:

a. Conventional GARCH models without any exogenous variables for the variance equation: Considering both normal and non-normal probability distributions and symmetric and asymmetric specifications for the conditional volatility a total of eighteen models are estimated for comparative analysis.

b. GARCH models augmented with the lagged returns of the macroeconomic variables (lagged first difference). These models are estimated to test whether there is any lead-lag relation between the macroeconomic variables and the conditional volatility of the Indian stock market. These models are referred to as GARCH-L models. A total of ninety GARCH-L models are estimated for the analysis.

c. GARCH-Z models: The GARCH-Z models are the GARCH models augmented with the combined effect of all macroeconomic variables taken together in explaining the volatility of Sensex. A total of eighteen model specifications are estimated. All the first differences of the one-period lagged macroeconomic variables are taken together to assess the combined impact of the lagged returns in macroeconomic variables on the volatility of Indian stock index.

d. Following Lee (1994), GARCH-X models are estimated by introducing the lagged squares of the error correction term obtained from VECM estimation. This allows isolating the impact of only the long-run dynamic auto-adjustment process that causes the relationship between macroeconomic variables and the Indian stock market to stay in equilibrium. Number of GARCH-X models that are estimated for the purpose of comparison and analysis are eighteen.

e. Finally, GARCH-R models are estimated by including only the lagged squared residuals of the error correction equation to quantify the combined impact of both the long-run adjustment and the short-run dynamic response of the macroeconomic variables on the stock index volatility (eighteen models).

For assessing the economic value of these models first the significance of the regressors is taken as the qualification criteria for out-of-sample analysis. The out-of-sample forecasting results of these models are done using two loss functions i.e. the root mean squared error and the mean absolute error. All the above models are estimated under three different conditional distributions namely the normal distribution, student-t distribution and generalized error distribution (GED). The discussion of results follows in the next section.

5.8 Analysis of Augmented GARCH Model Estimations

5.8.1 Estimation of GARCH Models

The GARCH-type models that were estimated in this analysis GARCH (1,1), GARCH(1,1)-M, AR-GARCH(1,1), AR-GARCH(1, 1)-M, MA-GARCH(1, 1), MA-GARCH(1,1)-M, ARMA(1, 1)-GARCH (1,1), ARMA(1,1)-GARCH(1,1)-M, ARMA(2,2)-GARCH(1,1), and ARMA(2,2)-GARCH(1,1)-M. The same GARCH specifications were used for EGARCH and TARCH models and all the models were estimated under three different probability distribution assumptions.

Estimations results of GARCH model indicate that the GARCH-in-mean model does not adequately fit the data and the lagged period conditional variance coefficient is highly insignificant indicating that monthly stock returns do not take into account the past period volatility. The estimates of the asymmetric terms from the EGARCH and TARCH models are also highly insignificant and therefore our observation is that the monthly stock return volatility responds symmetrically to past period innovations and the symmetric GARCH model fare better in capturing the time varying monthly volatility of Indian stock returns.

After filtering all the models having statistically insignificant coefficients the best performing models selected on the basis of information criteria are ARMA(1,1)-GARCH(1,1) under normal distribution, GARCH(1,1) under student's-*t* distribution, and GARCH(1,1) under generalized error distribution. Clearly we can see that monthly sampled return volatility responds symmetrically and the leverage hypothesis may be rejected. The symmetric GARCH (1,1) model is the preferred model for estimating volatility on monthly sampled stock returns. The conditional mean equation is better described by both long-term average as well as the auto-regressive and the moving average terms.

However, as the subsequent analysis discusses the effect of macroeconomic variables and their long-run relationship on the conditional volatility, the conditional mean equation is modeled excluding any independent variables in the conditional mean equation. Since, the GARCH models with alternative specifications of the conditional mean is also likely to generate reliable forecasts of conditional volatility; exclusion of ARMA terms from the mean equation is purposefully done to analyze only the influence of macroeconomic variables on stock return volatility.

5.8.2 Results of GARCH-L Models

For model estimations, the GARCH models are augmented with one-period lagged value of individual macroeconomic variables in their first-difference. The sign and significance of the model estimated are used to conclude the whether there is any short-term relationship between the lagged changes in the macroeconomic variables and stock market volatility. The volatility models are augmented with all the macroeconomic variables considered in the VECM model i.e. long-term interest rate, consumer price index, WTI crude, money supply (M3), and exports. Since, at a time, only one independent variable is considered in estimating the variance equation the models with better predictive ability are selected on the basis of the significance value of the coefficient. The summary of the results of model identification are given in Table 5.15.

Model	**Variable**	**Coefficient**	**p-value**	**RMSE**	**MAE**
GARCH(1,1) Normal dist.	Δlong(-1)	-0.205	0.00	0.00262	0.00234
GARCH(1,1) Student's-t dist.	Δlong(-1)	-0.204	0.00	0.00262	0.00234
GARCH(1,1) Generalized error dist.	Δlong(-1)	-0.203	0.00	0.00258	0.0023

Table 5.15 Result of GARCH-L model

Under all three distributions the GARCH (1,1) model augmented with the one period lagged change in the long-term interest rate outperforms other models based on the significance of the coefficient. Thus, there exists a lead-lag relation between changes in the long-term interest rate and the market volatility and the independent variable contains incremental information for predicting the conditional volatility of the Indian stock market. However, the volatility of the Indian stock market is negatively related to changes in the long-term interest rate which suggests that the market volatility reacts positively as interest rates in the previous month declines and vice-versa. Economic theory suggests that the stock market returns are inversely related to changes in interest rates; however, our findings indicate that this inverse relationship exists when the volatility is modeled as a function of interest rates. The possible explanations for this counter intuitive result could be that most of the upward adjustments in the volatility on account of increase in the interest rates are discounted in the price in the current month itself and the market volatility in the month subsequent to increase in interest rates corrects any overreaction that might have happened contemporaneously with interest rate increase. However, in the context of these results it will also be valid to say that since the monthly volatility is better described by symmetric GARCH models, any increase in volatility can be symmetrically attributable to either rise or fall in prices. With regards to the persistence property, we find that the persistence of GARCH estimates notably decline when monthly sampled data are fitted to the GARCH model compared with daily sampling. Thus we can further conclude that the GARCH estimates are not only sensitive to size of the sample but also to the sampling frequency.

5.8.3 Results of GARCH-Z Models

Economic theory does not suggest the macroeconomic variables that have a definitive influence on stock market returns. Since, the focus of this work is to investigate on higher-order relationship, the choice of the model variables is arbitrarily left to the past research studies. However, the variables that we have identified to analyze their long-run relationship with the Indian stock market are generally expected to have an influence on the stock market returns. We further extend the existing empirical evidence by analyzing their combined impact on the market volatility. The results of the GARCH-Z estimations are given in Table 5.16

Model	Variables				
	ΔLong(-1)	**ΔCPI(-1)**	**ΔCrude(-1)**	**ΔM3(-1)**	**ΔExports(-1)**
GARCH (1,1) Normal dist	-0.2499*	-0.0362*	-0.0014	0.0294	0.00314
GARCH (1,1) Student's-t dist	-0.2343*	-0.0528	0.0073*	0.0025	-0.0031
GARCH (1,1) GED	-0.2288*	-0.0492*	0.0033	0.0083	-0.003
*** indicates *p*-value less than 5%**					

Table 5.16 Result of GARCH-Z model

In all estimated models the coefficients of the ARCH and the GARCH term are positive and significant and the persistence of GARCH coefficients is stationary i.e. less than unity. Again the asymmetric GARCH models perform poorly having highly insignificant coefficients. GARCH (1, 1) model augmented with the lagged variables give better results than rest of all other model estimations when the significance of the coefficients is compared.

Under the three different probability assumptions the variables with significant coefficients include long-term interest rates, consumer price index and crude prices. The long-term interest rate is significant in all the models and the consumer price index significantly affects the market volatility under the normal and generalized error distributions. Crude prices also influence market volatility when the GARCH errors are assumed to follow the student's-t distribution. The inflation parameter contains a negative sign indicating an inverse relationship between the market volatility and changes in the consumer price index.

It is generally argued that stock investment provides a hedge against inflation but majority of the empirical studies on relation between stock returns and inflation suggest a negative relation between the two. Empirical evidences show that stock market returns react negatively as inflation increases, however as the efficient market hypothesis suggests that any public information is quickly adjusted in the stock prices the impact on the stock returns due to an increase in inflation may be reflected contemporaneously rather than in the subsequent month. But when higher order relationships such as the impact on volatility due to lagged period changes in inflation is modelled then the results may differ from the one encountered in empirical studies on return predictability of these changes. Moreover, the model selection is based on the significance of the estimated coefficients and since in all cases the symmetric GARCH model qualify as an ideal choice, we cannot conclude that increase in volatility is only because of decline in prices. Similar conclusion holds true for crude prices as well. Importantly, the lagged period consumer price index and the crude prices have some informational content in predicting the volatility of the Indian stock market.

The out-of-sample forecasting performance of the augmented GARCH models is marginally higher than the conventional GARCH models. The RMSE and MAE statistic in the augmented GARCH models differ from traditional GARCH models in the fourth decimal. When the GARCH model is augmented with both lagged change in long-term interest rate and the consumer price index, the RMSE and MAE are found to be less than the GARCH model suggesting a marginal improvement in forecasting volatility. The out-of-sample forecasting results indicate that macroeconomic variables do have potential for improving the volatility prediction, and further study in this area is warranted.

However, as already mentioned above that the results are sensitive to variable selection and this is the first step taken in the direction to illustrate the predictive ability of macroeconomic variables in forecasting Indian stock market volatility. The out-of-sample results are also sensitive to the choice of probability distributions, different time periods, and specification of the conditional mean equation and therefore it will be desirable to compare the findings of this study with subsequent research in this area.

5.8.4 Results of GARCH-R and GARCH-X Models

So far, we discussed whether the macroeconomic variables in isolation or their combinations have any explanatory power in explaining the stock market volatility in the context of the Indian stock market. In an earlier section in this chapter we examined whether the macroeconomic variables are cointegrated with the Indian stock market and if so are there any dynamic self-adjusting short-run corrections that ensure this equilibrium to hold. We further investigate whether the presence of a long-run relationship between the macroeconomic variables and the Indian stock market can be utilized. For this, we use the error correction term of the VECM model to establish whether the short-run adjustments to long-run equilibrium have any significance in explaining the stock market volatility. Further, analysis on the economic value of the residuals of the VECM model is also estimated to analyze whether it contains any explanatory power in explaining the volatility of the Indian stock market.

Analysis of model estimates suggests that the lagged period squared residual of the VECM model is better fitted by the GARCH model under the assumption of normal distribution compared with any other distribution. Any evidence of asymmetry in the volatility process is rejected. The coefficients of both GARCH-R and GARCH-X models suggest that the short-run dynamic adjustments captured by the error correction term and residuals of error correction model are not statistically significant in explaining the conditional volatility of monthly sampled returns of the Indian stock market.

Chapter 6 Conclusions, Limitations and Future Scope of Work

6.1 Conclusions and Summary of Key Findings

This thesis is centered on modeling the time varying nature of the conditional volatility of stock market returns. The empirical data analysis done in this work exclusively focuses on the daily and monthly stock market return volatility observed in two of the most prominent Indian stock market indices. For illuminating the latent nature of the variability of asset returns and to examine their empirical regularities, the data on two highly liquid and diversified benchmark indices viz. S&P CNX Nifty and BSE Sensex were used. Subsequently, long-run equilibrium relationship between key macroeconomic economic variables and the Indian stock market was investigated to utilize the information content of economic variables in estimating and predicting the stock market volatility.

In this thesis several GARCH-*type*, (extensions of ARCH model), were examined and the properties of volatility, stock market reforms and global events, and influence of macroeconomic variables in prediction of the volatility of the Indian stock market were analyzed to observe the time-varying nature of volatility. The study entailed both considering alternative specifications for the conditional mean equation and the conditional variance equation to compare the out-of-sample forecasting efficiency using estimated coefficients. The empirical questions we seek to answer in this thesis were:

a) Whether the GARCH forecasts obtained from the out-of-sample forecasting of several alternative models produce reliable forecasts under different loss functions.

b) Does the Indian stock market shares a long-run association with macroeconomic variables and, if so, can the long-run relationship between the stock market and the economy-wide variables be utilized to estimate and forecast the conditional volatility of the domestic stock market.

For analyzing the intertemporal behavior of the underlying data generating process, both the symmetric and asymmetric GARCH models, under normal and non-normal probability distributions, are estimated using daily returns. Analysis of results on the statistical properties of volatility suggests that the conditional volatility of the Indian stock market is highly persistent which means that the volatility process have a long memory and any shock given to the volatility process significantly influence volatility many periods ahead. This finding suggests that innovations in stock returns take long time to die resulting in a slow mean reversion toward the long-term volatility. High persistence of volatility also advocates that the parameter estimates have a high degree of predictability. However, for valid forecasting it is imperative that the volatility persistence is not explosive. For this condition to hold, the sum of ARCH and GARCH parameters should be less than one. In all model estimations the persistence of volatility is found to be less than unity and therefore the GARCH model are appropriate for fitting Indian stock market returns to estimate the conditional volatility of returns. The persistence of volatility indicates that the volatility in the Indian stock market have long memory effects and any significant negative or positive news arrival is likely to impact future volatility for several days.

The stock market returns contain significant ARCH effects that suggest the presence of clustering of returns and usefulness of estimating the conditional volatility by fitting GARCH-type models. The stock market volatility is found to be sensitive to both local and global factors and both the symmetric and asymmetric models of conditional volatility adequately model the volatility of Indian stock market under different conditional mean specifications. The comparative analysis of GARCH models in terms of their predictive ability indicates that the choice of the optimal GARCH model is sensitive to the sample period. This finding is first encountered when a random sampling based on the five year sample size is done on stock return data from 1985 to 2014. Both symmetric and asymmetric GARCH models have significant predictive ability.

To ascertain whether the response of volatility to news is symmetric or asymmetric the GARCH models are fitted on smaller sub-samples, following the liberalization reforms, and each sub-sample overlap with significant events both domestic and international. For the analysis, a total of six sample periods, including the entire sample period, are considered for model estimation to determine the best model in each sub-sample based on its out-of-sample forecasting accuracy. First, the criteria for choosing the superior model is based on ranking of the models based on three separate information criteria in each sub-sample, and finally, the best model in every sample, as per the information criteria is ranked based on its out of sample forecasting results.

Different specifications of the conditional mean equation and the conditional variance equations are estimated under normal and non-normal probability distribution assumptions. Inclusion of the AR, MA and higher order ARMA terms in conditional mean specification improves forecasts of volatility compared to plain vanilla GARCH model without any independent variables for the mean equation. In majority of these estimations the auto-regressive and moving average terms better predict volatility of the Indian stock market compared to pure white noise specification of the conditional mean.

Since the stock market returns often violate normality assumptions, the probability distributions that capture fat-tails are also considered to achieve better estimation results. The assumption of the student’s t distribution best describes the volatility in the Indian stock market suggesting that the non-normal probability distribution assumption outperforms the models that assume normally distributed errors. Results of the comparative performance of GARCH models indicate that both the symmetric and asymmetric GARCH models are ideally suited for capturing the volatility in the Indian stock market. However, during the bull market phase of 2003-2007 and the revival phase post sub-prime crisis in both cases the asymmetric GARCH models perform better than symmetric GARCH models. Both the symmetric GARCH vs. asymmetric GARCH models equally outperform each other in our analysis and the symmetric GARCH models perform better than asymmetric models during times of extreme volatility in the market. This finding is in contrast with a commonly held belief that that the GARCH model underperform during the periods of excessive volatility. Leverage hypothesis is often referred to explain such a phenomenon. But surprisingly during the extreme bear phase overlapping the sub-prime crisis period the symmetric GARCH models outperform asymmetric models suggesting that the leverage hypothesis, alone, may not be adequate to explain why asymmetric GARCH models are better than symmetric ones especially during high volatile phase.

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GARCH model are acclaimed to underperform during the periods of excessive volatility. Leverage hypothesis is often referred to explain such a phenomenon. But surprisingly during the extreme bear phase overlapping the sub-prime crisis period the symmetric GARCH models outperform asymmetric models suggesting that the leverage hypothesis may not be adequate to explain why asymmetric GARCH models are better than symmetric ones especially during high volatile phase.

In all estimation results, the GARCH-in-mean (GARCH-M) specification does not provide any economic benefit in volatility estimation as the coefficient parameter of the lagged period estimated conditional variance GARCH is highly significant. This provides an explanation to the risk-premium hypothesis that investors in the Indian stock market do not increase their required return following an increase in market volatility. This finding suggests that the Indian stock markets have a high degree of resilience and after any significant fall, the markets revive confidently that renders the lagged period estimate of the conditional variance insignificant. This finding is consistent with the fact that the overall sample period the stock market is largely upward trending despite intermittent shocks.

Finally, the study brings together the influence of macroeconomic variables on stock market volatility within a co-integration and vector error correction framework to determine whether the co-integrating relationship and the presence of long-run equilibrium relationships among the macroeconomic variables and stock index can be utilized for improving market volatility forecasts. The study addresses a significant gap in the existing literature in the Indian context by utilizing the information content of macroeconomic variable through their long-run equilibrium relationship with the Indian stock returns. Comparisons are drawn between the conventional GARCH specifications with the GARCH models augmented with error correction terms to conclude whether including macroeconomic variables carry any incremental information content in forecasting the conditional volatility using GARCH models.

We find that individually the macroeconomic variables have explanatory power in explaining the volatility of the Indian stock market. The out-of-sample forecasts of volatility marginally improve when the combined effect of statistically significant macroeconomic variables are considered as independent variables in the GARCH specification. Investigating the effect of macroeconomic variables on the conditional volatility of the Indian stock market requires that the conditional variance model is augmented with the exogenous variables; therefore the information criteria may not provide a reliable model selection because its selection is based on the efficiency of the conditional mean equation. Therefore, under all the probability estimations both the symmetric and asymmetric GARCH models are estimated and their selection, for out-of-sample analysis, is based on the significance of the model parameters rather than information criteria.

The augmented GARCH model with one-period lagged long-term interest rate is the only variable with significant coefficient. This suggests that India's stock market volatility is negatively impacted by long-term interest rates. The inverse relation between long-term interest rate and the conditional volatility suggests that as the interest rate in the current period increases the expected volatility in the next period is likely to reduce which may be interpreted as changes in interest rates may have a transitory impact on stock returns contemporaneously but the effects soon die out. However, the finding explains a possible lead-lag relation of a higher order between long-term interest rates and the stock market volatility. Long-term interest rates under all probability assumptions have significant and negative coefficient. The persistence of volatility is close to 0.88 and the optimal conditional volatility model, based on out-of-sample forecasting efficiency is GARCH (1, 1).

Among GARCH models augmented with all lagged macroeconomic variables, the GARCH (1, 1) is the best model based on the statistical significance of the ARCH and the GARCH term and the out-of-sample forecasting accuracy. However, for the exogenous regressors of macroeconomic variables the significant coefficients are of long-term interest rates and CPI under normal distribution and GED and the long-term interest rates and crude prices have a positive coefficient suggesting presence of higher order lead-lag relationship. The transitory impact of crude may be negative on the stock market and that can be concluded only by contemporaneously modeling using VAR methodology.

The monthly return volatility of the market soon corrects itself causing the volatility to respond negatively to previous month’s rise in crude prices. Finally, we observe that the p-value of the error correction term in the GARCH-X estimation is very close to 5% which indicates that that further study on GARCH models by integrating them with macroeconomic variables may provide credible evidences on the short-run disequilibria correction among the macroeconomic variables and the stock market. This may have a potential for capturing India’s stock market volatility more efficiently by integrating GARCH models with different macroeconomic variables.

Thus, the key findings of this study provide insights into the time varying nature of the movement in the Indian stock market benchmark index which along with their implications are outlined below:

a) The persistence of volatility in the Indian stock market is high indicating presence of long-memory property in the time series data. The high-persistence also indicates high level of volatility which is typical to emerging stock markets.

b) The persistence of volatility is modelled using incremental information on daily returns. The volatility of Indian stock market is found to be stationary and the persistence value does not exceed unity. Hence, the GARCH estimates qualify for forecasting volatility.

c) During the periods of high-volatility the symmetric GARCH models out-perform the asymmetric GARCH models. This finding questions the leverage hypothesis that is used as an argument for supporting the asymmetric nature of volatility. The leverage hypothesis alone may not be able to explain the asymmetric nature of conditional volatility.

d) It is observed that the minimum number of observations required for estimating the GARCH model using the daily stock market returns should be at least three hundred. This has also been illustrated in the discussion on the evolution of the GARCH parameters.

e) The out-of-sample forecasting accuracy of GARCH models is found to be sensitive to the choice of the loss-function and the sample size.

f) Macroeconomic variables have significant long-run association with the BSE Sensex (monthly sampled). Domestic macroeconomic variables and their long-run relationship with the Indian stock market are found to significantly influence the conditional volatility within the GARCH framework. An important implication of this finding is that researchers and practitioners must give heed to the macroeconomic variables while modeling stock market volatility. The information content of macroeconomic variables for modeling Indian stock market volatility is found to be statistically significant and further research in this area is warranted.

6.2 Specific Contributions of Research

Key contributions of research are as under:

i) Comprehensive analysis of the properties of conditional volatility, specially the persistence property and the asymmetry property fills research gaps in the Indian context and provides empirical evidences on the intertemporal behavior of volatility. Studies prior to this work have neither provided any explanation on how the GARCH persistence varies as new information is included in volatility estimation, nor, have done a comparative analysis between the symmetric and asymmetric GARCH models using smaller sub-samples based on economic reforms and global economic crisis. The analysis of results provides evidence that there is no single model that outperforms other models in out-of-sample forecasting and that GARCH estimation done on a long-term data set may not be appropriate or should be interpreted with caution.

ii) Identification of superior models is based on several models that include ARMA specification of the conditional mean and the lagged variance in the mean equation (ARCH-M models). Model selection criteria are based first on the information criteria followed by forecasting performance as per out-of-sample results. In the Indian context, through the review of literature, we find that studies on out-of-sample forecasting are limited and we have attempted to address these gap in this comprehensive analysis.

iii) A major contribution of this study is that it provides empirical evidence that the macroeconomic variables share a long-run association with the stock index movement and such information can be utilized to model the conditional volatility of the stock market and obtain volatility forecasts.

iv) Another contribution of this research is the empirical verification that both the symmetric and asymmetric GARCH models are suitable for modeling the conditional volatility in the Indian stock market context. This finding has relevance for adopting adequate risk management strategies.

6.3 Limitations of the Study and Scope for Future Work

6.3.1 Limitations

The study has attempted to model the time varying volatility in the Indian stock market using only the GARCH-*family* models. Due to a tremendous interest of academicians and the market participant in modeling the conditional volatility numerous volatility modeling approaches have been proposed. Thousands of such models are applied by practitioners and researchers for estimating market volatility. This study focuses only on the GARCH specification which can be further enriched by using other types of modeling approaches for estimating and forecasting volatility. The data sampling frequency considered in this study is daily and monthly which is another limitation as recent advances have been made, majorly in the developed markets, toward modeling the volatility by considering the **high-frequency data**. Again comparing the results of volatility forecasting using tick-by-tick data with the observations made in this study will be of economic utility.

A major finding in this study is that the persistence of volatility in daily returns is very high and close to unity. If the persistence value becomes greater than one than the volatility process is said to be integrated and becomes non-stationary rendering all forecasting unreliable. Since, the findings in this study is consistent with other studies on volatility persistence the out-of-sample forecasting gives reliable results. However, this study makes no attempt for explaining the possible reasons behind the high degree of persistence and accurate implications of the high persistence can be made by estimating the half-life of a shock in the return process. The study on the half-life of a random shock will be useful in quantifying the number of trading days a shock takes to completely die out. This finding is expected to enable portfolio managers by taking adequate risk management strategies after a sudden shock to the volatility process is encountered.

In this study we identify that the choice of the optimal volatility model for the Indian stock market varies depending on the sampling frequency, the size of the sample, the time period under consideration, the choice of probability distribution, and the specification of the conditional mean equation. Though the results adequately explain the time varying nature of volatility in Indian markets but due to the above mentioned factors no single model outperform the other models in all conditional volatility estimations. Identification of the optimal GARCH model for the Indian stock market is also left for further exploration.

As mentioned in earlier discussion that a baffling decision that confronts a researcher while fitting the GARCH models with exogenous variables is the choice of the most appropriate variables. The stock market volatility is expected to be influenced by factors such as global volatility, stock market reforms, firm-specific variables, and the macroeconomic variables. Given the fact that the number of degrees of freedom is lost as more explanatory variables are included in the study and due to limited sample size, it is not possible to consider all proxies of the relevant variables simultaneously. Hence, as a suggestion for future work the independent variables may be first classified into different categories and then the forecasting accuracy of each category is separately examined. In the analysis of impact of macroeconomic variables on the Indian stock market volatility, the main objective was to demonstrate whether the presence of co-integration among the variables can be used for modeling volatility. The results indicate presence of incremental informational content in the macroeconomic variables and further extension to this work can be done by considering more variables as proxy for the macroeconomic variables.

The limitations of the study include following:

a) The time-series under consideration may have undergone structural changes that usually overstate the persistence of the GARCH estimation. The structural changes, if at all exist, make the model parameters unstable and thus may distort the forecasts. Identification of structural breaks is not carried out in this study and dividing the data period into sub-samples based on the structural break dates may have been more desirable. However, the study on the persistence property, in this thesis, is exclusively done to partially address the issue of regime changing and structural breaks in the series. The analysis of ARCH and GARCH parameters on a sixteen year data is found to be stationary. (Perron, 2006), in his review article, mentions about the possible interplay between structural breaks and the presence of unit root and mentions that several tests for structural breaks rejects the null hypothesis of no structural breaks when the process contains a unit root. Several methods of identifying structural breaks of conditional volatility exist in the literature and these studies on structural changes in volatility are vast and still emerging which can be taken up for further research in the area.

b) The variables that are considered for analyzing the impact of macroeconomic variables on stock market volatility are based on the past literature studies. The economic theory does not propound any clear guideline for variables selection and several competing variables qualify as desirable candidates. The qualification criteria for variables selection is based on the review of literature. However work can be further extended by incorporating other macro variables or dropping some of these variables to find reliability of outcomes.

c) The third limitation of this study is that it completely ignores the spillover effects from foreign stock markets that may contribute to the domestic stock market volatility. Incorporating the spill-over effect would require the study to extend into multivariate GARCH estimation, which is left for further study.

6.3.2 Scope for Future Work

Keeping above limitations in the backdrop, future scope for research in the area summarized as under.

a) The results of volatility estimation indicate superior forecasting ability of GARCH models in capturing the Indian stock market volatility. The finding suggests the presence of higher order statistical dependence in stock returns which is an indication of rejection of the weak-form Efficient Market Hypothesis. Therefore, it is plausible that the GARCH conditional variances may be used to model the investor sentiments and improve the estimation of the uncertainty component in the asset price movement.

b) The study on the statistical dependence between the stock market and macroeconomic variables indicate presence of long-run association. The findings can be further improved by investigating dynamic dependence and lead-lag relationship between macroeconomic variables from the real sector and financial sector.

c) Estimation of GARCH conditional variance by modeling the dynamic conditional correlations between the macroeconomic variables and the stock returns within the multivariate GARCH framework.

d) Out-of-sample forecasting results are found to be sensitive to the choice of loss functions. Further improvements for obtaining optimal volatility model for the Indian stock market by considering variety of loss functions while comparing out-of-sample forecasting accuracy.

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His basic interests lie in Entrepreneurship, Strategic Management, Values in Management, Capital Markets and Financial Management. He has published four books in the area of Entrepreneurship, General Management, Ethics in Management, and Grassroots Entrepreneurship. He has published more than 50 research papers in national and international journals and has presented papers in international and national conferences in India and abroad. He has delivered more than 60 invited talks and chaired sessions in National and International conferences. Two students have successfully completed their PhD under his supervision and another seven are pursuing in their advance stages. He has examined more than twelve PhD theses of different universities.

He has undertaken research projects in the area of entrepreneurship development funded by **National Entrepreneurship Network;** Strategies to Meet Manpower Requirements for Power Sector up to 2020 funded by **NSTMIS, Department of Science &Technology**, Government of India; educational excellence funded by **Aditya Birla Group** and successfully got grants for setting up Technology Business Incubator at BITS Pilani and for extending seed fund support to start-ups under **Technology Incubation & Development of Entrepreneurs (TIDE)** in the areas of Electronics and ICT.

He has been serving as Guest Faculty with a number of leading management institutions and colleges of various Banks. He has served as Nominee Director on the Boards of a number of companies; expert member **Biotechnology Industry Research Assistance Council** (BIRAC), Department of Biotechnology Government of India; expert member of **UPSC**, member of **Governing Body of STIDE** of Central University of Rajasthan, member of committees for selection of faculty in different institutions, member of Boards of Studies of different universities.

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He is a member of the **National Entrepreneurship Network (NEN) India Faculty Advisory Board**. He has been honoured with **distinguished faculty award** in recognition and appreciation of his dedication, interest, enthusiasm and attitude in accomplishing his assigned mission of teaching by BITSAA International in 2011, **Global excellence award for outstanding contribution to management education – 2012** by Management Teachers Consortium (MTC) and conferred with **Entrepreneurship Educator and Mentor Special Jury Award** for promotion of Entrepreneurship Education by NEN in collaboration with Ministry of Skill and Entrepreneurship Development, British Council and Intel.

Empirical Investigation and Analysis of Volatility Forecasting Models for the Indian Stock Market

THESIS

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Chapter 6 Conclusions, Limitations and Future Scope of Work

6.1 Conclusions and Summary of Key Findings

This thesis is centered on modeling the time varying nature of the conditional volatility of stock market returns. The empirical data analysis done in this work exclusively focuses on the daily and monthly stock market return volatility observed in two of the most prominent Indian stock market indices. For illuminating the latent nature of the variability of asset returns and to examine their empirical regularities, the data on two highly liquid and diversified benchmark indices viz. S&P CNX Nifty and BSE Sensex were used. Subsequently, long-run equilibrium relationship between key macroeconomic economic variables and the Indian stock market was investigated to utilize the information content of economic variables in estimating and predicting the stock market volatility.

In this thesis several GARCH-*type*, (extensions of ARCH model), were examined and the properties of volatility, stock market reforms and global events, and influence of macroeconomic variables in prediction of the volatility of the Indian stock market were analyzed to observe the time-varying nature of volatility. The study entailed both considering alternative specifications for the conditional mean equation and the conditional variance equation to compare the out-of-sample forecasting efficiency using estimated coefficients. The empirical questions we seek to answer in this thesis were:

a) Whether the GARCH forecasts obtained from the out-of-sample forecasting of several alternative models produce reliable forecasts under different loss functions.

b) Does the Indian stock market shares a long-run association with macroeconomic variables and, if so, can the long-run relationship between the stock market and the economy-wide variables be utilized to estimate and forecast the conditional volatility of the domestic stock market.

For analyzing the intertemporal behavior of the underlying data generating process, both the symmetric and asymmetric GARCH models, under normal and non-normal probability distributions, are estimated using daily returns. Analysis of results on the statistical properties of volatility suggests that the conditional volatility of the Indian stock market is highly persistent which means that the volatility process have a long memory and any shock given to the volatility process significantly influence volatility many periods ahead. This finding suggests that innovations in stock returns take long time to die resulting in a slow mean reversion toward the long-term volatility. High persistence of volatility also advocates that the parameter estimates have a high degree of predictability. However, for valid forecasting it is imperative that the volatility persistence is not explosive. For this condition to hold, the sum of ARCH and GARCH parameters should be less than one. In all model estimations the persistence of volatility is found to be less than unity and therefore the GARCH model are appropriate for fitting Indian stock market returns to estimate the conditional volatility of returns. The persistence of volatility indicates that the volatility in the Indian stock market have long memory effects and any significant negative or positive news arrival is likely to impact future volatility for several days.

The stock market returns contain significant ARCH effects that suggest the presence of clustering of returns and usefulness of estimating the conditional volatility by fitting GARCH-type models. The stock market volatility is found to be sensitive to both local and global factors and both the symmetric and asymmetric models of conditional volatility adequately model the volatility of Indian stock market under different conditional mean specifications. The comparative analysis of GARCH models in terms of their predictive ability indicates that the choice of the optimal GARCH model is sensitive to the sample period. This finding is first encountered when a random sampling based on the five year sample size is done on stock return data from 1985 to 2014. Both symmetric and asymmetric GARCH models have significant predictive ability.

To ascertain whether the response of volatility to news is symmetric or asymmetric the GARCH models are fitted on smaller sub-samples, following the liberalization reforms, and each sub-sample overlap with significant events both domestic and international. For the analysis, a total of six sample periods, including the entire sample period, are considered for model estimation to determine the best model in each sub-sample based on its out-of-sample forecasting accuracy. First, the criteria for choosing the superior model is based on ranking of the models based on three separate information criteria in each sub-sample, and finally, the best model in every sample, as per the information criteria is ranked based on its out of sample forecasting results.

Different specifications of the conditional mean equation and the conditional variance equations are estimated under normal and non-normal probability distribution assumptions. Inclusion of the AR, MA and higher order ARMA terms in conditional mean specification improves forecasts of volatility compared to plain vanilla GARCH model without any independent variables for the mean equation. In majority of these estimations the auto-regressive and moving average terms better predict volatility of the Indian stock market compared to pure white noise specification of the conditional mean.

Since the stock market returns often violate normality assumptions, the probability distributions that capture fat-tails are also considered to achieve better estimation results. The assumption of the student’s t distribution best describes the volatility in the Indian stock market suggesting that the non-normal probability distribution assumption outperforms the models that assume normally distributed errors. Results of the comparative performance of GARCH models indicate that both the symmetric and asymmetric GARCH models are ideally suited for capturing the volatility in the Indian stock market. However, during the bull market phase of 2003-2007 and the revival phase post sub-prime crisis in both cases the asymmetric GARCH models perform better than symmetric GARCH models. Both the symmetric GARCH vs. asymmetric GARCH models equally outperform each other in our analysis and the symmetric GARCH models perform better than asymmetric models during times of extreme volatility in the market. This finding is in contrast with a commonly held belief that that the GARCH model underperform during the periods of excessive volatility. Leverage hypothesis is often referred to explain such a phenomenon. But surprisingly during the extreme bear phase overlapping the sub-prime crisis period the symmetric GARCH models outperform asymmetric models suggesting that the leverage hypothesis, alone, may not be adequate to explain why asymmetric GARCH models are better than symmetric ones especially during high volatile phase.

Different specifications of the conditional mean equation and the conditional variance equations are estimated under three probability distributions. Inclusion of the AR, MA and higher order ARMA terms in conditional mean specification improves forecasts of volatility compared to plain vanilla GARCH model without any independent variables for the mean equation. In majority of these estimations the auto-regressive and moving average terms better predict volatility of the Indian stock market compared to pure white noise specification of the conditional mean.

GARCH model are acclaimed to underperform during the periods of excessive volatility. Leverage hypothesis is often referred to explain such a phenomenon. But surprisingly during the extreme bear phase overlapping the sub-prime crisis period the symmetric GARCH models outperform asymmetric models suggesting that the leverage hypothesis may not be adequate to explain why asymmetric GARCH models are better than symmetric ones especially during high volatile phase.

In all estimation results, the GARCH-in-mean (GARCH-M) specification does not provide any economic benefit in volatility estimation as the coefficient parameter of the lagged period estimated conditional variance GARCH is highly significant. This provides an explanation to the risk-premium hypothesis that investors in the Indian stock market do not increase their required return following an increase in market volatility. This finding suggests that the Indian stock markets have a high degree of resilience and after any significant fall, the markets revive confidently that renders the lagged period estimate of the conditional variance insignificant. This finding is consistent with the fact that the overall sample period the stock market is largely upward trending despite intermittent shocks.

Finally, the study brings together the influence of macroeconomic variables on stock market volatility within a co-integration and vector error correction framework to determine whether the co-integrating relationship and the presence of long-run equilibrium relationships among the macroeconomic variables and stock index can be utilized for improving market volatility forecasts. The study addresses a significant gap in the existing literature in the Indian context by utilizing the information content of macroeconomic variable through their long-run equilibrium relationship with the Indian stock returns. Comparisons are drawn between the conventional GARCH specifications with the GARCH models augmented with error correction terms to conclude whether including macroeconomic variables carry any incremental information content in forecasting the conditional volatility using GARCH models.

We find that individually the macroeconomic variables have explanatory power in explaining the volatility of the Indian stock market. The out-of-sample forecasts of volatility marginally improve when the combined effect of statistically significant macroeconomic variables are considered as independent variables in the GARCH specification. Investigating the effect of macroeconomic variables on the conditional volatility of the Indian stock market requires that the conditional variance model is augmented with the exogenous variables; therefore the information criteria may not provide a reliable model selection because its selection is based on the efficiency of the conditional mean equation. Therefore, under all the probability estimations both the symmetric and asymmetric GARCH models are estimated and their selection, for out-of-sample analysis, is based on the significance of the model parameters rather than information criteria.

The augmented GARCH model with one-period lagged long-term interest rate is the only variable with significant coefficient. This suggests that India’s stock market volatility is negatively impacted by long-term interest rates. The inverse relation between long-term interest rate and the conditional volatility suggests that as the interest rate in the current period increases the expected volatility in the next period is likely to reduce which may be interpreted as changes in interest rates may have a transitory impact on stock returns contemporaneously but the effects soon die out. However, the finding explains a possible lead-lag relation of a higher order between long-term interest rates and the stock market volatility. Long-term interest rates under all probability assumptions have significant and negative coefficient. The persistence of volatility is close to 0.88 and the optimal conditional volatility model, based on out-of-sample forecasting efficiency is GARCH (1, 1).

Among GARCH models augmented with all lagged macroeconomic variables, the GARCH (1, 1) is the best model based on the statistical significance of the ARCH and the GARCH term and the out-of-sample forecasting accuracy. However, for the exogenous regressors of macroeconomic variables the significant coefficients are of long-term interest rates and CPI under normal distribution and GED and the long-term interest rates and crude prices have a positive coefficient suggesting presence of higher order lead-lag relationship. The transitory impact of crude may be negative on the stock market and that can be concluded only by contemporaneously modeling using VAR methodology.

The monthly return volatility of the market soon corrects itself causing the volatility to respond negatively to previous month's rise in crude prices. Finally, we observe that the p-value of the error correction term in the GARCH-X estimation is very close to 5% which indicates that that further study on GARCH models by integrating them with macroeconomic variables may provide credible evidences on the short-run disequilibria correction among the macroeconomic variables and the stock market. This may have a potential for capturing India's stock market volatility more efficiently by integrating GARCH models with different macroeconomic variables.

Thus, the key findings of this study provide insights into the time varying nature of the movement in the Indian stock market benchmark index which along with their implications are outlined below:

a) The persistence of volatility in the Indian stock market is high indicating presence of long-memory property in the time series data. The high-persistence also indicates high level of volatility which is typical to emerging stock markets.

b) The persistence of volatility is modelled using incremental information on daily returns. The volatility of Indian stock market is found to be stationary and the persistence value does not exceed unity. Hence, the GARCH estimates qualify for forecasting volatility.

c) During the periods of high-volatility the symmetric GARCH models out-perform the asymmetric GARCH models. This finding questions the leverage hypothesis that is used as an argument for supporting the asymmetric nature of volatility. The leverage hypothesis alone may not be able to explain the asymmetric nature of conditional volatility.

d) It is observed that the minimum number of observations required for estimating the GARCH model using the daily stock market returns should be at least three hundred. This has also been illustrated in the discussion on the evolution of the GARCH parameters.

e) The out-of-sample forecasting accuracy of GARCH models is found to be sensitive to the choice of the loss-function and the sample size.

f) Macroeconomic variables have significant long-run association with the BSE Sensex (monthly sampled). Domestic macroeconomic variables and their long-run relationship with the Indian stock market are found to significantly influence the conditional volatility within the GARCH framework. An important implication of this finding is that researchers and practitioners must give heed to the macroeconomic variables while modeling stock market volatility. The information content of macroeconomic variables for modeling Indian stock market volatility is found to be statistically significant and further research in this area is warranted.

6.2 Specific Contributions of Research

Key contributions of research are as under:

i) Comprehensive analysis of the properties of conditional volatility, specially the persistence property and the asymmetry property fills research gaps in the Indian context and provides empirical evidences on the intertemporal behavior of volatility. Studies prior to this work have neither provided any explanation on how the GARCH persistence varies as new information is included in volatility estimation, nor, have done a comparative analysis between the symmetric and asymmetric GARCH models using smaller sub-samples based on economic reforms and global economic crisis. The analysis of results provides evidence that there is no single model that outperforms other models in out-of-sample forecasting and that GARCH estimation done on a long-term data set may not be appropriate or should be interpreted with caution.

ii) Identification of superior models is based on several models that include ARMA specification of the conditional mean and the lagged variance in the mean equation (ARCH-M models). Model selection criteria are based first on the information criteria followed by forecasting performance as per out-of-sample results. In the Indian context, through the review of literature, we find that studies on out-of-sample forecasting are limited and we have attempted to address these gap in this comprehensive analysis.

iii) A major contribution of this study is that it provides empirical evidence that the macroeconomic variables share a long-run association with the stock index movement and such information can be utilized to model the conditional volatility of the stock market and obtain volatility forecasts.

iv) Another contribution of this research is the empirical verification that both the symmetric and asymmetric GARCH models are suitable for modeling the conditional volatility in the Indian stock market context. This finding has relevance for adopting adequate risk management strategies.

6.3 Limitations of the Study and Scope for Future Work

6.3.1 Limitations

The study has attempted to model the time varying volatility in the Indian stock market using only the GARCH-*family* models. Due to a tremendous interest of academicians and the market participant in modeling the conditional volatility numerous volatility modeling approaches have been proposed. Thousands of such models are applied by practitioners and researchers for estimating market volatility. This study focuses only on the GARCH specification which can be further enriched by using other types of modeling approaches for estimating and forecasting volatility. The data sampling frequency considered in this study is daily and monthly which is another limitation as recent advances have been made, majorly in the developed markets, toward modeling the volatility by considering the **high-frequency data**. Again comparing the results of volatility forecasting using tick-by-tick data with the observations made in this study will be of economic utility.

A major finding in this study is that the persistence of volatility in daily returns is very high and close to unity. If the persistence value becomes greater than one than the volatility process is said to be integrated and becomes non-stationary rendering all forecasting unreliable. Since, the findings in this study is consistent with other studies on volatility persistence the out-of-sample forecasting gives reliable results. However, this study makes no attempt for explaining the possible reasons behind the high degree of persistence and accurate implications of the high persistence can be made by estimating the half-life of a shock in the return process. The study on the half-life of a random shock will be useful in quantifying the number of trading days a shock takes to completely die out. This finding is expected to enable portfolio managers by taking adequate risk management strategies after a sudden shock to the volatility process is encountered.

In this study we identify that the choice of the optimal volatility model for the Indian stock market varies depending on the sampling frequency, the size of the sample, the time period under consideration, the choice of probability distribution, and the specification of the conditional mean equation. Though the results adequately explain the time varying nature of volatility in Indian markets but due to the above mentioned factors no single model outperform the other models in all conditional volatility estimations. Identification of the optimal GARCH model for the Indian stock market is also left for further exploration.

As mentioned in earlier discussion that a baffling decision that confronts a researcher while fitting the GARCH models with exogenous variables is the choice of the most appropriate variables. The stock market volatility is expected to be influenced by factors such as global volatility, stock market reforms, firm-specific variables, and the macroeconomic variables. Given the fact that the number of degrees of freedom is lost as more explanatory variables are included in the study and due to limited sample size, it is not possible to consider all proxies of the relevant variables simultaneously. Hence, as a suggestion for future work the independent variables may be first classified into different categories and then the forecasting accuracy of each category is separately examined. In the analysis of impact of macroeconomic variables on the Indian stock market volatility, the main objective was to demonstrate whether the presence of co-integration among the variables can be used for modeling volatility. The results indicate presence of incremental informational content in the macroeconomic variables and further extension to this work can be done by considering more variables as proxy for the macroeconomic variables.

The limitations of the study include following:

a) The time-series under consideration may have undergone structural changes that usually overstate the persistence of the GARCH estimation. The structural changes, if at all exist, make the model parameters unstable and thus may distort the forecasts. Identification of structural breaks is not carried out in this study and dividing the data period into sub-samples based on the structural break dates may have been more desirable. However, the study on the persistence property, in this thesis, is exclusively done to partially address the issue of regime changing and structural breaks in the series. The analysis of ARCH and GARCH parameters on a sixteen year data is found to be stationary. (Perron, 2006), in his review article, mentions about the possible interplay between structural breaks and the presence of unit root and mentions that several tests for structural breaks rejects the null hypothesis of no structural breaks when the process contains a unit root. Several methods of identifying structural breaks of conditional volatility exist in the literature and these studies on structural changes in volatility are vast and still emerging which can be taken up for further research in the area.

b) The variables that are considered for analyzing the impact of macroeconomic variables on stock market volatility are based on the past literature studies. The economic theory does not propound any clear guideline for variables selection and several competing variables qualify as desirable candidates. The qualification criteria for variables selection is based on the review of literature. However work can be further extended by incorporating other macro variables or dropping some of these variables to find reliability of outcomes.

c) The third limitation of this study is that it completely ignores the spillover effects from foreign stock markets that may contribute to the domestic stock market volatility. Incorporating the spill-over effect would require the study to extend into multivariate GARCH estimation, which is left for further study.

6.3.2 Scope for Future Work

Keeping above limitations in the backdrop, future scope for research in the area summarized as under.

a) The results of volatility estimation indicate superior forecasting ability of GARCH models in capturing the Indian stock market volatility. The finding suggests the presence of higher order statistical dependence in stock returns which is an indication of rejection of the weak-form Efficient Market Hypothesis. Therefore, it is plausible that the GARCH conditional variances may be used to model the investor sentiments and improve the estimation of the uncertainty component in the asset price movement.

b) The study on the statistical dependence between the stock market and macroeconomic variables indicate presence of long-run association. The findings can be further improved by investigating dynamic dependence and lead-lag relationship between macroeconomic variables from the real sector and financial sector.

c) Estimation of GARCH conditional variance by modeling the dynamic conditional correlations between the macroeconomic variables and the stock returns within the multivariate GARCH framework.

d) Out-of-sample forecasting results are found to be sensitive to the choice of loss functions. Further improvements for obtaining optimal volatility model for the Indian stock market by considering variety of loss functions while comparing out-of-sample forecasting accuracy.