INFORMATION CONTENT AND PREDICTABILITY OF IMPLIED VOLATILITY: EVIDENCE FROM THE INDIAN EQUITY MARKET

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BY

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DECLARATION

I, **Mr. Siba prasada panda** hereby declare that this thesis entitled, "**Information Content and Predictability of Implied Volatility: Evidence from the Indian Equity Market"** submitted by me under the supervision of **Prof. Naresh Kumar Sharma** is a bonafide research work which is also free from plagiarism. I also declare that it has not been submitted previously in part or in full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodganga/INFLIBNET.

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Introduction, Issues and Objectives of the Study

1.0. Introduction:

Over the years, a lot of emphasis has been placed on forecasting the volatility of financial markets by academicians, policy makers, traders, proprietary trading firms and investors, as volatility forecasts are vital for taking financial decisions, such as implementation and evaluation of asset pricing theories and risk management. For modeling the financial time series volatility statistician put numerous effors. Engle (1982) Autoregressive Conditional Heteroskedasticity (ARCH) model is one of the pioneering contribution in this area of research. To model time varying conditional hetroskedasticity Engle's proposes a model where variance of series is estimated using past innovations, in addition to the autoregressive mean equation. To capture the dynamics of the conditional variance, Bollerslev (1986) introduced the Generalized ARCH (GARCH) model, in which time varying volatility as a function of both past variance of error term derived from mean equation and past time varying volatility. There are other historical volatility forecasting models, which use past returns like Simple Moving Average (SMA) and Exponential Weighted Moving Average (EWMA). Since all these models use past return series they are called "Backward Looking Volatility" (BLV) models.

On the other hand, there is another school of thought who emphasis on option pricing and advocates that implied volatility is the best predictor of relalized volatility. Based on option pricing model of Black and Scholes (1973), the option price is determined by five factors, namely spot price, strike price, risk free interest rate, time to maturity, and volatility. In this framework, all informations are available in the market except volatility because volatility will be determined only when we have todays and future price of any financial asset. Suppose we have call or put market price then, if we put call or put market option prices in the model, then the model by inverting the formula we will get the market average volatility upto the contract exipry date. Which mean when all the parameters (spot price, strike price, risk free interest rate, time to maturity) are known, then there is a direct relationship between market option price and volatility. The volatility which we have calculated by this procedure is called implied volatility.

According to option pricing models the financial markets are infromationally efficient that's why the current option price contain all available information of the market. Because of that the implied volatility which claculated from option pricing model is the best predictor of future realized volatility. That's why we call it as "Forward looking Volatility" because it is calculated using today's information and not the past information. The same information can also be captured by the ARCH School of models using historical prices. When we have historical prices, we can estimate the asset's volatility, which correctly contain all information. Using those historical data, we can calculate not only the volatility, but also the conditional volatilities by employing more complex time series models like GARCH and EGARCH as we discussed above.

In addition to the historical prices, the market has other information, the returns of other financial markets, past news, current market news and future news (e.g., monetary policy, fiscal policy, war etc.). In other words, if the market is efficient then the implied volatility should contain all the available infromation more than the historical volatility which is calculated from historical returns data. That's why it is generally believed that option prices is the best predictor of future volatility of the assets. Basically there are mainly two reasons for this belief. Firstly, it is belief that the option prices have the ability to contain all publicly available information including all information that contained in the past pricesand secondly it is belief that if option price are not able to represent an optimal forecast of the future volatility then there are certain strategies which push the option price to the accurate level. Since there is a significance of modeling and predicting the financial asset volatility, it is essential for the asset manager to develop reliable models and compare it with implied volatility.

Beckers (1981) concludes that the option market is inefficient and the current option price does not reflect all available information. Similar type of analysis was used by Canina and Figlewshi (1993). They find that implied volatility does not contain any information about the future realized volatility.Day and Lewis (1992), studied S&P 100 index options and Lamoureux and Lastrapes (1993), who studied ten stocks options have concluded that implied volatility is biased and inefficient forecaster of future realized volatility. Christensen and Prabhala (1998) develop a new method in order to avoid overlapping data problem. They use monthly non overlapping observation for option market. They found that implied volatility outperform historical volatility in forecasting future volatility in a monthly non overlapping data set.Jorion (1995) examine currency option and found that time series models of volatility based on returns are outperformed by implied volatility forecasts despite the former having the advantage of calculating the estimate parameter.

This brings us to the issues of how to test whether the implied volatility has greater predictability compared to other volatility models which use past returns of S&P CNX Nifty index for calculation of volatility. Before discussing more of the option market, the study first tries to give a broad view of the derivatives market.

In today's financial market derivatives are an important class of asset. The derivatives segment recommended various types of risk management and allow innovative trading investment strategies for the investor. For over 30 years, derivative market has been small and domestic but now the scenario has changed. Today's the derivatives market is very dynamic and has grown enormously.

1.1. Overview of Global Derivatives Market:

In general, the market participants view financial market as the equity segment. However, the financial market is far broader, covering fixed income securities, foreign exchanges, commodities, derivatives, and other asset classes of financial instruments. In recent years, one segment of the market that has witnessed a high growth in the global financial market is the derivatives market. The derivative market instruments are comprised of forward, futures, options, swap, interest rate derivative products, weather derivatives, energy derivatives, carbon derivatives, and structured products such as credit linked notes, credit default swaps, total return swaps, collateral bond obligations, collateral mortgage obligations, residential mortgage based securities and other asset backed securities. In the current scenario, these are the main instruments to reduce uncertainty. Derivatives instruments is not a new concept, it has been traded since Mesopotamian empire, 1,700 BC, when commodity trader hedge their position by means of forward and future contracts, whose trading was not very different from forward and futures contract traded in today's financial market. The incredible dimension and growth of the world derivatives market can be explained as follows. Based on the annually conducted survey by World Federation of Exchange (WFE), in 2012 it is estimated that in the derivative markets, 21 billion derivative contracts were traded on all exchanges worldwide[1].

Historically, the derivatives have shown a high growth. The size of the market increased by approximately 25 percent per year during December 1998 to June 2008. In the second half of 2008, however, the market activities declined for the first time in recorded history in the wake of U.S. subprime real estate mortgage crisis. The global derivatives market is more than five times larger than global bond and equity markets combined[2].

1.2. Emergence of Derivatives Market in India:

Derivatives are not a new concept for the Indian financial system. For the first time in 1875 the Bombay Cotton Trade Association started futures trading and in early 1900s, India was the world's largest futures trading market. But after 52 years in 1952, the regulatory body of India banned cash settlement and options trading. After the ban the investors are trading derivatives in the forwards market. In the last 10 years, government regulation towards derivatives market has changed, allowing for an increased role pricing of market and less doubt of derivatives trading. The best example of the government initiative by removing the ban on futures trading commodity futures trading in 2000, and emergence of Multi Commodity Exchange and National Commodity Derivatives Exchange.

In the equity segment, Bombay Stock Exchange (BSE) invented a carry forward system called "badla"[3]as a solution for providing liquidity in the secondary market.

[1] Source: World Federation of Exchange annual report 2012 (published in Thursday, 07 March 2013) www.world-exchanges.org/

[2] Source:The Global Derivatives Market – A Blueprint for Market Safety and Integrity(September 2009) white paper published in deutsche-boerse.com

[3]"Badla" –"allowed investors to trade single stocks on margin and to carry forward positions to the next settlement cycle. Earlier, it was possible to carry forward a position indefinitely but later the maximum carry forward period was 90 days. Unlike a futures or options, however, in a badla trade there is no fixed expiration date, and contract terms and margin requirements are not standardized". https://www.newyorkfed.org/medialibrary/media/research/economists/sarkar/derivatives_in_india.pdf

The badla system was only confined to forwards trading. However, the system led to a number of undesirable practices over the passage of time and deeply hurt the investor’s interest. As a result, the Securities and Exchange Board of India (SEBI) banned badla system in March 1994. After that there is no trading on derivatives contact. In June 12, 2000 NSE introduced Index futures. The index futures contracts are based on the popular market benchmark S&P CNX Nifty[4]. After index futures on June 4, 2001 NSE introduced Index option, and options and futures on individual securities on July 2, 2001 and November 9, 2001, respectively. In August 2010, NSE introduced global derivatives index futures on the trading floor. As of 2013, the NSE trades futures and options on 210 individual stocks. Excluding S&P CNX Nifty Index there are 9 other indices[5] in National Stock Exchange. Out of 10 indices, only Dow Jones index doesn’t have option contract. All the above derivatives contracts are cash settled contracts not physical deliveable contracts[6]. In 2008, for the benefit of the investors, NSE introduced a new index called VIX. It is also referred to as the fear index or the fear gauge. The VIX represents the expectations of stock market volatility over the next 30 days period. Among all derivatives contract, index option contributes around 72% of the whole derivatives market turnover in 2012 and only CNX nifty index option is around 70%.

1.3. Relevance of the Study:

In the financial market, it is almost impossible to trade in the financial instruments without knowing its volatility level. Most of the market participants have an idea that volatility means an irregular movement or wide swing in stock prices. However, some investor and asset manager in order to take trading decision think beyond unexpected changes in asset price and examine the relationship between asset price and forecasted volatility. Broadly, there are two measures of forecasting volatility:historical volatility and implied volatility.The simple method of calculating historical Volatility is through standard deviation and in the sense that we are

[4] S&P CNX Nifty (Nifty) “is the headline index on the National Stock Exchange of India Ltd. (NSE). It is a diversified 50 stock index comprising large and highly liquid securities, covering 25 sectors of the economy. It almost covers 60% of the market Capitalization”.-nseindia.com

[5] These are S&P CNX Nifty, Bank Nifty, CNX INFRA, CNX PSE, Dow Jones, FTSE 100, S&P 500, MINI NIFTY, CNX IT, & Nifty Midcap 50.

[6] “Settlement represents the physical exchange of the security and its payment” -nseindia.com.

assuming the standard deviation of the time series to be constant across the time period of computation. The other sophisticated way of measurement of historical volatility is conditional volatility, which varies over time.

The implied volatility is not based on historical prices of stocks. It is based on the current change in option price of the underlying asset which “implies” about the future volatility of the asset. Both historical volatility and implied volatility expressed on an annualized basis. Professional option traders are more interested in knowing implied volatility compare to historical volatility because of implied volatility is forward-looking nature. We can’t directly observed the implied volatility which is act as a proxy for future volatility and also can’t be hedged or offset with other financial trading instruments. It represents the market expectations of the stock’s future price movements. When traders are trading options, they are actually trading in implied volatility. This is because of the fact that when there is an earnings announcement or a major policy decision coming up, the implied volatility is expected to be very high, which gives information about the volatility in the market. That means a high implied volatility shows an expected large movement in the market either upward or downward. Conversely, low implied volatility means that the market believes that the stock price movement will be rather conservative. Now the question arises whether, in a growing derivatives market, the implied volatility has a better predictability than the historical methods in the presence of continuous changes in domestic and foreign investors perceptions and macroeconomic policies of a country? Can the option trader rely on implied volatility measure available in the market? This study is an endeavor to answer such questions.

1.4. Objectives of the Study:

In the light of the above discussion, the objectives of the study are set as follows:

1. To investigate the information content of implied volatility against the “backward-looking” volatility of S&P CNX Nifty index option in India.
2. To investigate the predictive power of implied volatility against the” backward-looking” volatility of S&P CNX Nifty index option in India.

3. To examine whether implied volatility provides a superior monthly ahead volatility forecast for S&P CNX Nifty index compared to other "backward –looking" volatilities.
4. To compare the information content of the implied volatility from call and put options on the S&P CNX Nifty index in the conditional volatility framework.
5. To assess the "backward-looking" volatility in the context of the newly emerged volatility Index, i.e. (VIX) as constructed by NSE in India.

1.5. Methodology:

The study uses different time series tools to study the different issues raised above. In particular, to study the information contained in implied volatility compared to "backward-looking" volatility, we have used Moving Average, Exponential Moving Average, Generalized Autoregressive conditional volatility (GARCH) and Exponential Generalized Autoregressive conditional volatility models (EGARCH) and a linear regression with an Auto-regressive model. Linear regression with Generalized Method of Moments (GMM) has been used to study the predictability of implied volatility against the "backward-looking" volatilities. To study the predictability of implied volatility in an out-of-sample frame work, the study has used Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). To compare the implied volatility with an ARCH form of model we have used GARCH and EGARCH model with lagged implied volatilities as one of the independent variables in the variance equation. Finally, study the predictability of VIX, the study has used liner regression method.

1.6. Data Sources and Sampling Design:

Among all indices S&P CNX Nifty is the most recognized liquid Index in Indian financial market. That's why the present study consider this index for the analysis. It is calculated through a free flot market capitalization method. The index consists of 50 highly liquid scripts drawn from diversified sector. In NSE the S&P CNX Nifty index options contracts have a maximum of three months trading cycle (one month-Near month contract,two month contract-middle month and, threemonth- Far month contract). A fresh contracts are introduced after the expiration of the near month contract. The NSE provides a minimum of seven strike prices for every option type (call and put) during the trading month. The present study is based on the daily closing prices of net dividend of S&P CNX Nifty index and associated options on S&P CNX Nifty, traded on the National Stock Exchange (NSE) from May 31st, 2001 to June 30th, 2011 for spot market and June 4th, 2001 to June 23rd, 2011 for option market. Daily spot returns are calculated using the differences of log prices on successive trading days. The option prices used are the nearest expiry call and put options in the near month contract with more than 6 days to expiry. All implied volatilities are calculated for nearest-to-the money options. The one-month MIBOR (Mumbai Interbank Offer Rate) was taken as the risk free interest rate. The present study has also used VIX data from 2nd March 2009 to 31st Dec 2013.

1.7. Scope of the study:

The present study is only restricted to; the implied volatility of CNX Nifty index option even though one can extend the analysis at the individual stock option level. The study limits its data range from May 31st, 2001 to June 30th, 2011 of the spot market and June 4th, 2001 to June 23rd, 2011 of the option market. The focus of the study is to find out the information content and predictive power of Black-Scholes implied volatility against the "backward-looking" volatility of S&P CNX Nifty index option in India. However, there are different sophisticated models in the literature which are beyond the scope of this study. The study calculates "backward-looking" volatility by using the methods like MA, EWMA, GARCH and EGARCH model, but there are other models like TGARCH and GJR-GRACH models which are not considered in this study. The impact of Global Meltdown in 2008 is not considered in this analysis. Comparing implied volatility with conditional volatility in "in-the-sample" framework, some researchers are averaging the Conditional variance based option maturity, but this study is only using One-day ahead conditional volatility for comparison. In the last objective, the study focused the predictive power of newly emerged VIX index in India, but the robustness of the results is very weak because of two reasons, firstly time series data always require a long time period, whereas in this study it is only 57 observations. Secondly, till now NSE has not allowed traders to trade in the VIX. However, the present study is a comprehensive first attempt towards understanding the various issues relating to, implied volatility analysis in India and there exists scope for further research.

1.8.Organization of the Thesis:

This study is organized into eight chapters, including the present one. The current chapter motivates and introduces the study, bringing out the scope and objective, methodology, variables and data sources. Chapter-2 deals with the literature review. In Chapter-3, we have presented the methods of calculating Moving Average (MA), Exponential Weighted Moving average (EWMA), Generalized Autoregressive Conditional Volatility (GARCH), Exponential Generalized Autoregressive Conditional Volatility (EGARCH) and implied volatility and also explain the empirical methodology for the study. The investigation of information Content of implied volatility against the “backward-looking” volatility is analyzed in Chapter-4. Chapter-5 investigates the predictive power of implied volatility against the “backward–looking” volatility in a in the sample framework and also examines whether implied volatility provides the best month ahead volatility forecast for S&P CNX Nifty index compared to other “backward-looking” volatility. The empirical analysis of information content of the implied volatility from call and put options on the S&P CNX Nifty index using GARCH and EGARCH models of conditional volatility is explained in Chapter-6. Chapter-7 investigates the forecastability of VIX against “backward-looking” volatility. Finally, Chapter-8 concludes the thesis with a summary of major findings of the study.

Chapter-2

Theoretical Underpinning and Review of Literature

2.0 Introduction

There has come a large amount of literature on forecasting of volatility in the past decades. One of the main argument is that among these volatility who is give a superior forecast. The implied volatility which is derived from option price or the time series models such as GARCH and EGARCH. This chapter not only goes into a review of literature of the study, but also explains briefly the derivatives market. This chapter is divided into two sections: one present global derivatives market and section two presents the review of literature.

2.1. Global derivatives Market

The American region dominates the single stock options markets (Table-2.1). In this region, the aggregated top five volumes have changed little (-2.4%) from 2011 to 2012. Table 2.1 also shows that BM&FBOVESPA is the biggest market for single stock options.

Table-2.1: Top 5 Exchanges in the World by number of single stock options traded

Exchange	Contracts Traded in 2012	Contracts Traded in 2011	% Change
BM&FBOVESPA (US)	929,284,637	838,325,494	10.85%
NASDAQ OMX (US)	639,089,751	700,991,781	-8.83%
NYSE Euronext (US)	594,616,836	634,144,955	-6.23%
Chicago Board Options Exchange (US)	494,303,386	516,137,672	-4.23%
International Securities Exchange (US)	457,082,239	431,111,381	6.0%

Source: World Federation of Exchanges

In stock futures, top five exchanges combined volumes have increased by 9% from 2011 to 2012 (Table-2.2). NYSE Liffe Europe exchange market placed first in most of single stock futures trading. The National Stock Exchange (NSE), India stood in fourth place in single stock futures in the global market in terms of contract traded on the exchange in 2012.

Table-2.2: Exchanges by number of single stock futures traded

Exchange	**Contracts Traded in 2012**	**Contracts Traded in 2011**	**% Change**
NYSE Liffe Europe	246,541,679	250,441,783	-1.6%
MICX/RTS	241,480,871	362,583,891	-33.4%
EUREX	196,260,661	174,288,806	12.6%
National Stock Exchange	153,122,207	160,878,260	-4.8%
Korea Exchange	100,490,960	59,966,166	67.6%

Source: World Federation of Exchanges

In stock index option Table-2.3 shows that the Korean exchange stood at first place in terms of trading volume in 2012. If we see the worldwide trading volume then in 2011 around 64% and in 2012 around 43% of the index option volume are traded in KOSPI 200 options traded in Korean exchange[7]. NSE stood at 2nd position and BSE stood in 5th place in terms of trading in 2012. In stock index futures it stood in fifth place in 2012. On the BSE volumes multiplied by more than 1000 on BSE 30 SENSEX index options after the trading incentive offered by the exchange for the trading community and introduction of new index i.e., BSE 100..

[7] WFE/IOMA Derivatives Market Survey 2012 Report published in May 2013
www.world-exchanges.org

Table-2.3: Exchanges by number of stock index option traded

Exchange	Contracts Traded in 2012	Contracts Traded in 2011	% Change
Korean Exchange	1,575,394,249	3,671,662,258	-57.1%
National Stock Exchange	819,528,329	870,923,298	-5.9%
Eurex	382,644,407	468,383,997	-18.3%
Chicago Board Options Exchange	304,351,269	320,393,391	-5.0%
Bombay Stock Exchange	234,568,615	392,508	59661.0%

Source: World Federation of Exchanges

The index futures voulme traded in NSE has decreased significantly in 2012. The US derivatives market still dominates the stock index futures.

Table-2.4: Exchanges by number of stock index Futures traded

Exchange	Contracts Traded in 2012	Contracts Traded in 2011	% Change
CME Group	588,494,089	735,845,814	-20%
Eurex	383,583,126	486,325,501	-21.1%
MICEX/RTS	322,870,350	381,643,441	-15.4%
Osaka Stock Exchange	149,999,140	137,199,290	9.3%
National Stock Exchange	112,292,325	155,713,851	-27.9%

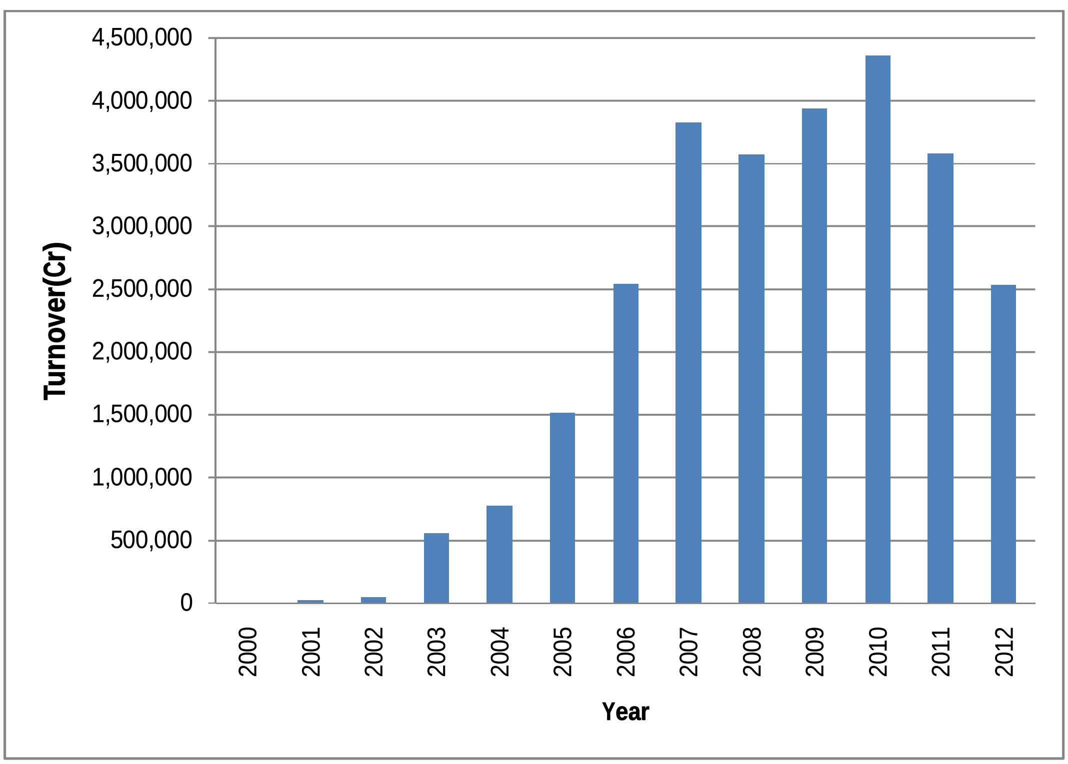
Source: World Federation of Exchanges

It is evident from the data presented in Tables 2.1 and 2.4 given below that the Indian derivatives market has emerged in the top five places among all developed derivatives exchanges. Only in case of stock option NSE is in 10^{th} position.

2.2. Growth of Indian Derivatives Market

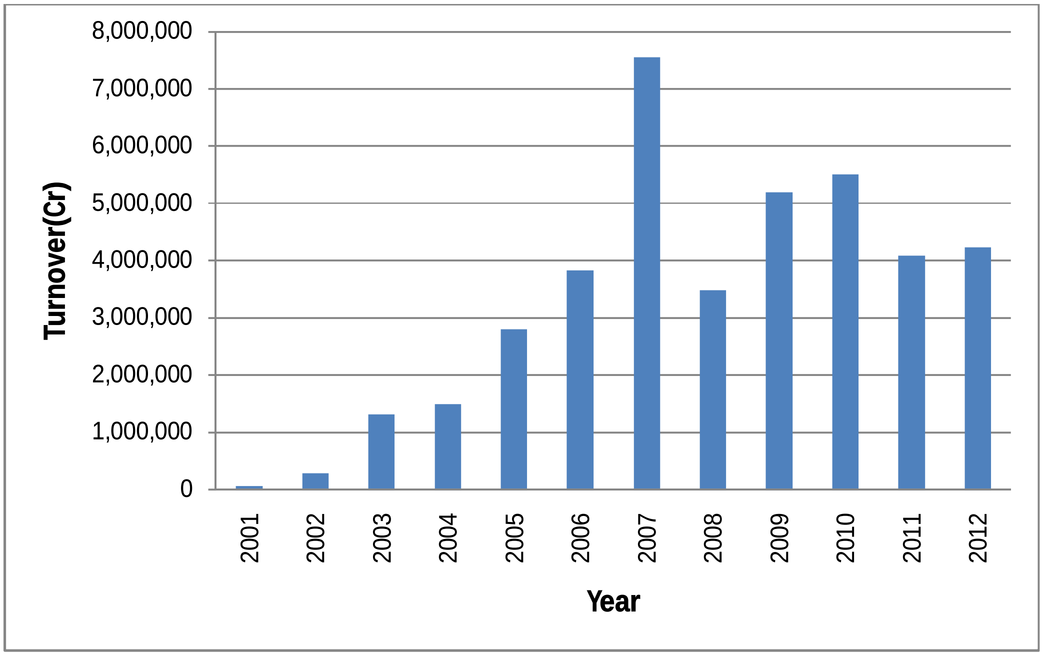
From the beginning the volume of stock indexes futures and individual stocks futures have grown rapidly. In particular, stock futures have become more popular in the trading community, accounting for about half of NSE's total derivatives turnover in the year 2006. But after 2009 Index options turnover started to increase and in 2012 it has 72% of market share (Fig-2.5). As we can see from the below Figure, that single stock options are much less popular than index options. It has only 6% of market share in terms of turnover in 2012. Initially the share of index futures turnover was consistently high, but its market share has shown a diminishing trend subsequently after 2006. Likewise, stock futures held a very high market share in earlier years till about 2007, when it had a market share of 58%, but by 2012 its market share had declined to 14% and even its turnover volumes showed a decline in these later years.

Fig-2.1- Turnover of S&P CNX Nifty Index Futures



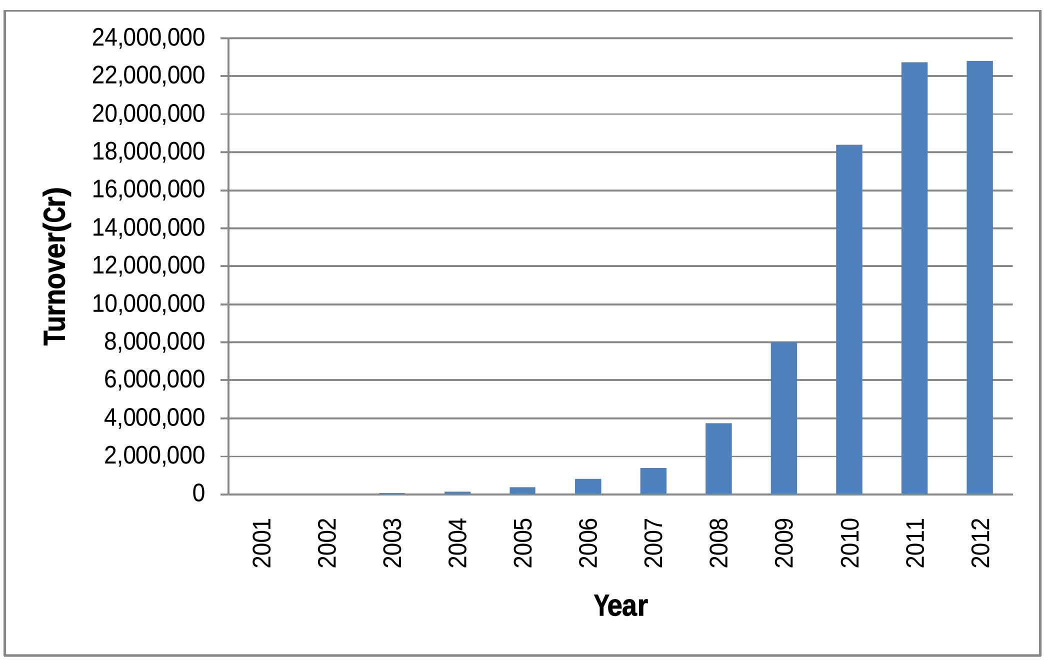
Source: NSE website

Fig-2.2- Turnover of Stock Futures on NSE



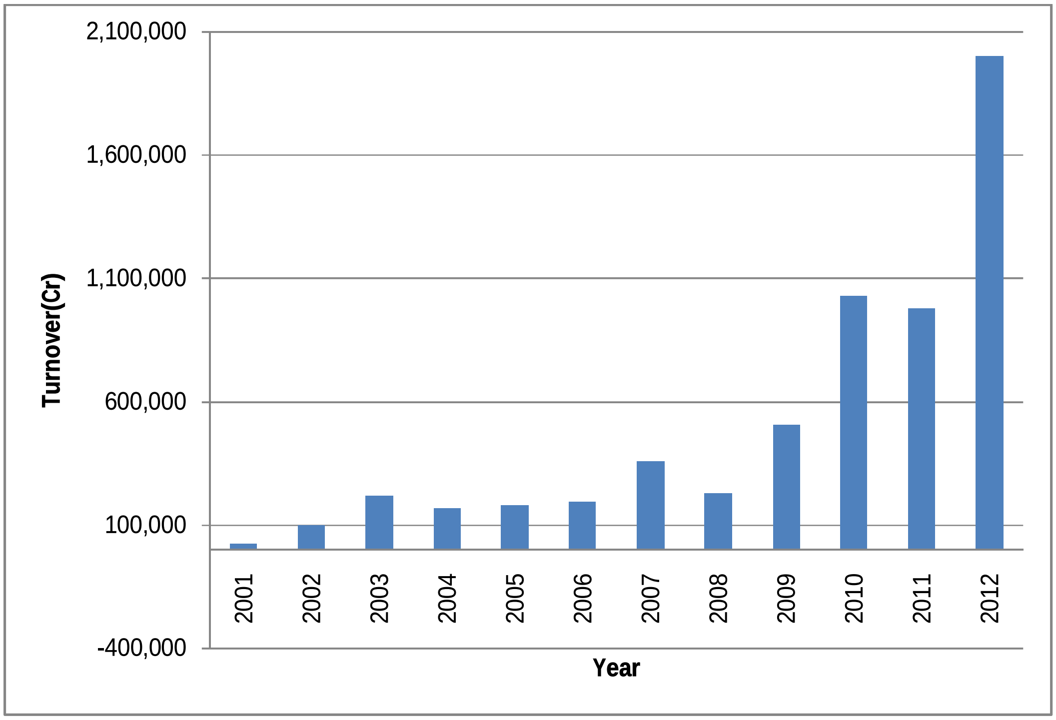
Source: NSE website

Fig-2.3- Turnover of S&P CNX Nifty Index Option



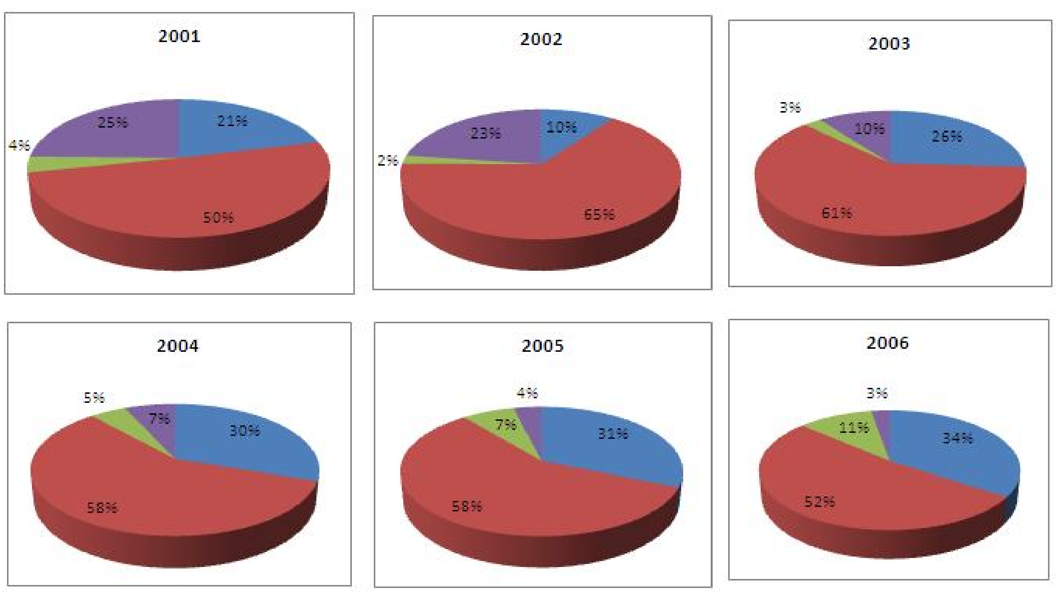
Source: NSE website

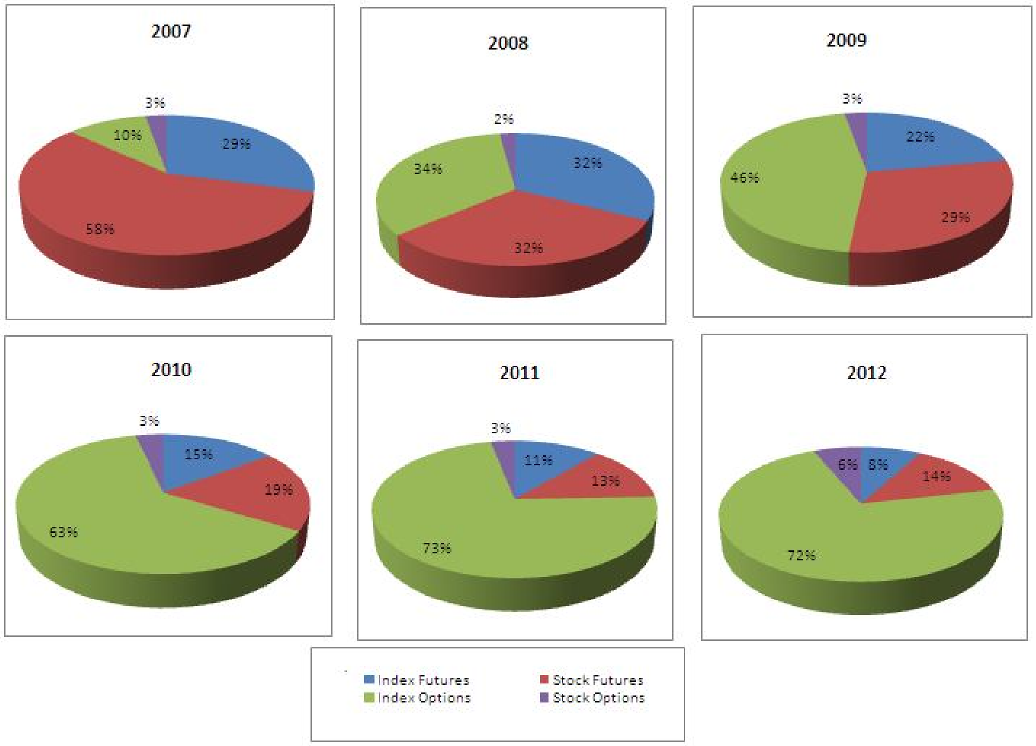
Fig-2.4: Turnover of Stock Option on NSE



Source: NSE website

Fig-2.5: Share of Turn over on NSE Equty Derivatives Marekt





Source: NSE website

2.3. Review of Literature

Implied volatility is consider to be the "the market's forecast" of future realized volatility. There are plentiful evidence that implied volatility contain more information about future realized volatility compare to time series model where the realized volatility is calculated through past returns.

Early studies generally found that implied standard deviation (ISDs) contain significant information for future volatility. Latane and Redeleman (1976), Chiras and Manaster (1978), and Beckers (1981), analyze the predictability of ISDs of stocks traded in Chicago Broad Option Excahange (CBOE) through regression method where they put future volatility as dependent variable and weighted implied volatility as independent variable. They find that weighted implied volatility contain more information about future volatility compare to histrorcial volatility.

Hull and White (1987) show that implied volatility is approximately equal to the future realized volatility in the case of at-the-money option. Scott and Tucker (1989) analyze the predictability implied standard deviation (ISDs) in PHLX currency options, but themethodology doesn't agree proper tests of hypothesis. They examine the predictability ISDs through simple regression with five currencies, three contracts, and thirteen dates. Their results show that the least square standard errors are severely biased because of the correlations across observations. That's why they are invalidating the hypothesis test.

Day and Lewis (1993) compare GARCH(1 ,1), EGARCH (1, 1), implied volatility and historical Volatility. To check the accuracy of these model they use simple regression where they put realized volatility as a dependent variable and all other methods as independent variable. For checking the out of sample accuracy they used Mean Error (ME), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). They also check the accuracy of implied volatility in a conditional variance frame by including it as independent variable in the GARCH and EGARCH models. The result show that GARCH(1,1),EGARCH(1,1) and implied volatility contain information about realized volatility. Lamoureux and Lastrapes (1993), examine options on ten stocks, conclude that implied volatility is a biased and inefficient forecaster of realized volatility. Historical volatility contains more predictive power than mplied volatility. The major difference in both the studies is that Lamoureux and Lastrapes study"one-day-ahead" and Day and Lewis study a "one-week-ahead" forecasting power of implied volatilities.

Duffie and Gray (1995) find that implied volatility is a superior forecast than historical and GARCH volatility model in both "in-the-sample" and "out-of-the-sample" frame work for the crude oil, natural gas and heating oil markets. They also found that in the "out-of-sample" frame the historical volatility perform better than implied volatility.

In general research in currency option show that implied volatility perform better than historical volatility. Jorion (1995) investigates the information contained power of implied volatility in the currency market. He finds that GARCH and EGARCH model are outperformed by implied volatility. But implied volatility is a biased forecaster. Galati and Tsatasaronis (1996) examine the currency option in 'over-the counter' market. They also found that implied volatility is better predictor compare to historical volatility. But for a long term horizon both the volatility methods are unable to predict the future volatility.Xu and Taylor (1996) examine the information efficiency of implied volatility of four currency options (Pound, Yen, Franc and, Mark) traded in Philadelphia Stock Exchange. They have used data from 1985 to 1992. They follow the methodology of Day and Lewis (1993) examine the predictability of implied volatility. But their methodology are little bit different from Day and Lewis (1993). They use GED distribution in the GARCH frame work to better account to fat-tailed in the return series. The result show that implied volatility contain more information than historical volatility. They also find that in “out-of-sample” frame implied volatility outperform GARCH and historical volatility. Amin and Ng (1997) focuses short term forward rates(Eurodollar) options on the Chicago Mercantile Exchange market. They concluded that, implied volatility predicts future volatility better than time series models.Christensen and Prabhala (1998) use the data of S&P 100index option and find out that implied volatility outperform historical volatility in forecasting future realized volatility. Canina and Figlewski (1993) use a non-overlapping data set they analyze the predictability of implied volatility before and after October-1987 stock market crash. They find that implied volatility ismore biased before than after the crash.

S. Hansen (1999) studies information content power of implied volatility in the illiquid KFX index. He wants to find out that whether there is any biasedness in the implied volatility because of illiquidity in the market. He finds that implied volatility is an unbiased forecaster and contain more information compare to historical volatility.

Namit Sharma (1998) compares two backward looking volatility measures (simple moving average and GARCH model) and implied volatility methods in the crude oil futures market from the period November 1986 to March 1997. The result show that implied volatility is superior forecast of future volatility compare to GARCH and simple moving avarge method for a two weeks forecast horizon. But in four weeks horizon simple moving avarge outperforms both implied and GARCH volatility models. A. M.P. Neves (1998), states that the GARCH (1,1) model has notonly contain more information and but also has a better predictability compare to implied volatility in currency option.

Jeff Fleming (1998), investigates biasness in the implied volatility calculation. He examines that the whether biasness in implied volatility is due to “measurement error” and “misspecification of the model”. According to Fleming it is very difficult to examine the biasedness in the implied volatility. For checking predictability he has used GMM estimation to deal with overlapping data problem. He also find that bisedness arises because of the trading strategies by option trader after the 19987 market crash.

Malz (2000) concludes that implied volatility contain more information about future realized volatility compare to historical volatilityin the the 30-year T-bond option on futures. Martens and Zein (2002) find that implied volatility provides better forecaster of future realized volatility compared to GARCH models in stock, exchange rate and oil. Ederington and Guan (2002) examine the implied volatility of S&P500 futures options data and conclude that “implied volatility has strong predictive power and generally subsumes the information in historical volatility”.Pierre Giot (2002) measured the efficiency, information content and un-biasedness of volatility forecasts based on the VIX/VXN implied volatility indices, Risk Metrics and GARCH type models. His empirical application focused on the S&P100 and NASDAQ100 indices. He found that VIX/VXN indices contained more information both in forecasting volatility and risk assessment.

Bandi and Perron (2006) examine the long-run relation between implied volatility and realized volatility in the VIX index over the period 1988-2003. They find that implied volatility is an unbiased estimator of future realized volatility. Holger Claessen and Stefan Mittnik (2004) examines different strategies for predicting DAX index option. He concludes that option price model contains more information compare to GARCH model.

S.C. Andrade, E. J. Chang, B.H. Tabak (2001) use a GMM estimation to deal with telescoping observations find that implied volatilities give superior forecasts of realized volatility compare to GARCH(p,q), and Moving Average models. Mayhew and Stivers (2003) compare implied volatility with time series models in the individual stocks. They find that implied volatility is a superior predictor of realized than historical volatility. They provide the strongest support for implied volatility.

They show that implied volatility “captures most or all of the relevant information in past return shocks, at least for stocks with actively traded options.”They show that the predictive power of implied volatility is directly related to volume.In the same way Donaldson and Kamstra (2005) compare implied volatility with time series model for S&P 500 call option. They find that in liquid option, implied volatility is a better predictor of future volatility compare to time series model but the opposite happen in case of illiquidity options. Irrespective of option volume, they find that both implied volatility and time series model provide additional information for the future volatility.

Taylor, Yadav and Zhang (2010) analyze the predictability of implied volatility in both S&P index and 149 US firm stock options. They use regression and ARCH models to compare historical volatility, “at-the-money” implied volatilities and “model-free” volatility expectations for 149 stocks. They find that, “at-the-money” implied volatilities mostly outperform the “model-free” volatility expectations. Vladimir M. Lonesco (2011) shows that implied volatility is an inefficient estimator of future realized volatility and not able to outperformed historical volatility in case of FTSE, S&P 500, and DAX index.

Ming Jing Yang (2012) examines the predictive power of the volatility index (VIX) in emerging markets from December 2006 to March 2010. The study reveals that the models including both the option market information and volatility indicator have a stronger predictive power.The Taiwan stock index options (TVIX) outperforms the historical volatility and the GARCH volatility for predicting the volatility of the Taiwan’s stock market.

Szakmary et al. (2003) study options on 35 different Futures contracts on a variety of asset class in the futures options market. Their study find that implied volatility is not completely unbiased estimator, it has more informative power than the past realized volatility. In the stock options market, Godbey and Mahar (2005) analyze the information content of implied for call and put option by extracting its volatility from options on 460 stocks that constitute in the S&P500 index. They find that compare to past realized volatility and GARCH (1, 1) estimate, implied volatility is a superior forecaster of future volatility. Addition to this they highlight that the information content of implied volatility depends on the options trading volumes. The information contain decreases as option volumes decrease.

Kroner et al. (1993) find that in a commodity market volatility forecasts combining implied volatility and GARCH model tend to perform better than individual forecasted methods. Vasilellis and Meade (1996) find that GARCH model has significant incremental information compare to implied volatility. For their analysis they use twelve companies traded in the London Stock Exchange for the period from March 1986 through September 1991. Gwilyn and Buckle (1999) studied the predictability of implied volatility for FTSE 100 index. For the analysis they have taken FTSE index option on a daily basis from June 21st 1993 to May 19th1995 and found that implied volatilities contain more information compare to historical volatilities. However, their analysis finds that implied volatilities are biased estimator.

J R. Varma (2002), states that volatility is severely underpriced in the Indian option market. He finds that the theory of put-call parity doesn't hold in Indian option market. According to him both call and put has different shape of volatility simle. He examines that the implied probability distribution is more highly peaked and has thinner tails than the normal distribution.

D. Misra, R Kannan and S. D. Misra (2006), examine the nature of volatility with respect to type, time and moneyness. They show that at the money implied volatility is higher than deeply in the money and out of the money options implied volatility on CNX Nifty. They also find put implied volatility is higher than call implied volatility.
Maheswaran. S and N. Ranjan (2005), find that implied volatility is an unbiased predictor of future realized volatility in Taiwan and Hong Kong, whereas in South Korea and India market the implied volatility is a poor predictor of future realized volatility. Panda, Swain, and Malhotra (2008) examine the information content of call and put option separately for S&P CNX nifty for the period June 2001 to October 2004. They have used instrumental variables methods and found that implied volatility contains more information than historical volatility but both the implied volatility are biased estimator of realized volatility.

Kumar (2008) shows that implied volatility estimators have contain more information about the future volatility compare to historical volatility methods calculated for S&P CNX Nifty Index from the period January 2002 to December 2006. He also finds that the call implied volatility has a better predictive power compare to put implied volatility. In addition to that he also finds that implied volatility is an unbiased and efficient forecaster.

Devanadhen and Rajagopalan (2009) study the forecasting efficiency of implied volatility in S&P CNX Nifty index option from January 2002 to December 2008 by using non-overlapping option contracts. They omitted the first year of trading because of the liquidity issue. For theirs analysis they have taken option contract whose exercise to future price ratio range value from .95 to 1.05 (at-the-money) and the trading volume are high. They implement Merton model for computation of implied volatility, which generalizes of the Black-Scholes (1973) model by relaxing the assumption of no dividend payment. The result shows that both implied call and put volatility are better than the historical volatility in forecasting realized volatility, but both call and put implied volatility are upward biased predictor. Their result show that at-the-money implied volatility is slightly biased and informationally efficient in predicting the future realized volatility.

2.8. Conclusion

The chapter provides an overview of derivatives instruments and participants. Derivatives are developed in response to some fundamental changes in the global financial market. They, if properly handled, should help improve the flexibility of the system and bring economic benefits to the investors and professional traders. They also provides a detailed review of empirical analysis for implied volatility predictability in different market Index, commodity, currency, stocks option. This chapter also gives us inputs of different econometrics models to measure the predictive power of implied volatility. As we can see numerous studies have attempted at international market for testing the implied volatility structure and forecasting efficiency of implied volatility, whereas studies on Indian market are quite limited. Previous Indian studies fail to provide any strong evidence on the relationship between implied and realized volatility because of small sample size, all the studies are roughly 5 to 6 years, because that point of time the market in on initial stage. Another limitation is most of the studies use non overlapping data structure. So far no attempt has been made on relationship between implied and realized volatility on an overlapping data structure and an out of sample forecastability of implied volatility in the Indian market. Hence, the current study attempts to shed light forecasting efficiency of the implied volatility of S&P CNX Nifty Index option in India to fill the gap in the existing literature.

CHAPTER-3

Methodology for Estimating Volatility

3.0. Introduction

Financial market volatility forecasting continues to be one of the significant areas of research in the field of finance for academicians, policymakers, investors, traders and professionals. There are diffrent methods to predict the realized volatility in the financial markets. Some methods of volatility explain the volatility using past time series data existing in the financial market. These volatility measures are called “Backward-looking” which means the calculation is done by historical prices or the past price information. Unlike these historical measures, there is another method that relies on current prices to measure volatility and not the historical prices. For this volatility calculation, one uses a pricing model whose inputs are the current option price, current spot price, strike price, time to maturity and interest rate. This is called the “Forward looking” volatility method because it relies on current price and not the historical price, and this current price reflects the most up-to-date information. This measure is called the implied volatility. Later in this chapter, the study will discuss why it is called implied. It reflects the participant’s expectations about future market conditions. Under rational expectations hypothesis, “the market uses all the available information to form its expectations about future volatility”, and hence based on these hypothesis implied volatility which is calculated by the help of option market price reveals the market’s true volatility estimate. In addition, if the market is efficient, with a given currently available information the estimated implied volatility is the best possible forecast volatility. Which means that implied volatility counted all information that is required to, which means to explain future realized volatility

This chapter is divided into five sections. The basic calculations of “backward looking” volatilities are presented in section-1. Section-2 shows how the study calculates implied volatility. Section-3 describes the calculation of realized volatility. Test of stationarity is explained in section-4. Finally the last section explains the methodology used for this study.

3.1. Backward Looking Measures of Volatility

3.1.1. Moving Average Method

The simple moving average is the simplest approach to calculate volatility. Moving average is calculated by taking the average of the rolling window of the data series. The order of rolling window is denoted as "*m*" and the process is denoted by; MA (*m*).For example, in the financial markets technical analysts use MA (200) days moving average method for trading. The technical analyst also uses slower and faster moving average and their cross over to take the decision of long and short position in the financial markets. However, the study has considered a 20-days rolling window Moving Average process by considering the fact that the analysis is dealing with the near month contract. For calculation of moving average we are assuming a zero mean daily return. After assuming zero mean daily return we averaged the square of the last 20 trading day's returns. On the succeeding trading day, a new created return becomes presented for calculating the volatility. To retain a 20-day measurement window, we have dropped the initial observation and added the recent observation, and then the average is recomputed. Symbolically, R_t. is the daily return at time 't". Assuming a zero mean daily return, the moving average volatility is calculated as follows:

$$\sigma^2_{t,MA} = \frac{1}{m}\sum_{i=1}^{m} R^2_{t-i+1} \times 252 \qquad (3.1)$$

Where $\sigma^2_{t,MA}$ is the daily estimate of annualized forecasted volatility in period t. In this model all the observation in calculation contain equal weights. However, it may fail to capture dramatic fluctuations in the volatility of the market. The smoothing effect as per the above mentioned moving average process in the Equation-3.1 becomes more problematic when the rolling window gets longer. To overcome this limitation, a more sophisticated method is the Exponentially Weighted Moving Average (EWMA) approach.

3.1.2. Exponentially Weighted Moving Average Method – EWMA

It is the simple extension of simple moving average method, which gives weight to the recent observation compare to the older observation. This methods has two important advantages compare to simple moving average model. First, volatility responds faster to large movement in the market as recent observation carry more weight than the past observation. Second, with a large movement in the market, the volatility also decline exponentially. Where as in simple moving average methods the following a large movement in the market, there is a relatively sudden changes in volatility. Assuming zero mean returns, we can derive the variance forecast of the next day, given data available at time t as

$$\sigma^2_{t,EWMA} = (\lambda \sigma^2_{t-1} + (1-\lambda) R_t^2) \times 252 \qquad (3.2)$$

where, $\sigma^2_{t,EWMA}$ is the estimate of the annualized variance for period t, which also becomes the forecast of future volatility for all period t. In Equation-3.2 λ ($0 < \lambda < 1$) is the ‘decay factor’, which defines how much weight is given to recent versus past observation. The decay factor by many studies is set at 0.94 for the daily observation.

3.1.3. Models of the ARCH Family

The ARCH model was initially developed in the macro-economic context. Later the model has been found to be extremely useful in explaining the time varying second moment or volatility. The research thereafter surged ahead tremendously and literally hundreds of papers have been published with various extensions, modifications and empirical applications. Some very good surveys of the developments in this line may be found in the literature [Bollerslev, et al (1992, 1993), Nelson (1991), Pagan (1990) etc.]. Here we do not attempt to review those developments again; rather our attempt would be to highlight some important aspects. In the ARCH family model, there are two equations, one is conditional mean equation and another is a conditional variance equation.

To concretize our ideas now let the conditional mean equation may be represented as:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} ...... + \beta_p x_{pt} + u_t \quad \text{and } u_t \sim N(0, \sigma_t^2) \qquad (3.3)$$

In Equation (3.3), the dependent variable y_t varies over time.

Similarly, conditional variance of u_t may be denoted as σ^2_t, which can be represented as:

$$\sigma_t^2 = \text{var}(u_t \mid u_{t-1}, u_{t-2}......) = E[(u_t - E(u_t))^2 \mid u_{t-1}, u_{t-2},.......] \quad (3.4)$$

It is usually assumed that $E(u_t) = 0$, so:

$$\sigma_t^2 = \text{var}(u_t \mid u_{t-1}, u_{t-2},.........) = E[u_t^2 \mid u_{t-1}, u_{t-2},.......] \quad (3.5)$$

In the ARCH model, the conditional variance σ^2_t, is depending on the previous value of the squared error. This may be represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (3.6)$$

In Equation (3.6) since σ_t^2 is a conditional variance, its value must always be strictly positive. In Equation (3.6), the non-negativity condition would be $\alpha_o \geq 0$ and $\alpha_1 \geq 0$.

3.1.3.1. GARCH (p,q) Model

The ARCH model as discussed above may call for long-lag structure to model the underlying volatility in the market. Keeping this view in mind, a more parsimonious and a broad class of models was developed by Bollerslev (1986) and Taylor (1986). In GARCH model the conditional variance is depending upon its own lags and the past innovation. Based on above discussion the conditional variance equation for GARCH (p, q) model is represented as:

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + ...+ \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + ...+ \beta_p \sigma_{t-p}^2 \quad (3.7)$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (3.8)$$

Where, $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ For i=1,…..,q and j=1,…p.

Here σ^2_t is known as the conditional variance. There is a restriction that the parameters should be positive in both ARCH and GARCH models. This also implies that any shock is always an indication of the increase in conditional volatility forever. The GARCH model mentioned above has few limitations: (a) GARCH model in the above form is unable to capture the asymmetric response of volatility; (b) the parameter restrictions imposed to keep the conditional variance positive is very often questioned; and (c) it fails to describe the cyclical and non-cyclical behavior of the conditional volatility. As we have discussed, these models ignore an important empirical feature of stock market volatility, i.e. its asymmetric nature. Since the model incorporates only the magnitude of the shocks (innovations) and not their signs, it completely rules out the possibility on the part of the volatility modeled in this framework to respond differently to positive and negative news. To capture this asymmetric effect on volatility Nelson's (1991) formulated EGARCH model.

3.1.3.2. Asymmetric and 'leverage' Effects

The basic GARCH model discussed in the previous section has a symmetric effect on the volatility. In other words, GARCH model consider that good and bad news have the similar effect on the market volatility. In real scenario this assumption is frequently violated because the volatility increases more after bad news than after good news. This asymmetry is generally referred to as "leverage" effect. This leverage effect is documented by Black (1976). He noted that a drop in the value of a stock (negative returns) increases the financial leverage that makes the stocks riskier, and, hence, increases the volatility. However, it seems that "leverage effect is too small to account for the asymmetry" (Christie, 1982, Schwert, 1989).

An alternative view in this context is provided by the 'volatility feedback' hypothesis [Campbell and Hentschell, 1992, Pindyck, 1984, French et al, 1987]. According to 'volatility feedback' hypothesis, changes in the magnitude of the time varying volatility may have effects on required stock returns, and, in turn, on the level of stock prices.

With the above leverage effect, the asymmetric nature of volatility may be explained by differentiating between two cases: (a) large and small shocks, and (b) positive and negative shocks. Now let us explain the asymmetric nature of volatility that we are really interested in, i.e. how volatility responds differently to positive and negative news. When the market is faced with a large piece of negative news (a large drop in prices of equities), at the outset, it increases the current as well as the future level of volatility. As discussed by Capital Asset Pricing Model (CAPM), this increased conditional volatility at the market level is to be compensated by a higher expected rate of return leading to a decline in the current value of the market and prices dampening further. The market wide fall in prices induces a higher level of leverage at the market level rendering the stocks more riskier and increasing their volatility. Thus, the initial increase in volatility gets fed up. The result, however, may be different in the case of positive news (a large rise in the prices of equities). In a similar fashion, the positive news increases volatility with consequent drop in prices and offsets the initial rise in prices. The initial price rise leads to reduced leverage that in turn leads to decline in conditional variance, and, consequently it raises the prices. Thus, in the case of positive news, volatility feedback and leverage effects have different impacts on stock prices.That's why the commonly used model to capture asymmetric effect is the EGARCH model.

3.1.3.3. EGARCH (p,q) Model

Consequent to the above discussion, to ensure positivity, one could model the conditional volatility as lnσ_t instead of σ_t. This is the idea underlying Nelson's (1991) Exponential GARCH (EGARCH) model. In formal terms, an EGARCH may be specified as follows:

$$\ln\sigma_t^2 = \omega + \sum_{j=1}^{p}\beta_j \ln\sigma_{t-j}^2 + \sum_{i=1}^{q}\alpha_i |z_{t-i}| + \sum_{i=1}^{q}\theta_i z_{t-i} \quad (3.9)$$

Where, $z_t = \dfrac{u_t}{\sigma_t}$. Note that the left-hand side of the Equation (3.9) is the log of the conditional variance. Without putting any constrain in the coefficient the log form of the model confirms the non-negativity.The term z_{t-I} is the asymmetric effect. If θ_i >0, volatility tends to rise (fall) when the lagged standardized shock, $z_{t-i} = \dfrac{u_{t-i}}{\sigma_{t-i}}$, is positive (negative). The determination of shocks to the conditional variance is given by $\sum_{j=1}^{p}\beta_j$. The simplest form of EGARCH (1, 1) is as follows:

$$\ln\sigma_t^2 = \omega + \beta_1 \ln\sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} \quad (3.10)$$

3.1.3.4. Statistical Inference of ARCH/GARCH Models

Before going to the ARCH/GARCH model[8] we have to specify the error distribution. After specifying the ARCH/GARCH model, it is estimated through both conditional

[8] Since an ARCH process is a special case of a GARCH process, without loss of generality, the statistical inference about the GARCH model can be made applicable to ARCH models as well.

mean and variance equation. As we have discussed, the main feature of the GARCH model is that the variance equation follow ARMA process. Hence, the residuals from the estimated mean equation should exhibit autocorrelation function (ACF) and partial autocorrelation functions (PACF) depicting a white noise pattern. A visual examination of the estimated ACF and PACF will confirm this. These properties are tested through two procedures, one is through Ljung-Box Q-statistic and another is through ARCH LM test.

Through Ljung-Box Q-statistic:

Step-1: Estimate the $\{Y_t\}$ sequence using the "best fitting" ARMA model and obtain the estimated squared residuals, $\hat{u}_t^2$, and their variance, $\hat{\sigma}^2 = \sum_{t=1}^{T} \hat{u}_t^2 / T$, where T is the number of residuals.

Step-2: Calculate and plot the sample autocorrelations of the squared residuals as,

$$\hat{\rho}(i) = \frac{\sum_{t=i+1}^{T} (\hat{u}_t^2 - \hat{\sigma}^2)(\hat{u}_{t-i}^2 - \hat{\sigma}^2)}{\sum_{t=1}^{T} (\hat{u}_t^2 - \hat{\sigma}^2)^2}$$

Step-3: In large samples, the standard deviation of $\hat{\rho}(i)$ can be approximated as $\sqrt{(1/T)}$. Individual $\hat{\rho}(i)$ significantly different from zero indicates the presence of GARCH errors. The Ljung-Box Q-statistic, $Q = T(T+2)\sum_{i=1}^{n} \hat{\rho}^2(i)/(T-i)$ can be used to test the significance of groups of $\hat{\rho}(i)$. The hypothesis testing for autocorrelation coefficients jointly may be formulated as

H$_0$: LB.Q < χ_α^2(n): No auto correlation

H$_1$: LB.Q > χ_α^2(n): Auto correlation

Where, χ_α^2(n), is the critical value of χ^2 distribution for α level of significance and n degrees of freedom.

Here, rejecting the null hypothesis of uncorrelated $\hat{u}_t^2$ is equivalent to rejecting the presence of no ARCH or GARCH errors. In practice, '*n*' can be taken up to *T/4*.

The other formal method is the Lagrange Multiplier (LM) test. It has the following steps:

Step-1: Use the OLS to estimate an 'appropriate' AR(p) model for the $\{Y_t\}$ sequence.

Step-2: Obtain the estimated squared residuals, $\hat{u}_t^2$, and estimate an AR(q) model for these residuals:

$$\hat{u}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \hat{u}_{t-i}^2$$

Obtain R^2 from this regression

Step-3: The test statistic is defined as TR^2 (the number of observations multiplied by the coefficient of multiple correlation) from the last regression, and is distributed as a $\chi^2(q)$.

For the test, the null and alternative hypotheses are

H_0 : $\alpha_1 = 0$ and $\alpha_2 = 0$ and $\alpha_3 = 0$ and ... and $\alpha_q = 0$

H_1 : $\alpha_1 \neq 0$ or $\alpha_2 \neq 0$ or $\alpha_3 \neq 0$or ... or $\alpha_q \neq 0$.

Thus, the test is one of a joint null hypothesis that all q lags of the squared residuals have coefficient values that are not significantly different from zero. If the tabular value is greater than calculated value from the χ^2 distribution, then we reject the null hypothesis of "no ARCH or GARCH" effects in the squared residuals.

The logic behind the LM test is quite simple: if squared residual at time't' is predicted by its past values, then the presence of ARCH effect in the data is confirmed. Once the ARCH effect has been recognized under the assumption of the normality, GARCH model for a sample of T observations can be estimated using the maximum likelihood method. However, in practice, the normality assumption of innovations has been criticized as the parameters often show that the unconditional distribution is leptokurtic and it is not always capable of capturing the presence of excess kurtosis in the unconditional distribution of the data. This motivated the need to develop another method called quasi-maximum likelihood (QML) procedure proposed by Bollerslev and Wooldridge (1992). The estimated parameters in this method are consistent, even if the residuals are not conditionally normally distributed.

3.2. Forward Looking Measures of Volatility

The forecasting models that we have discussed in sections above calculate volatility through historical price in other words, the volatilities are calculated from the past information. That is why we call them backward looking volatility. Whereas implied volatility is a forward looking measure of volatility.By putting all the variables in the pricing model there is one to one relationship between option price and implied volatility. In other words, taking implied volatility as the true volatility (variance) of the underlying stock value, a theoretical pricing model (such as Black-Scholes model) provides the value of the option which is equal to the current market price of that option. Many studies have concluded that implied volatility are the best predictor of future volatility[9]. Denoting the market price and model value for a given option as C_{MARKET} and C_{MODEL} respectively, and implied volatility as σ_{IV}, we can write

$$\mathbf{C_{MODEL}(\sigma_{IV}) = C_{MARKET}} \qquad (3.11)$$

Option implied volatility is reversing the pricing model by putting the actual option price which contains the actual transaction and expectations of the market and thus is fundamentally “Forward-looking”. “Recall that this measurement incorporates the most current market information and thus it should reflect market expectations better than the historical measure”[10]. That’s why implied volatility provides information about what the investors except regarding the market condition in future. Implied volatility is implied by two things: first is the option market price and second is the option pricing model. Based on all the above discussion, we are now going to explain how through the Black-Scholes Model we will get implied volatility.

3.2.1. Black-Scholes Option Pricing Model

Black and Scholes (1973) pricing model for European call and put option on a non-dividend-paying-stock is a function of current stock price, the time to expiration, the exercise price, the risk free rate of interest, and the volatility of the underlying asset.

[9] Jorion (1995), Flemming (1998)
[10] See Fama (1971, 1990)

To get the model price there are number of assumptions to be satisfied (i) price of the underlying asset should be log normally distributed (ii) there should not be no arbitrage opportunity (iii) securities trading should be continuous (iv) there are no transaction costs or taxes, and (v) the risk free interest should be constant through out the expiration period.

The basic Black-Scholes model involves options on non-dividend paying assets is given as.

$$C = S_0 N(d_1) - Ke^{-rT} N(d_2) \quad (3.12)$$

$$P = Ke^{-rT} N(-d_2) - S_0 N(-d_1) \quad (3.13)$$

where,

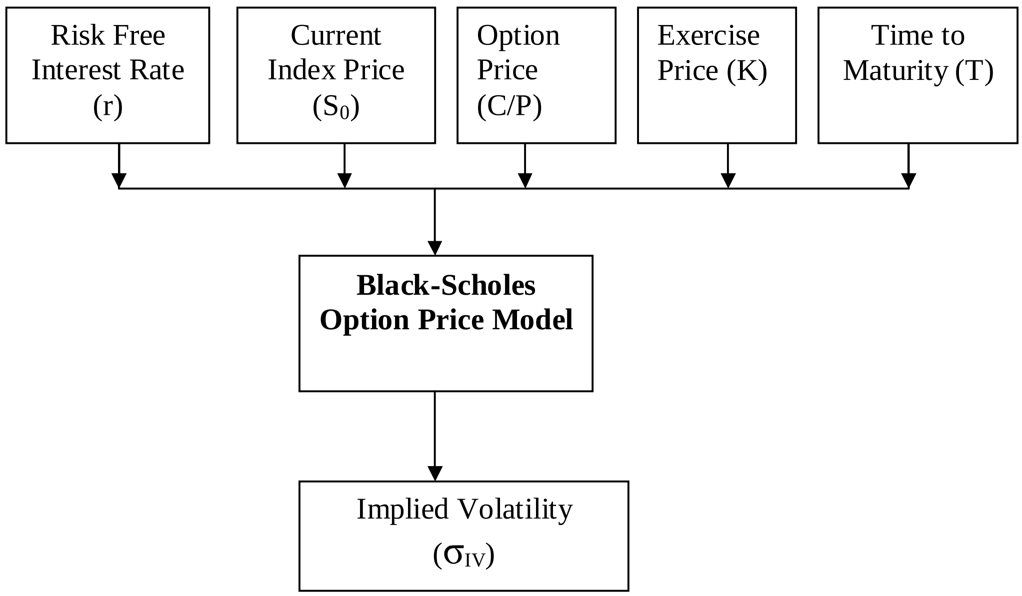
$$d_1 = \frac{\ln(S_0 / K) + (r + \sigma^2 / 2)T}{\sigma\sqrt{T}}$$

$$d_2 = \frac{\ln(S_0 / K) + (r - \sigma^2 / 2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$$

Where, C denotes the call option price , P denotes the put option price, N (d) denotes the cumulative normal distribution evaluated at d, S_0 is the Current asset price, T is the time to maturity of the option, K is the strike price, 'σ' is the volatility of the underlying asset and r is the risk free interest rate.

We can get the model price by putting all the five parameters (S_0, K, T, r, andσ) in to the model. All the parameters except volatility are existing in the market and the value of volatility i.e.σ can be calculated from historical data. Suppose now the model goal is to find out the volatility, i.e., implied volatility. Now, the same formula can be used to do so: the value of volatility is estimated by inserting all the variables (S_0, K, T, and r) in the right hand side of the equation (3.12 and 3.13) and the observed market price on the left hand side of the equation (3.12 and 3.13). The resulting estimated value of volatility is called the Black-Scholes implied volatility, because that number represents the volatility of the underlying asset that is implied by quoted option price and the Black-Scholes model. The above explanation is graphically shown in the chart given below (Figure 3.1).

Figure 3.1: Chart for Implied Volatility Calculation



3.2.1.1. Error-in-Variables

If the implied volatility seeming to be biased and inefficient then obvious reason will be that the implied volatility is measured with error. The biasedness in the implied volatility arises because of two reasons, first "errors-in-variables" and second, implied volatility's failure to subsume other forecasts. There are three types of measurement errors: "Using the wrong option pricing model creates specification error, nonsynchronous trading in the market, and Jump in prices"[11]. Firstly, the Black-Scholes model in Equation (3.12) and (3.13) consider no dividends payments in the asset and the transaction cost is zero prior to expiration of the contract. But the real scenario is different from theory. Stocks included in S&P CNX Nifty index pay dividends and there are also transaction costs associated to these stocks trading. If we disregard dividends in the model then it will reduce the call and put value, which cause of reducing call and put true volatility.As the dividends are relatively uniform

[11] Christensen and Prabhala (1998)

for the Nifty the difference between implied volatility and true implied volatility should be roughly constant for all time period.

Secondly, infrequent trading in the option market may cause measurement errors in the implied volatility. For our analysis we have used both option and index closing prices. The methodology of calculating both the closing price are same i.e. last 30 mints weighted average method. But the options are not fluctuating as frequently as the cash market in our data period. When the exchange calculated the closing price of option that point of time it may consider the price earlier during the day because there is no trading at the time of closing. Whereas cash markets do not suffer from the same liquidity problem as the option market. By this mismatch there is a information gap between the two markets. When, the new information enters into the both the markets, the spot market capture the news instantly compare to the option market because of illiquidity in the option market. Suppose the news is good then spot price will be higher immediately whereas it will take time for the option price to go high. The opposite occurs when the market declines. Because of this mismatch there is a statistical problem by considering multiple time series which are not sampled simultaneously.

Finally, the assumption of the Black-Scholes formula in Equation (3.12) and (3.13) assumes that index levels should follow a log-normal distribution with deterministic volatility. Suppose there is a jump in the underlying prices because of the unexpected news in the market then the model does not price the option correctly. Therefore the implied volatility which we calculated can be misspecified. This presents a systematic bias in the implied volatilities. “Even if the Black-Scholes formula is correct, market microstructure effects may cause additional measurement errors” (Harvey and Whaley, 1991).

3.2.2. Computational Methodology of VIX index

Volatility Index is a measure of market’s expectation of volatility over the near term. For the first time in 1993 Chicago Board of Options Exchange (CBOE) was introduce the VIX index with the underlying asset as S&P 100 Index option prices. Later in 2003, CBOE revised the methodology. After its introduction it has become an indicator for the market participant to track the volatility. Investors use it to measure the market volatility and accordingly take their investment decisions. India VIX uses the computation methodology of CBOE (Chicago Board of Option Exchange), with suitable amendments to adapt it to the NIFTY options order book. The formula used in the India VIX[12] calculation is:

$$\sigma^2 = \frac{2}{T}\sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \quad (3.14)$$

Where

σ India VIX/100,

T Time remaining for expiration = {$M_{\text{Current tranding day}}$ + $M_{\text{Settlement day}}$ + $M_{\text{Other trading days}}$}/ Minutes in a year

Where, $M_{\text{Current day}}$ = Number of minutes remaining until midnight of the current day

$M_{\text{Settlement day}}$ = Number of minutes from midnight until closing hours of trading on expiry day

$M_{\text{Other days}}$ = Total number of minutes in the days between current day and expiry day excluding both the days

K_i Strike price of i[th] out-of-the-money option contarct ; a call if $K_i > F$ and a put if $K_i < F$,

ΔK_i Interval between strike prices - half the distance between the strike on either side of K_i

$$\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$$

R Risk-free interest rate to expiration i.e. the relevant tenure NSE MIBOR rate (i.e. 30 days or 90 days) is being considered as risk-free interest rate for the respective expiry months of the NIFTY option contracts

$Q(K_i)$ Midpoint of the bid ask quote for each option contract with strike K_i

F Forward index taken as the latest available price of NIFTY future contract of corresponding expiry

K_0 First strike below the forward index level, F

[12] Souce: nseindia.com

3.3. Realized Volatility

In the last section we have described the calculation method for both backward and "forward-looking" volatilities. But now the question arises how to find out which one among them is the best predictor of the future realized volatility. For that, first we have to calculate the actual future volatility or realized volatility. Then we use this future realized volatility as an endogenous variable in the information content and predictability regression. For the analysis we assume that S&P CNX index price follow log normally distribution. Based on this assumption, returns are calculated to their log differences in prices. Therefore, a one-day behind return is calculated as:

$$R_{t-1,t} = \ln (S_t) – \ln (S_{t-1}) \qquad (3.15)$$

Where, St denotes the S&P CNX nifty closing price at time t. Similarly, the one-day ahead return is calculated as:

$$R_{t,t+1} = \ln (S_{t+1}) – \ln (S_t) \qquad (3.16)$$

At time t, the one-day-ahead return is not yet observable. In future analysis the squared of one-day-ahead returns will serve as a measure of actual volatility for the next day to be compared with volatility forecaststhat are available at time t. The square of the daily return series calculated in Equation-3.15 and 3.16 serve as a source for either input in a measurement technique or as a measure of volatility for future analysis.

We have multiply both the equation by square root of 252 to make it annualized assuming 252 trading days in a year. The one-day behind return series is used to calculate all of the historical or backward looking measures of volatility such as MA (20), EWMA, GARCH and EGARCH.

Whereas the one-day-ahead return series explained in Equation (3.16) in an annualized form is used as a dependent variable in the information content regressions. i.e., $\sqrt{R^2_{t,t+1} \times 252}$. This squared one-day-ahead return is the dependent variable in the information content regressions in Chapter-4. The return series is also used to calculate the realizedvolatility used as the dependent variable in the predictability regressions in Chapter-5. The procedure for calculating this process as follows:

$$\sigma_{t,T}^{2} = \frac{1}{(T-t)} \sum_{i=1}^{T-t} R_{t+i}^{2} \times 252 \qquad (3.17)$$

where, $\sigma^2_{t,T}$ is the realized volatility, and (T-t) are no of days to expiry of the option contract. So, for example, if there are 30 days to expiry of the option contract then realized volatility of the underlying asset is determined by averaging the squared returns over those 30 days. On the next day, the previous day's return would be dropped from the measurement since only 29 days to expiry of the option contract.

Table 3.1: Description of Forecasting Models

MODEL	CONDITIONAL VARIANCE EQUATION
Moving average method-MA	$\sigma^2_{t,MA} = \frac{1}{m}\sum_{i=1}^{m} R^2_{t-i+1} \times 252$
Exponential weighted moving average method -EWMA	$\sigma^2_{t,EW} = (\lambda\sigma^2_{t-1} + (1-\lambda)R^2_t) \times 252$
Generalized Autoregressive Conditional Heteroskedasticity-GRACH(p,q)	$\sigma^2_t = \alpha_0 + \sum_{i=1}^{q}\alpha_i u^2_{t-i} + \sum_{j=1}^{p}\beta_j \sigma^2_{t-p}$
Exponential Generalized Autoregressive Conditional Heteroskedasticity-EGARCH(p,q)	$\ln\sigma^2_t = \alpha_0 + \sum_{j=1}^{p}\beta_j \ln\sigma^2_{t-j} + \sum_{i=1}^{q}\alpha_i u_{t-i} + \sum_{i=1}^{q}\theta_i[\lvert u_{t-i}\rvert - E[\lvert u_{t-i}\rvert]]$
Call implied volatility	$C(S,T) = S_0 N(d_1) - Ke^{-rT}N(d_2)$ $d_1 = \frac{\ln(S_0/K) + (r+\sigma^2/2)T}{\sigma\sqrt{T}}$, $d_2 = \frac{\ln(S_0/K) + (r-\sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$
Put implied volatility	$P(S,T) = Ke^{-rT}N(-d_2) - S_0 N(-d_1)$ $d_1 = \frac{\ln(S_0/K) + (r+\sigma^2/2)T}{\sigma\sqrt{T}}$, $d_2 = \frac{\ln(S_0/K) + (r-\sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}$
Realized volatility	$\sigma^2_{t,T} = \frac{1}{(T-t)}\sum_{i=1}^{T-t} R^2_{t+i} \times 252$
VIX Index	$\sigma^2_{t,VIX} = \frac{2}{T}\sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$

3.4. Testing for Stationarity

In time series analysis if the parameter such as mean, variance and covariance are not change over time then it is said to be (covariance or weakly) stationary. Most of the macroeconomic time series data and financial data are known to be a non-stationary. Based on the statistical properties if we use a non-stationary series for our analysis then leads to a misleading results. That's why it becomes necessary to test the stationarity of the series before doing any econometric analysis.

The first order autoregressive process is presented as:

$$Y_t = \alpha_0 + \alpha_1 t + \beta Y_{t-1} + u_t \qquad (3.18)$$

where Y_t is the stochastic process, α_0, α_1 and β are parameters and u_t is an error. α_0 is called intercept.The nature of the time series described by the Equation (3.18) depends on the parameter values i.e., α_1 and β. If $\alpha_1 \neq 0$ and $|\beta|$ <1, then Y_t follows a deterministic trend. If $\alpha_0 = 0$, $\alpha_1 = 0$ and $\beta = 1$, the series is said to follow a simple random walk. If $\alpha_0 \neq 0$, $\alpha_1 = 0$ and $\beta = 1$, the series is a random walk with drift.

There are several tests for testing for the non-stationarity these include the Dickey-Fuller, Augmented Dickey-Fuller and Phillips-Perron tests to check the presence of unit root in the data. These tests are necessitated because the usual Student's t-test is inappropriate to test the null hypothesis, $\beta = 1$ in equation (3.18).

3.4.1. Dickey-Fuller and Augmented Dickey-Fuller Tests

Dickey-Fuller test start with a simple AR(1) model of following form

$$Y_t = \beta Y_{t-1} + u_t \qquad (3.19)$$

Where, Y_t is the analysis avariable, t is the time period, β is a coefficient, and u_t is the distrubances term. If $|\beta|$ =1 then the series is a unit root process. Naturally it would be even more non stationary if $|\beta| \geq 1$. The model can be rewritten in a modified form as below:

$$\Delta Y_t = \delta Y_{t-1} + u_t \qquad (3.20)$$

where, $\Delta Y_t = Y_t - Y_{t-1}$. The null hypothesis is that the $\{Y_t\}$ process has a unit root, i.e. $H_0: \delta = \beta - 1 = 0$.

Based on the above format there are three main version of the tests

1. Test for Unit root

$\Delta Y_t = \delta Y_{t-1} + u_t$

2. Test for Unit root with drift

$\Delta Y_t = \mu_0 + \delta Y_{t-1} + u_t$

3. Test for Unit root with drift around a stochastic trend

$\Delta Y_t = \mu_0 + \mu_1 t + \delta Y_{t-1} + u_t$

In all case, the null hypothesis is that there is a unit root, δ=0.

More generally, if the given time series follows a pth order autoregressive process [AR(p)] or even autoregressive moving average process [ARMA(p,q)], then the comprehensive DF test called ADF test can be used . Specifically, if the original time series follows AR(p), it can be represented as,

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + u_t \qquad (3.21)$$

After suitable mathematical manipulation, equation (3.21) can be rewritten as,

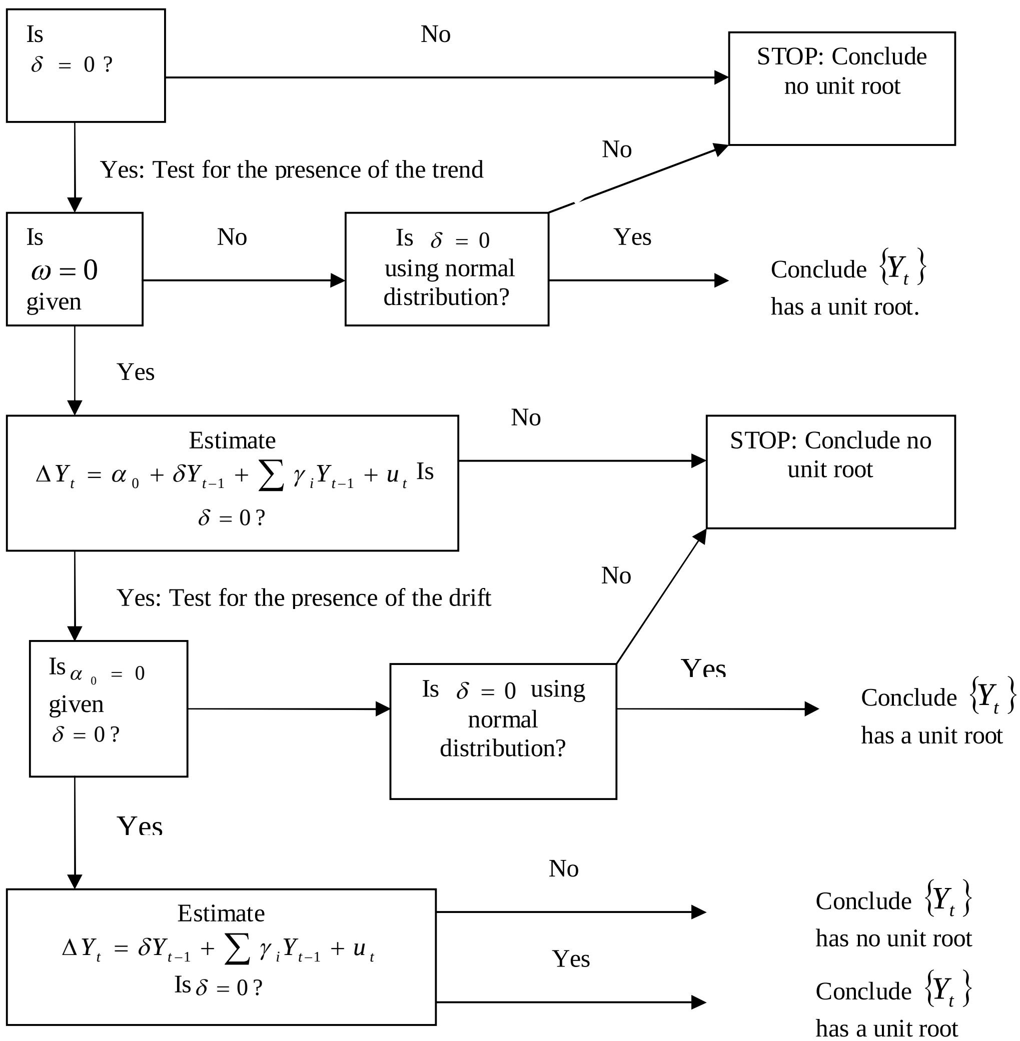
$$\Delta Y_t = \alpha_0 + \delta Y_{t-1} + \sum_{i=2}^{p} \gamma_i \Delta Y_{t-i+1} + u_t \qquad (3.22)$$

Where, $\delta = -(1 - \sum_{i=1}^{p} \beta_i)$ and $\gamma_i = \sum_{j=i}^{p} \beta_j$.

There are different forms of Augmented Dickey-Fuller tests like Dickey-Fuller test, which are adding a trend terms in equations (3.22), and also excluding intercept term, α_0, from these equations. When p=1 the DF is converted to ADF test. Commonly used Student's t-statistic can't be used to test the e significance of δ in equations (3.22). Initially, Dickey-Fuller and later MacKinnon have developed the appropriate test statistic, known as τ-statistic, and its critical values using Monte Carlo simulations. Dickey-Fuller have also used F-test values, known as Φ_1, Φ_2, and Φ_3, for pair-wise joint tests of significance for α_0 and α_1.The above discussed procedure can be compactly shown in the form of a flow chart as given below in Figure 3.2. To check for unit root of a $\{Y_t\}$ process, estimate the following equation and follow the flow chart below.

$$\Delta Y_t = \alpha_0 + \delta Y_{t-1} + \omega t + \sum_{i=2}^{p} \gamma_i \Delta Y_{t-i+1} + u_t \qquad (3.23)$$

Figure 3.2: Flow Chart for ADF Unit Root Test



Source: Enders (1995), p. 257.

3.4.2. Phillips-Perron Test

Phillips and Perron (1988) have developed more comprehensive theory of unit root non-stationarity. The tests are similar to ADF test, but they incorporate an automatic correction to the DF procedure to allow for auto correlated residuals. Another advantage of PP test is that it can also be applied to frequency domain approach, which is more recent and an alternative to the usual time domain approach, to time series analysis. The tests usually give the same conclusion as the ADF tests, and the calculation the PP test statistic is quite involved and hence not given here. However, the PP test seems to be biased towards rejecting the null hypothesis of a unit root, when the error series follows a negative moving average process. In such situations, it is recommended to use the ADF test, rather than the PP test.

More recently, Kwiatkowski, Phillips, Schmidt and Shin (1992), known as KPSS, have proposed one more unit root test, which has stationarity of the series as the null hypothesis against the alternative of unit root, quite opposite to the earlier tests.

3.5. METHODOLOGY

3.5.1. Information Content

To examine the information content power of forecasting volatility models the study is using information content regression which was designed by Jorion (1995). The annualized Daily actual volatility (one-day-ahead volatility) is calculated by squaring the one-day-ahead returns and then multiplying with square root of 252 to make it annualised (Section 3.3). This value of annualized one-day-ahead volatility is represented as the dependent variable in all of the informational content regressions and all forecasting methods of volatilities presnt as the independent variables in this information content regression. A classic informational content regression is as follows:

$$\sqrt{R_{t,t+1}^{2} \times 252} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t+1} \tag{3.24}$$

R_{t+1} is the next day forecasted return and $\sigma_{t,i}$ is estimated annualized volatility forecast. The estimated annualized forecasting volatility models: the call implied standard Volatility (i.e., $\sigma_{t,CIV}$) from call option prices, the put implied Volatility (i.e., $\sigma_{t,PIV}$) from put option prices, Moving average method ($\sigma_{t,MA}$), Exponentially weighted moving average method ($\sigma_{t,EWMA}$), Generalizedautoregressive conditional heteroskedasticity ($\sigma_{t,GARCH}$) or the Exponential Generalizedautoregressive conditional heteroskedasticity model ($\sigma_{t,EGARCH}$). Here in our study we have run three types of informational content regressions. The first set of regression consists of six simple OLS regressions, where all six daily forecasted volatilities are run separately, as discussed above. In the second set of OLS regressions we are using a multiple regression where we are using the call or put implied volatility as one of the independent variables and one of the other four forecasted volatility as another independent variable. By that we are having four multiple regressions for both call and put implied volatility. These are as follows:

$$\sqrt{R_{t,t+1}^{2} \times 252} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t+1} \qquad (3.25)$$

$$\sqrt{R_{t,t+1}^{2} \times 252} = \alpha + \beta_1 \sigma_{t,PIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t+1} \qquad (3.26)$$

Where R_{t+1} is the next day forecasted return, and $\sigma_{t,i}$ are, respectively, the forecasted volatility from MA(20), EWMA, GARCH and EGARCH model at the period t. In the last case we are putting both call implied ($\sigma_{t,CIV}$) and put implied volatility ($\sigma_{t,PIV}$) as the independent variables to know among these which one contains more information for the next day.

$$\sqrt{R_{t,t+1}^{2} \times 252} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,PIV} + \varepsilon_{t+1} \qquad (3.27)$$

In all the above equations the coefficient of the forecasted volatility is important i.e., β_1. Where the value of the coefficient is high and significant, that volatility contains more information about the one- day-ahead volatility.

3.5.2. Methodology for Predictability Analysis

3.5.2.1.In the sample

To compare the abilities of both "Backward-looking" and "Forward-looking" volatility to predict the future volatility over the remaining life of the option, in an in-the-sample framework, the study has used a simple OLS regression. In simple regression the study has taken realized volatility as the dependent variable and other forecasting models as independent variables. The calculation of realized volatility has already described in Section 3.3. This daily realized volatility series is denoted by *t, T,* where *t* represents the current date and *T* represents theoption contract expiration date. The simple predictability regression as follows:

$$\sigma_{t,T} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t,T} \tag{3.28}$$

Where the $\sigma_{t.T}$ is the realized volatility and estimated volatility forecast, $\sigma_{t,i}$ may again include the implied standard deviation(i.e., $\sigma_{t,IV}$) from option prices both for call and put, Moving average ($\sigma_{t,MA}$), Exponentially weighted moving average method ($\sigma_{t,EWMA}$), *Generalized* autoregressive conditional heteroskedasticity ($\sigma_{t,GARCH}$) or the Exponential Generalized autoregressive conditional heteroskedasticity model ($\sigma_{t,EGARCH}$). In order to test the unbiasedness and efficiency of the independent variables in the Equation-3.28 we use a Wald test. If $\sigma_{t,i}$ contains some information about future volatility then β should be nonzero. Second, if it is an unbiased forecast of realized volatility, then $\alpha = 0$ and $\beta = 1$. Finally, if implied volatility is efficient forecastor of realized volatility then the residuals ε_t should be white noise and uncorrelated with any variables in the market information set. For our analysis we will run three forms of predictability regression. In the first form of regression we put we run all six individual forecasted volatility separately in different regressions as an independent variable with same dependent variable i.e., the realized volatility. In the second form of regression we have used call implied volatility or put implied volatility as one of the independent variable and other forecasted volatilities as other independent variable as our objective is to compare forward looking and backward looking volatility (equations - 3.29 and 3.30). In the third form of regression we compare the forecastability of call and put implied volatility by putting both as independent variables. By that it is easy for us to know among these which has a better forecastability to predict the future volatility (equation - 3.31). As we have discussed above that for comparison between "forward- looking" and "backward-looking" we use multiple regressions. These multiple regression are as follows;

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t,T} \quad (3.29)$$

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,PIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t,T} \quad (3.30)$$

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,PIV} + \varepsilon_{t,T} \quad (3.31)$$

where, $\sigma_{t,T}$ is the average realized volatility and $\sigma_{t,CIV}$ is the call implied volatility, $\sigma_{t,PIV}$ is the put implied volatility and $\sigma_{t,i}$ are, respectively, the forecasted volatility calculated from MA(2), EWMA, GARCH and EGARCH model at the period t. If implied volatility (both call and put) and other forecasted volatility contain independent information that is useful to predicting future volatility then the estimated parameter β_1 and β_2 should both be nonzero. Alternatively if the information in one forecast is a subset of the information contain in the other forecast, the estimated coefficient of the former forecast should be nonzero.

The above calculation of realized volatility aseries do have a high serial correlation[13]. Serial correlation will not affect the unbiasedness or consistency of regression estimators, but it affects its efficiency. It arises by using overlapping data samples. There is an overlapping observation in the dependent variable we are calculating realized volatility. It is debatable in a time series data structure for the calculation of realized volatility over the remaining life of the option. Because of the method is recursive nature. That's why the successive realized volatilities contain a significant amount of redundant information about the return series. Let's suppose there is an option which will expire after 22 days, then its realized volatility is the average of actual one-day ahead squared returns for the next 22 days'. On the next day, the realized volatility is the average of actual one-day ahead squared returns for the next 21 days'. Following this method the there is an overlapping in the dependent variable i.e., realized volatility in the predictability regression because the 21 days one-day ahead squared returns are also present in the calculation of realized volatility considering option which will expire in 22 days. Since the possibility of measurement errors in independent variables could be seen in these types of series, Fleming (1998) used Generalized Method of Moments (GMM) estimation in order to deal with

[13] Serial correlation occurs in time series studies when the error associated with a given time period carry over into future time periods.

overlapping data series. We have also performed GMM of Hansen (1982) along with Newey and West (1985) approach to estimate hetroskedasticity and autocorrelation consistent variance-covariance matrix estimation, using lagged independent variables as instruments. That means the specification in equations - 3.28 to 3.31 can be evaluated using a GMM method of Hansen(1982) by estimating α and β in the movement vector

$$g_T(\alpha,\beta) = \frac{1}{NK}\sum_{t=1}^{NK}(\sigma_{t,T} - \alpha - \beta\sigma_{t,i})Z_{t,i} \qquad (3.32)$$

where the term NK is defined as the number of observation, and Z_t represents a vector of instrument. Here we have taken lagged of the independent variable as instrumental variable. Under our hypothesis, the estimate of α and β should be indistinguishable from zero and one, respectively and $\varepsilon_{t,T} = \sigma_{t,T} - \alpha - \beta\sigma_{t,i}$ should be orthogonal to every subset of Z_t of full information available in period t. In the same fashion the study convert equation 3.29, 3.30 and 3.31 in a GMM frame work. Our regression above do not correct the error in variables problem (Section 3.2.1.1) induced by mis-measurement of the implied volatility.

3.5.2.2.Out of the sample

In the last section the study has explain the methodology to find out the predictability of forecasting models in "in the sample" frame work. For measuring the predictability of the estimators it is better to analyzer both "in the sample" and "out of the sample" performances of the volatility forecasting model. The emphasis of this section is on the forecasting accuracy of 'h' day's ahead implied volatility compared to other "backward –looking" volatility in an out-of-the-sample framework. Here 'h' period is approximately 30 days or in other words a month. For the analysis the study has taken the data from 1st June 2001to 30th June 2011. The study divided the entire sample in to two parts. The first part covers the data set from 1st June 2001 to 31st May 2006 and the second part covers data set from 1st June 2006 to 30th June 2011. First part of the data set is used to estimate the model parameters of GARCH and EGARCH model, which are used to construct an out-of-the-sample h day ahead volatility data set. The second part is used to calculate the next h days Realized volatility, Implied volatility, Moving Average, and Exponential Weighted Moving

Average The different methods of volatility forecasting model for h day ahead are described below.

Realized volatility

The realized volatility over a time time horizon of h days is calculated by taking the square root of the average of the futures squared returns($R_{t-1,t} = \ln(S_t) - \ln(S_{t-1})$) over this h period. At the time t the annualized realized volatility for the next h days is

$$\sigma_{t,h}^{RV} = \sqrt{\frac{1}{h}\sum_{i=1}^{h} R_{t+i}^{2} \times 252} \qquad (3.33)$$

Where, is $\sigma_{t,h}^{RV}$ the realized volatility in the out-of-the-sample framework and h is the days to expiry of the option contract.

Implied volatility

For both call and put implied volatility calculation we are picking up the options which are at the money and 'h' days to expiry of the contract in the out-of-the-sample period for calculating both. Here h is taken approximately 30 days.

Call Implied Volatility**:** $E_{CIV}(\sigma_{h \to 30, CIV}) = \sigma_{t,h}^{CIV}$ (3.34)

Put Implied Volatility**:** $E_{PIV}(\sigma_{h \to 30\ PIV}) = \sigma_{t,h}^{PIV}$ (3.35)

Moving Average (20) Model

The h day's ahead annualized Moving Average model is

$$E_{MA}(\sigma_{h \to 30}) = \sigma_{t,h,}^{MA} \qquad (3.36)$$

We are picking up the moving average volatility on the day where there is 'h' days to expiry an option in the out of sample period.

Exponential Moving Average Method

Here we are considering volatilities that apply an exponential weighted scheme putting progressively less weight on distant observations. Such volatility is exponential smoother or Risk Metrics volatility, where daily variance evolves as

$$\sigma^2_{t,EWMA} = \lambda\sigma^2_{t-1} + (1-\lambda)R_t^2 \qquad (3.37)$$

Following JP Morgan we simply fix λ = 0.94 for all the daily index returns. The annualized forecast for h day volatility is therefore simply

$$E_{EWMA}(\sigma_{h\to 30,EWMA}) = \sigma^{EWMA}_{t,h} = \sqrt{\sigma^2_{t,EWMA}} \qquad (3.38)$$

From the above equation we will get h day's ahead EWMA volatility

ARCH family model

For constructing the "out of sample" data set for GARCH and EGARCH models the study has first estimated the most appropriate GARCH and EGARCH for index returns within the sample data. Using the data set (1st Jan 2001 to 31st May 2006) the above models are first estimated. Then the parameter of the models would be used to construct out of sample GARCH and EGARCH forecasted value for 30 days. The 30 days predicted volatility would be then averaged, and then multiply with square root of 252 to make it annualized which is compared to the realized volatility "average volatility" over that period. After the calculation of first average 30 days GARCH and EGARCH forecasted values the parameters in the GARCH and EGARCH model are again re-estimated by adding the approximately latest 30 calendar days or approximately 22 observations and deleting the approximately first 30 calendar days in the previous sample or approximately 22 observations. After that the study estimate GARCH and EGARCH and forecast the new 30 days and then averaging it to match with the realized volatility. We continue this procedure up to 31st may 2006. Each time we are averaging 30 forecasted values to get the GARCH and EGARCH forecasted value for the out of sample predictability. At each forecast date the following GARCH and EGARCH forecasts can be calculated as

GARCH : $$E_{GARCH}(\sigma_{h\to 30}) = \sqrt{\frac{1}{30}\left[\sum_{h=1}^{30}\sigma^2_{t+h,GARCH}\right]} \times \sqrt{252} \qquad (3.39)$$

EGARCH: $E_{EGARCH}\ (\sigma_{h\to 30}) = \sqrt{\frac{1}{30}\left[\sum_{h=1}^{30}\ln\sigma^{2}_{t+h,EGARCH}\right]}\times\sqrt{252}$ (3.40)

By this above methods we get 61 avarge forecasted values. All other forecasted models is generate on the day where aprroximately h day ahead to expiry of the option contract. For comparision of all forecasting model we have taken four error statistics

Error statistics

MSE (Mean Square Error): $\frac{1}{N}\sum_{T=1}^{N}(\sigma_T^{RV}-\sigma_T^{f})^2$ (3.41)

MAE (Mean Absolute Error): $\frac{1}{N}\sum_{T=1}^{N}\left|\sigma_T^{RV}-\sigma_T^{f}\right|$ (3.42)

RMSE (Root Mean Square Error): $\sqrt{\frac{1}{N}\sum_{T=1}^{N}\left(\sigma_T^{RV}-\sigma_T^{f}\right)^2}$ (3.43)

MAPE (Mean Absolute Percentage Error): $\frac{1}{N}\sum_{T=1}^{N}\left|\frac{\sigma_T^{RV}-\sigma_T^{f}}{\sigma_T^{RV}}\right| * 100$ (3.44)

In the above expression σ_T^{RV} is the realized volatility and σ_T^{f} forecasted models, it may include call implied volatility σ_T^{CIV}, put implied volatility σ_T^{PIV}, Moving average volatility σ_T^{MA}, GARCH volatility σ_T^{GARCH} or EGARCH volatility σ_T^{EGARCH}. N denotes the number of forecast model using each method.

3.5.3. Implied Volatility in ARCH Type Model

The present study is based on Day and Lewis (1992) methodology. Here in our analysis we are not taking the lagged implied volatilities as the only independent variable in the conditional variance equation. The study has added lagged implied volatility as an independent variable in the GARCH and EGARCH frame work and for knowing the predictive power of implied volatility by putting the Wald test (β_1 = 0, α_1 = 0 and implied coefficient = 1) in the GARCH model and (β_1 = 0, α_1 = 0 and θ_1 =0 and implied coefficient=1) in the EGARCH model. Here the study has used GARACH and EGARCH model frame work as on section - 3.5.2 because the data set is same. Day and Lewis had used weekly returns and weekly option expiry for their analysis, whereas we are using the daily returns for conditional volatility and option expiry more than 6 days. By using this method there is a problem of mismatch. Because GARCH and EGARCH model predicts the conditional variance for the next day whereas the implied volatility characterizes as the average daily volatility over the remaining lifetime the option contract. Now the question arises which is best. That's why the study objective is to find whether the lagged implied volatility[14] has contained more information than the lagged conditional volatility in a GARCH and EGARCH equation. In other words the study aims to find out whether the implied volatility is an important determinant of conditional volatility than its own past. Our analysis is different from Day and Lewis in that we are using both call and put implied volatilities separately for the information content power while Day and Lewis have used only call implied volatility.

3.5.4. Predictability of VIX for One month Expiry Contract.

In this section we compare VIX with other forecasting models. For this analysis we have used a simple regression format which we have discussed in Chapter-3, sections 3.5.1 and 3.5.2, by taking future or realized volatility as the dependent variable and other forecasting models as independent variables. We have already mentioned that India VIX is computed "using the best bid and ask quotes of the out-of-the-money near and mid-month NIFTY option contracts which are traded on the F&O segment of NSE and it indicates the investor's perception of the market's volatility in the near term". The index depicts the expected market volatility over the next 30 calendar days. As VIX is considering out of the money, near and middle month contract, we are not comparing the Black-Scholes implied volatility with VIX. Now, our main objective is to find out the predictability of VIX compared to "backward-looking" volatility measures. By convention, S&P CNX Nifty options expired last Thursday of every month. Therefore, we have collected the VIX on the Friday that immediately follows the expiration, which is represented as average expected market volatility over the next 30 calendar days. In order to match it with "backward-looking" volatility we have also taken the average volatility of that 30 calendar days for Realized, Moving average, Exponential Moving Average, GARCH and EGARCH volatility on that date**.** We do so because on Friday the contract is near month and one

[14] Both call and put implied volatility

month to expiry. If Friday is a holiday, then the study has considered the next business day. The key feature of this sampling procedure is to remove the non-overlapping problem and no mismatch issues in the dataset.

To study the predictability of VIX with “backward-looking” volatility we have used the simple OLS regression same as used in sections 3.5.1 and 3.5.2 where realized volatility is the dependent variable and other forecasting models are independent variables. The simple predictability regression as follows:

$$\sigma_{t,T} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t,T} \tag{3.45}$$

$$\sigma_{t,T} = \alpha + \beta_1\sigma_{t,VIX} + \beta_2\sigma_{t,i} + \varepsilon_{t,T} \tag{3.46}$$

where, the $\sigma_{t.T}$ is the Realized Volatility and estimated volatility forecast, $\sigma_{t,i}$ may again include the VIX (i.e., $\sigma_{t,VIX}$), Moving Average ($\sigma_{t,MA}$), Exponentially Weighted Moving Average method ($\sigma_{t,EWMA}$), Generalized Autoregressive Conditional Heteroskedasticity ($\sigma_{t,GARCH}$) or the Exponential Generalized Autoregressive Conditional Heteroskedasticity model ($\sigma_{t,EGARCH}$). In order to test the unbiasedness and efficiency, we go for a hypothesis test. If $\sigma_{t,i}$ contains some information about future volatility then β should be nonzero. Second, if it is an unbiased forecast of realized volatility, then $\alpha = 0$ and $\beta = 1$ as specified in equation - 3.45. If VIX and other forecasted volatility contain independent information that is useful to predicting future volatility, the estimated β_1 and β_2 should both be nonzero (equation - 3.46). Alternatively if the information in one forecast is a subset of the information contained in the other forecast, the estimated coefficient of the former forecast should be nonzero.

CHAPTER-4

Information Content Volatility of S&P CNX Nifty Index Option

4.0. Introduction

There is a continuing debate on whether backward or forward looking models of volatility workas better predictors of future realized volatility. Here, in our analysis, we have considered two methods for comparison. The first one is through an information content method and other is the predictability method. In this chapter, all forecasting volatility models are compared, which were explained in Chapter-3, and weaim to findthe method that has better information content about one-day-ahead volatility. One of the significant contributions focusing on comparison is from Jorion in 1995 where he compares both forward and "backward-looking" volatility methods in order to check the ability of predicting one-day-ahead volatility. To analyze this, he runs a simple regression where he puts one-day-ahead volatility as dependent variables and implied volatility, MA(20) and GARCH(1,1) as independent variables, which he signifies as "information content regression"

Jorion analyzed the daily market returns of the Japanese Yen from July 1985 to February 1992, Swiss Franc from March 1985 to February 1992,and Deutsche from 1985 to February 1992 and concluded that the implied volatility as a predictor of one-day-ahead volatilityout-performs all historical volatility measures. The present study is an endeavor in this direction in the context of Indian options market. However, the present study differs from Jorion in two aspects. Firstly, we are using MA (20), EWMA, GARCH (1, 1) and EGARCH (1, 1) as explanatory variables in the information content regression in order to capture the long memory of volatility measures. Secondly, Jorion has considered implied volatility as a weighted average of call and put option contracts, whereas we are analyze call and put implied volatility for at-the-money (near-the-money) option in isolation. The reasoning behind this is as follows; first, the Indian derivatives market is nearly 10 years old and still in the developing stage. A close observation reveals that the 'out of the money' and 'in the money' contracts contain very less liquidity during this 10 years. There also exists a lack of liquidity in the ‘deep in the money’ and ‘deep out of the money’ for both call and put options in India compared to the developed markets such as U.S. and Europe. Therefore, it’s not appropriate to use ‘out of the money’ and ‘deep out of the money’ or ‘in the money’ and ‘deep in the money’ contracts for our analysis. This might be possible due to the fact that insufficient liquid market may give wrong information. That is the reason why our study is only confined to ‘near month contract’ for both call and put, respectively. Second, in respect of liquidity of the market, the behavior of the call and put are different. This is the major reason for undertaking the analysis of implied volatilities in the context of both call and put option contracts separately. The rest of the chapter is structured as follows; Section-4.1deals with the empirical analysis of the study followed by the concluding remarks of the chapter in Section 4.2.

4.1. Empirical Analysis

The variables considered in the empirical analysis consist of the closing price of the S&P CNX Nifty index, closing price of the option (both call and Put) on the underlying asset S&P CNX Nifty, strike price associated with near month ‘at the money’ call and put, and MIBOR rate. The data is sourced from the official website of the National Stock Exchange (NSE), Mumbai, India. The study is spanned over the period from 1st June, 2001 to 24th June, 2011, in case of spot prices of S&P CNX Nifty and in case of option market the study period is from 4th June, 2001 to 23rd June, 2011. The data for risk free interest rate MIBOR (Mumbai Inter-Bank Offer Rate), is from 4th June, 2001 to 23rd June, 2011.

For computing MA(20), EWMA and ARCH family of models, we have converted the index value into a continuously compounded rate of return (R_t) by taking the first difference of the natural logarithmic of prices, i.e. R_t = (ln S_t –ln S_{t-1}).For ARCH family model, the study has used the return series (R_t). The graphical behavior of the closing price and its return are presented in Fig-4.1 and Fig-4.2. The method of calculation of MA (20) and EWMA is already explained in Chapter-3. This study has used two commonly established models in this sphere, that is Generalized Autoregressive Conditionally Heteroscedastic (GARCH) and Exponential Generalized Autoregressive Conditionally Heteroscedastic (EGARCH) model.

As the error terms are assumed to be normally distributedin linear regression in general and GARCH model in particular. It is possible to test this assumption by using Jarque-Bera (J-B) test statistic. The test uses the skewness and kurtosis values of the variable and compares them with the corresponding values of the normal distribution (skewness is equal to 0 and kurtosis is equal to 3). The J-B statistic is defined as $\frac{(n-k)}{6}\left[S_k^2 + \frac{(k-3)^2}{4} \right]$, follows a χ^2distribution with 2 degrees of freedom, where 'n' is the number of observations, 'k' being the number of parameters of the distribution under the null hypothesis of normality. For normal distribution, kurtosis is equal to 3. If the calculated value of J-B exceeds the theoretical value, we reject the null hypothesis of a normal distribution of the variable.

The summary statistics of both closing price and its corresponding returnseries are presented in the Table-4.1. we can seen from theTable-4.1 that both the closing priceand its respective return are skewed and non-normal in nature. The result shows that the returns are negatively skewed whereas closing prices arepositively skewed. The J-B test presented in Table-4.1 shows that we have rejected the null hypothesis of normality for index return. The histogram for the index return presented in Figure-4.3 also confirms that it is not normally distributed. We can also see that, the actual distribution of daily index returns has a fatter tail compared to a fitted normal distribution. The results is more concrete with the kurtosis value of 11.83 for the daily index return. Which shows that the index return indicating the presence of fat tail.

Based on the above observations, while calculating GARCH and EGARCH model, instead of the assumption of normality in the index return series, we use the Generalized Error Distribution (GED, Taylor 1994) for maximizing the likelihood function, from which the normal distribution is a special case. The density function of GED takes the following form.

$$f_{\upsilon}(x) = \frac{\upsilon \exp\left\{ -\frac{1}{2}\left|\frac{x}{\lambda}\right|^{\upsilon} \right\}}{\lambda\, 2^{1+1/\upsilon}\, \Gamma\left(\frac{1}{\upsilon}\right)} \qquad (4.1)$$

$$\lambda = \left[2^{-\frac{2}{\upsilon}} \frac{\Gamma\left(\frac{1}{\upsilon}\right)}{\Gamma\left(\frac{3}{\upsilon}\right)} \right]^{\frac{1}{2}}$$

Where, $\Gamma(.)$ denotes the Gamma function and $\upsilon > 0$, here, υ represents tail thickness of the distribution. It is estimated simultaneously with all other model parameters. When υ =2 we have a normal distribution, and for $\upsilon < 2$, the distribution has thicker tails than the normal. In our analysis we are considering the GED in our GARCH and EGARCH estimation because the error term u_t in GARCH and EGARCH model has fatter tails than the normal distribution.

To eliminate the first degree auto correlation among the returns the study has fit AR model. Among the different auto regressive orders, the AR (1) is found to be the best fitted model of the return series as per the appropriate statistical level of significance. For further analysis we have to test whether there is an autocorrelation among residual and square residual or not.To test whether there is presence of autocorrelation among residual and square residual we are doing a Ljung Box-Q statistics test.The test statistics based on the null hypothesis of "No Autocorrelation" against the alternative of the presence of autocorrelation, are reported in Table 4.2. From this results, it summarized that that the null hypothesis is strongly rejected in the case of residual and squared residuals. The rejection of null hypothesis permits us to apply GARCH and EGARCH models. Before proceeding towards further analysis, the ARCH effect on the mean equation of the return series is tested. Lagrange Multiplier (LM) test that is used to measure the presence of ARCH effect in the data with null hypothesis of 'No ARCH effect', is strongly rejected in the index return at lag 4with one percent level of significance as reported in Table-4.2.

In Tables 4.3 and 4.4, the estimation results of AR (1) -GARCH (1, 1) and that AR (1)-EGARCH (1, 1) models are presented. The study has used the GARCH and EGARCH models of order (1, 1)because it is found to be the best model.The basis on which the EGARCH model is selected has already been discussed and this is that it incorporates the signs of the residuals in the volatility equation and thus distinguishes between bad and good news. Both the GARCH (1, 1) and EGARCH (1, 1) models are as follows;

Mean Equation:

AR (1): $R_t = c + \tau R_{t-1} + u_t$, $u_t \sim GED(0, \sigma_t^2)$ (4.2)

Variance Equations:

GARCH (1, 1): $\sigma_t^2 = \omega_0 + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2$ (4.3)

EGARCH (1, 1): $\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$ (4.4)

The results show a significant coefficient value in the mean equation, both in GARCH (1, 1) and EGARCH (1, 1) model. The DW statistics are 1.99 and 2.03, confirming the absence of serial correlation in residuals in GARCH (1, 1) and EGARCH (1, 1) model. In variance equation (Table-4.3 and 4.4) the coefficients are also seen significant in both the models. To test the degree of persistence in GARCH (1, 1) model, the Wald test is used in which the null hypothesis, $\alpha + \beta = 1$ against the alternative ($\alpha + \beta < 1$). Wald statistic reported in Table-4.3 shows that the null hypothesis is strongly rejected with a one percent level of significance. Thus, the test has confirmed the stationary of the variance and since $\alpha + \beta = 0.97$, i.e., less than unity, we may argue that the volatility may decay rapidly and revert to its mean value. Post estimation of GARCH (1,1) and EGARCH (1,1) model, ARCH LM test is carried out to verify whether the ARCH effect still exist. As reported in Table-4.3 and 4.4 the results reveal that in both GARCH (1, 1) and EGARCH (1, 1) model LM test showing a insignificant coefficient which shows that the null hypothesis of "No ARCH effect" is not rejected in both models. Variance series of GARCH and EGARCH model is generated using AR (1)-GARACH (1, 1) and AR (1)-EGARCH (1, 1) model.Square root ofthe series is used to get the standard deviation. Subsequently, the annualized standard deviation is computed by multiplying it with square root of 252 (√252),assuming there are 252 trading days in a year.

After measuring the backward looking volatilities (MA (20), EWMA, GARCH (1, 1) and EGARCH (1, 1)),we have moved to measure the implied volatility. For implied volatility, the study hasused near month contract as it is highly liquid. In the near monthcontracts, we have used the ‘near-the-money’ call and put option, having the same strike price and expiry time. The expiration in both call and put are more than 6 days. Up to 6 day expiration contract is used to avoid the rollover effect. Additionally, the logic forconsidering 6 days contracts is that, traders and investors generally roll their contracts within the last week of expiration. To address the liquidity issue, we have used nearest-to-the money options for the calculation of implied volatilities. For interest rate component in the Black-Scholes model the one-month MIBOR (Mumbai Interbank Offer Rate) has been used as the risk free interest rate.

Lastly, the important segment of the regression analysis i.e., one-day-ahead volatility is measured. The annualized volatility series is generatedas per the discussionof the methodology in Chapter-3. After generating the annualized volatility, the whole series is converted to one day ahead volatility. We have considered ‘t+1’ day annualized volatility in period ‘t’ for example, 5^{th} June 2001 realized (one day) volatility in 4th June 2001.

Before proceeding towards further regression analysis, the study presents the graphical analysis of each of the variables, and exercised unit root tests of all the series.

4.1.1. Graphical Analysis

The time series plot of all the estimated volatility series is presented in Fig-4.4 to 4.10 to analyze the nature of the data including ‘one-day-ahead’ volatility. The figures show that the one-day-ahead volatility has fluctuated more throughout the sample period than the others. Next, we present a comparison of graphical analysis between one-day-ahead volatility and other forecasting volatility models and presented in Fig-4.11 to 4.16. From these graphs, we can’t conclude which of the model fits well to one-day-ahead volatility. This issue has been addressed in the next section.

4.1.2. Descriptive Statistics and Unit Root Tests

Table-4.5 reports the descriptive statistics of one-day-ahead volatility and all other volatility forecasting models. Among all variables, the ‘put implied volatility’ not only has a high mean value, but also has fluctuated in a high range. All the volatility models have significant Jarque-Bera test statistic which confirms that the variables are not from a normal distribution. Everyone of the series isalso seen to be positively skewed. The results also show that the "backward-looking" volatility forecast methods move in a similar range.Call-put parity theory advocates that with the same underlying asset, strike price, and expiration date the call and put implied volatility should be same. However, it has be empirically observed that when we calculate implied volatility through option pricing both call and put implied volatility frequently diverge each other. The obvious reason for this deviation because of the different demand structure for call and put options. If we observe the Indian option market there is pressure of demand for more put than call, as financial institutional investors regularly long put options to hedge their cash position. There are often no market participants looking to short the same options to offset this demand. This leads to a high bidding for put option.Assuming an efficient market where there is no transaction costs or other frictions present both the call and put implied volatility should be equal. However, in real-world the scenario is different. The existence of imperfections in the market may allow to violate the theory of call-put-parity and makes the market inefficient.

One-day-ahead volatility has a minimum value of zero because the square root of square one-day-ahead return always gives us a positive number and if the closing price of two succeeding days are same then it will give a value of zero. This is exactly happening in our case.

For examining the stationarity the study has taken DF,ADF and PP with intercept and with intercept and time. For all the series the null hypothesis of unit root is rejected. The results of unit root tests are given in Table-4.6. The optimum lag length in ADF is choosen on the basis of AIC and for PP test and the bandwidth is selected by Newey-West method. The null hypothesis is rejected and hence, all the variables are stationary at their level.

4.1.3. Simple Information Content Regression

After analyzing the descriptive statistics and checking for stationarity, next step is to go for an information content regression. We start our discussion through the analysis of simple information content power of individual forecaster. Table-4.7, Part-I shows the individual OLS regression results. This section begins by examining each OLS regression separately (based on Chapter-3, Equation-3.24). Wald test is used with the null hypothesis of unbiasedness (α=0 and β=1). The OLS estimation finds serial correlation corresponding to a Durbin Watson statistic less than 2 (Table-4.8).This has warranted to build an AR (1) model to resolve the problem of serial correlation.

Through regression Equation- 3.24, we have analyzed the ability of all the volatility forecast methods which has been discussed in the previous section. By considering 'Call Implied Volatility' (CIV) as independent variable in the Equation-3.24, the study observed that the coefficient is statistically significant at one percent level with magnitude of 0.37. This further explains that, a 10% change in call implied volatility leads to 3.7% change in one-day–ahead volatility. Similarly, by considering 'Put Implied Volatility' (PIV) as independent variable in the equation-3.24, it is seen that the coefficient is statistically significant at one percentlevel but the magnitude is lower than call implied volatility (0.34). The reported R^2 value is also low at 0.12 in comparison to CIV which is at 0.13.

The Moving Average (MA (20)) as an exogenous variable shows a greater co-efficient value of 0.55 in comparison to both call and put implied volatility. The coefficient is significant at one percent level with the R^2 value of 0.16.

Nevertheless, the EWMA as an exogenous variable shows a better result than CIV, PIV and MA (20) volatility method which is consistent with earlier literature. In our analysis, it shows coefficient value of 0.63 with a one percent level of significance. This indicates that among all these methods, EWMA is the best estimate of historical volatility to predict one-day-ahead volatility.

Finally, the results of ARCH type of models with other "backward-looking" volatilities and "forward-looking" volatility models are compared to conclude the robustness of the forecasting power of one day ahead volatility of S&P CNX Nifty index. The results are reported in the Table 4.7, Part-I. In this table, both the coefficient of GARCH (1, 1) and EGARCH (1, 1) explain one day ahead volatility with a coefficient value of 0.67 and 0.77, respectively at the one percent level of significance. However, it is important to note that EGARCH (1, 1) has a higher value of the coefficient than the GARCH (1, 1) model.

In the next step, the coefficients of all six of these regressions consisting of both "backward-looking" and "forward-looking" volatility measures to forecast the one day ahead volatility are compared. In a nutshell, these results are summarized as follows. First, it is clear that all the "backward-looking" volatility measures performed better than the call implied and put implied volatility. Second, the coefficient of call implied volatility (0.37) is slightly higher than of put implied volatility (0.34) with marginally higher R^2 statistic in call implied volatility. Third, the EGARCH (1, 1) model outperforms the rest five forecasting models with a coefficient value of 0.77 at one percent level of significance. Forth, the performance of the put implied volatility is not so encouraging with a low coefficient value of 0.34.

Wald test statistics shows (Table-4.7, Part-I) that all six regression models reject the null hypothesis of unbiasedness at one percent level of significance. Biasedness in the implied volatility estimator arises because of the error in the variable. Errors-in-variables explained implied volatilities failure to subsume other forecasts. The measurement error arises because of the specified error from using the "wrong options model", such as "non-synchronous trading", and a "jump in prices".

4.1.4. Multiple Information Content Regression

Table 4.7, Part-II,compare put and call implied volatility with other forecasting volatility models in a multiple information content regression. All these regressions include the Call implied (CIV) or Put implied Volatility (PIV) as one of the independent variables along with one of the backward looking volatility such as MA(20), EWMA, GARCH (1, 1) and EGARCH (1,1). However, it is worth mentioning that there are eight regressions (OLS) that are run by taking the all the possible combinations. We have also used a Wald test with a null hypothesis (α=0, β_1=1 and β_2=0) for call and put implied volatility as an efficient and unbiased estimator for One-day-ahead volatility.

Comparing the CIV with other volatility forecasting models throws light on the following important findings. In comparison with MA (20), the CIV has a lower coefficient value of 0.18 at one percent level of significance. The MA (20) has a significant coefficient, but has a high magnitude of 0.41. This regression shows a low R^2 value of 0.17. Similarly, the EWMA significantly outperformed CIV. The coefficient of EWMA is 0.49 and it is statistically significant at one percent level. On the other hand, CIV has a lower significant coefficient value of 0.15. The estimation result also shows the value of R^2at 0.17.

In connection to the GARCH (1, 1) model, the results of the CIV are not as encouraging as it came with a coefficient value of 0.14 at one percent level of significance. The GARCH (1, 1) has a better coefficient value in comparison to the coefficient value of MA (20) and EWMA in the regression that involves CIV as one of the independent variables. However, in the EGARCH (1, 1) specification, as per the Chapter-3, Equation-3.26, the CIV has a low coefficient value of 0.13 and it is significant at one percent level in comparison to the conditional variance series EGARCH.The coefficient of EGARCH is highly statistically significant at one percent level with a coefficient of higher magnitude, 0.66.

The efficiency of PIV model in comparison to other volatility forecasting models in similar lines of CIV is presented here. In comparison with MA (20), PIV demonstrates one percent level of statistical significance, with a low magnitude, 0.13. Whereas, MA (20) model has a coefficient value of 0.45 at one percent level of significance. Similarly, when we compare with EWMA, PIV continued to perform poorly. However, in between PIV and GARCH (1, 1) model, the GARCH (1, 1) model performed better than PIV. The coefficient of GARCH (1, 1) is significant at one percent level with a magnitude of 0.59. Similarly, in between PIV and EGARCH (1, 1), surprisingly the coefficient of PIV is lower than 0.10 and is significant at one percent level. Thus, from the analysis of the results in Table 4.7, we conclude that the EGARCH (1, 1) model has outperformed PIV with a coefficient of good magnitude of 0.7 and highly significant at the one percent level. Finally, while comparing the results between CIV and PIV, Table 4.7 in Part-III, shows that both CIV and PIV have low co-efficient values. The result also shows that CIV has outperformed PIV with a coefficient value of 0.26 at one percent level of significance. The PIV is significant but it has a low coefficient value. Therefore, it is worth noting that the call and put implied volatility are not same in case of near the money option having the same strike price and time to expiry. This may be the reason for getting the different forecasting ability of both CIV and PIV. This may be due to mispricing of volatility in the Indian option market[15].

4.2. Conclusion

This chapter tests the information content power of daily implied volatility over the next day in comparison to backward looking volatility measures. From the empirical analysis, we have obtained several key conclusions that may be helpful for the traders while taking the decisions for complex option strategies. The findings are as follows. First, in two variable information content regressions, EGARCH (1, 1) is outperforming all volatility forecasting models. Second, all the "backward-looking" volatility measures contain more information for the next day than the implied volatilities. Third, compared to PIV, CIV contains more information to explain one-day-ahead volatility. Fourth, in a multiple regression model, EGARCH (1, 1) model is seen to have outperformed all other volatility forecasting models. Fifth, PIV failed to explain one-day-ahead volatility and the model seems to be inferior compared to historical volatility model MA (20) and CIV. It is also observed that, implied volatility is a biased forecaster. The biasedness in the implied volatility estimator arises because of the error in variables. Errors-in-variables explained implied volatilities failure to subsume other forecasts. The measurement error arises may be because of the specification error by using the "wrong options model", "non-synchronous trading", and a "Jump in prices".

[15] J.R.Varma (2002), D.Misra,R.Kannnan & S.D.Misra (2006)

Fig-4.1: Trends in Index Closing Price

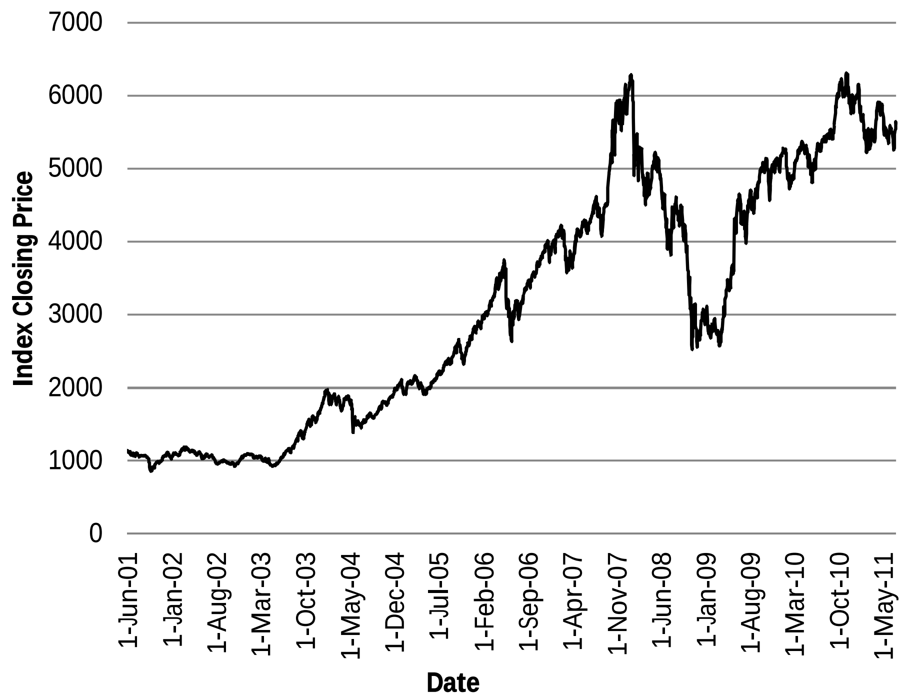


Fig-4.2: Trends in Return

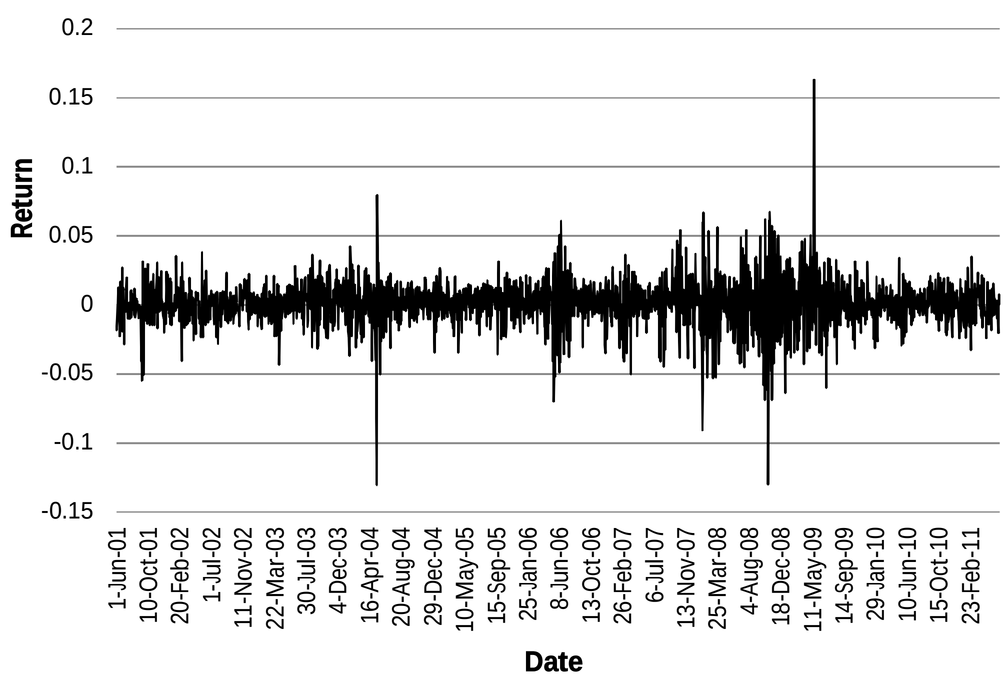


Table-4.1: Basic statistics of closing Price of S&P CNX Nifty and its return

Variable	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	J-B
Index Closing Price	3115.91	6312.45	854.2	1685.55	0.2134	1.6232	217.45*(0.01)
Index Closing Price Return	0.0006	0.16	-0.13	0.016	-0.28	11.834	8205.78*(0.01)

Note: *: Indicates the rejection of null hypothesis of normal distribution in J-B test at 1%.

Fig-4.3 Histogram Showing the Distribution of Return Series

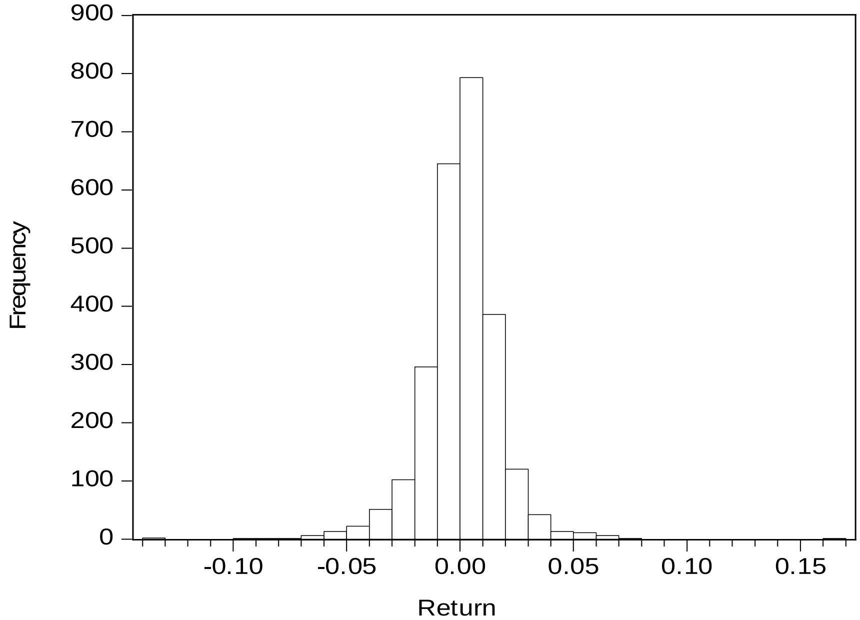


Table-4.2: Estimated Test Statistics for ARCH Effect

	Q^2 (5)	Q^2 (10)	Q^2 (20)	LM (4)
Squared Residual of AR (1) Model	354*	524.10*	696.38*	211.854* (57.73)
	Q(5)	Q(10)	Q (20)	
Return of S&P CNX Nifty	19.10*	33.71*	58.27*	
Squared Return of S&P CNX Nifty	331.76*	499.13*	659.07*	

Note :*: 1% level of Significance, Q and Q^2 are the LB Q statistics for the return and squared return, and square residuals, respectively. The selection of lag length of LB Q test and LM test are 5, 10, 20 and 4 respectively.F-statistic is in parenthesis

Estimation Of GRACH(1,1) Process

AR (1): $R_t = c + \tau R_{t-1} + u_t$, $u_t \sim GED(0, \sigma_t^2)$

GARCH (1,1): $\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2$

Where, R_t is defined as the return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Table-4.3: Parameter estimates of the GARCH (1, 1) model

Model-GARCH(1,1)	
Mean Equation	
C	0.001* (5.22)
R_{t-1}	0.07* (3.47)
Variance Equation	
ω	0.000* (4.83)
u_{t-1}^2	0.13* (8.43)
σ_{t-1}^2	0.84* (49.27)
GED Parameter	1.44* (34.83)
Log likelihood	7209.55
AIC	-5.73
SC	-5.72
DW	1.99
LM (4)	2.859 (0.71)
Wald Test	7.35* (7.27)

Notes: :*: 1% level of Significance, Asymptotic t-statistic are in parenthesis and LM (4) represents LaGrange Multiplier statistic to test the presence of additional ARCH effect in the residuals from AR(1)-GARCH(1,1). The F-statistics for LM test is also in parenthesis.

Estimation Of EGRACH(1,1) Process

AR (1): $R_t = c + \tau R_{t-1} + u_t$, $u_t \sim GED(0, \sigma_t^2)$

EGARCH (1,1): $\ln\sigma_t^2 = \omega + \beta_1 \ln\sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$

Where R_t is defined as the return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Table-4.4: Parameter estimates of the EGARCH (1,1) model

Model-EGARCH(1,1)	
Mean Equation	
C	0.0009* (3.91)
R_{t-1}	0.08* (4.19)
Variance Equation	
ω	-0.59* (-8.33)
Ln σ_{t-1}^2	0.95* (133.80)
$\|z_{t-1}\|$	0.261* (9.66)
z_{t-1}	-0.11* (-7.24)
GED Parameter	1.46* (35.77)
Log Likelihood	282.25
AIC	-5.74
SC	-5.73
DW	2.03
LM (4)	2.350 (0.58)

Notes: :*: 1% level of Significance, Asymptotic t-statistic are in parenthesis and LM (4) represents LaGrange Multiplier statistics to test the presence of additional ARCH effect in the residuals from AR (1) - EGARCH (1,1) models. The F-statistics for LM test is also in parenthesis.

Fig-4.4: Trends in One-Day-Ahead Volatility (ODAV)

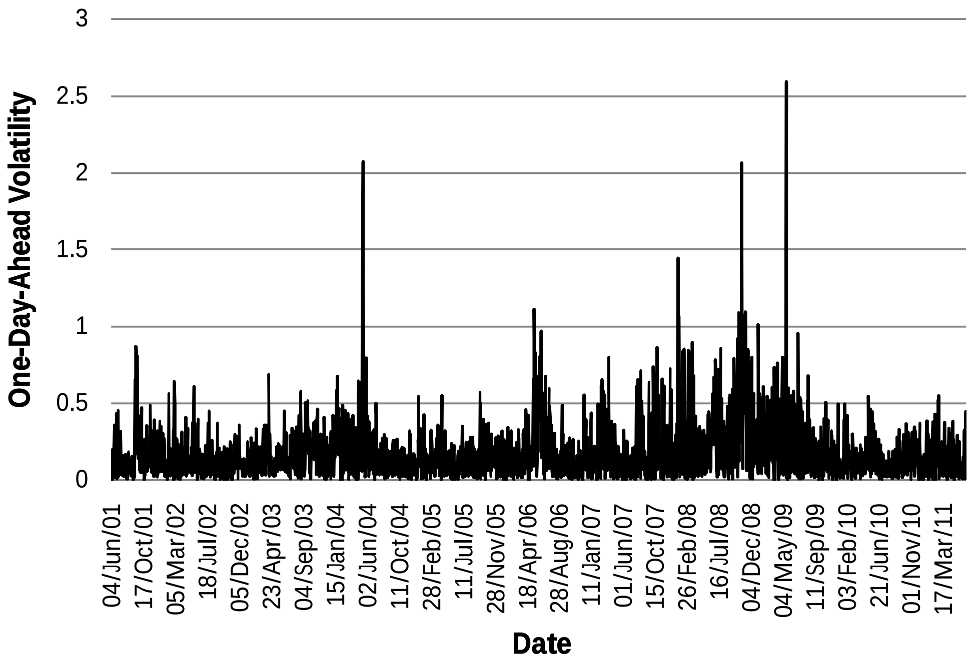


Fig-4.5: Trends in Call Implied Volatility (CIV)

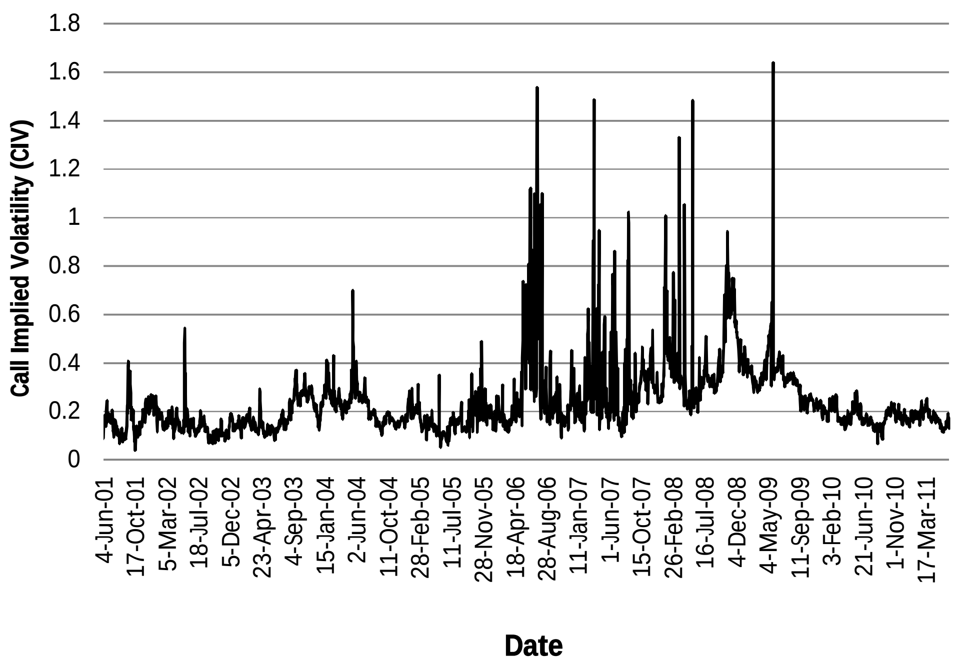


Fig-4.6: Trends in Put Implied Volatility (PIV)

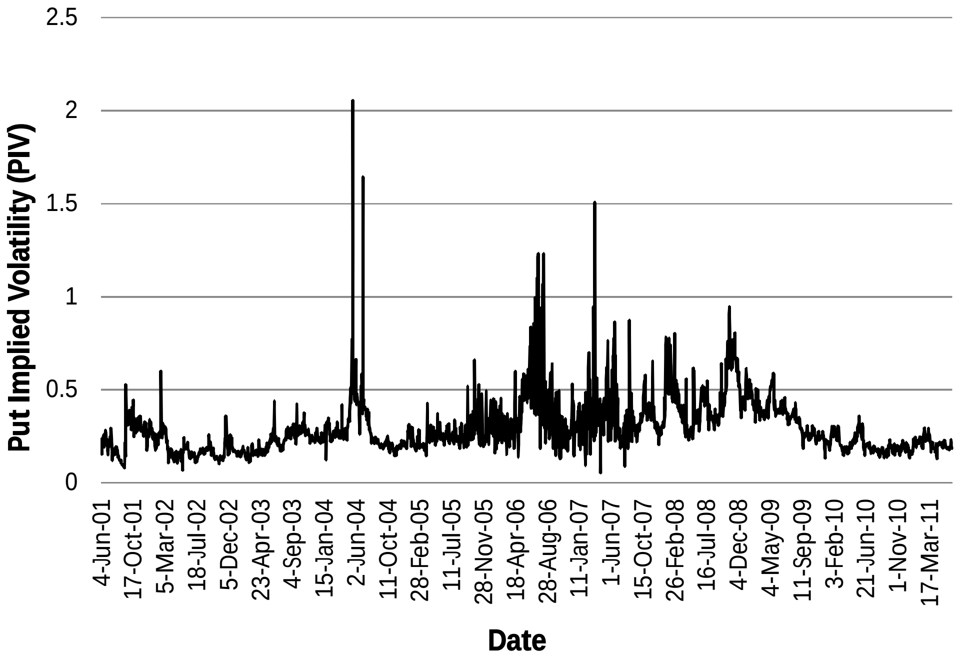


Fig-4.7: Trends in MA(20) Volatility

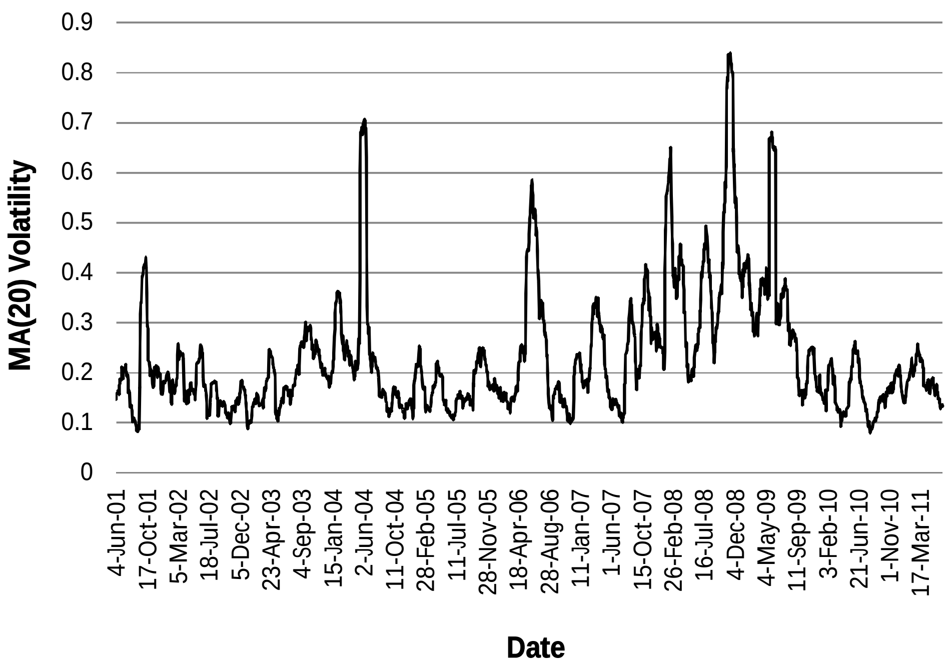


Fig-4.8: Trends in EWMA Volatility

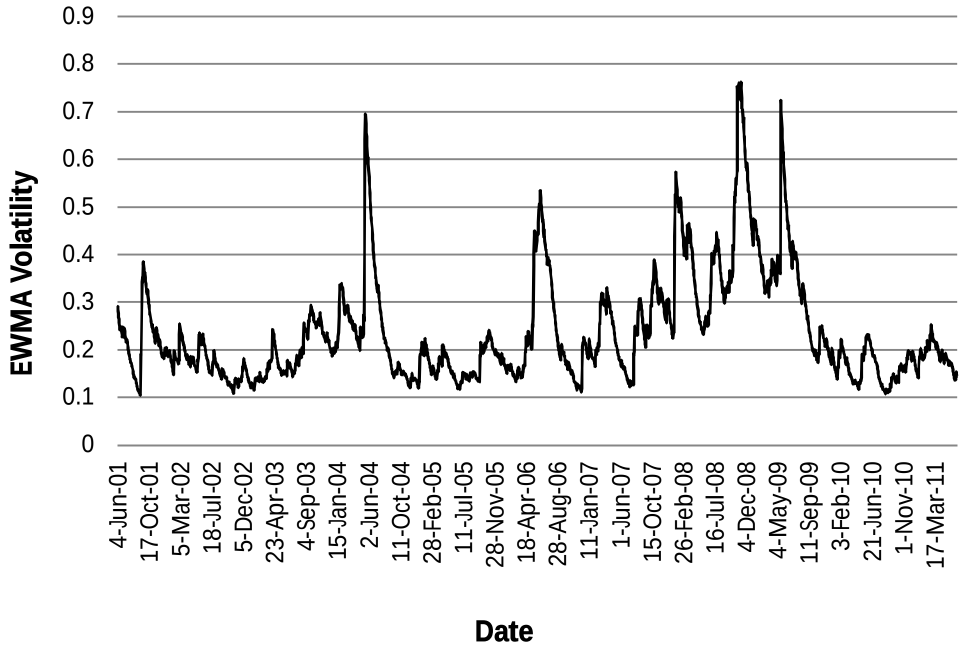


Fig-4.9: Trends in GARCH (1, 1) Volatility

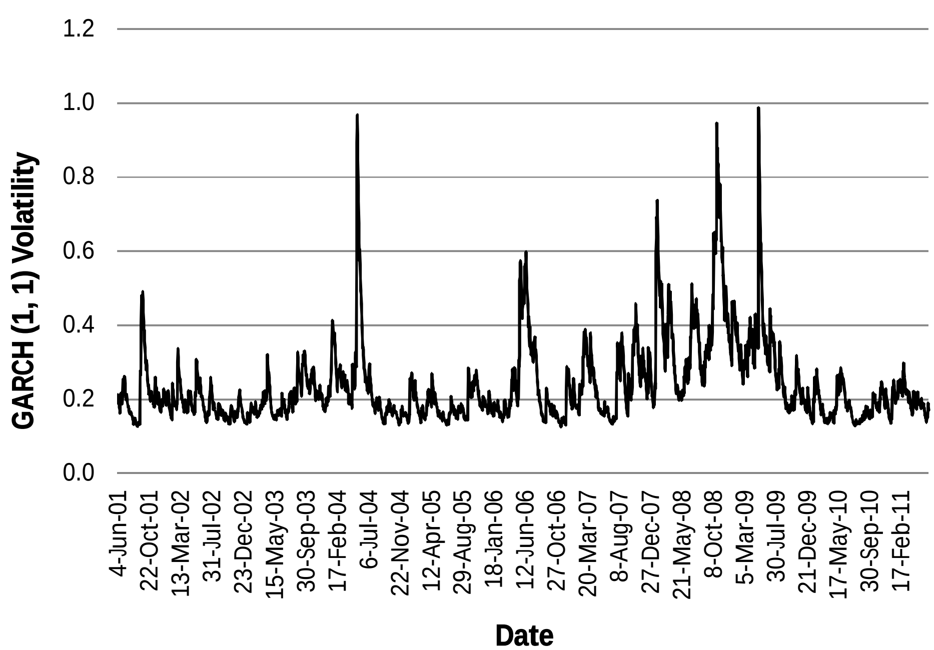


Fig-4.10: Trends in EGARCH (1, 1) Volatility

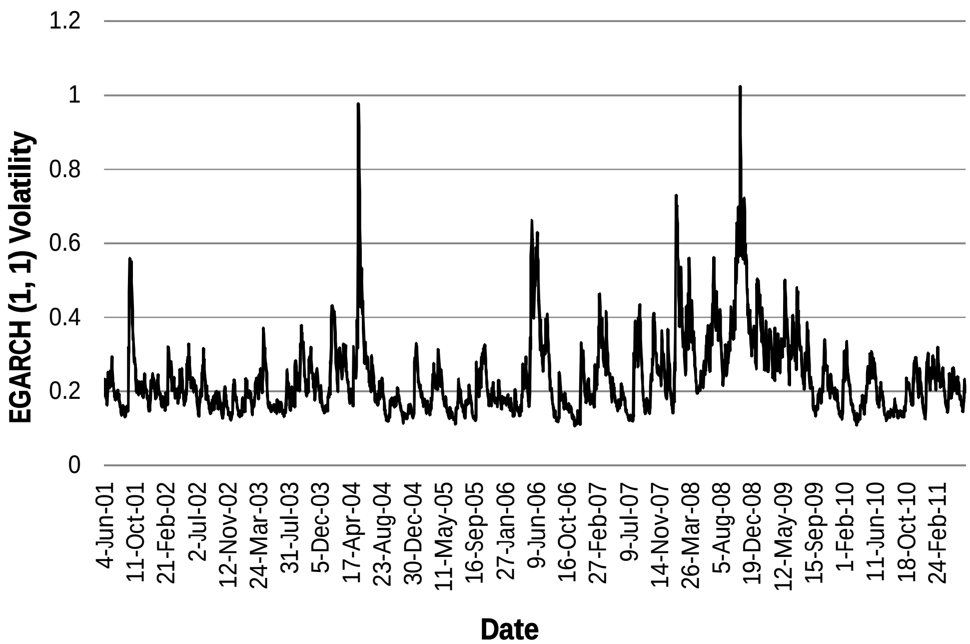


Fig-4.11: Comparison between One-Day-Ahead and Call Implied Volatility

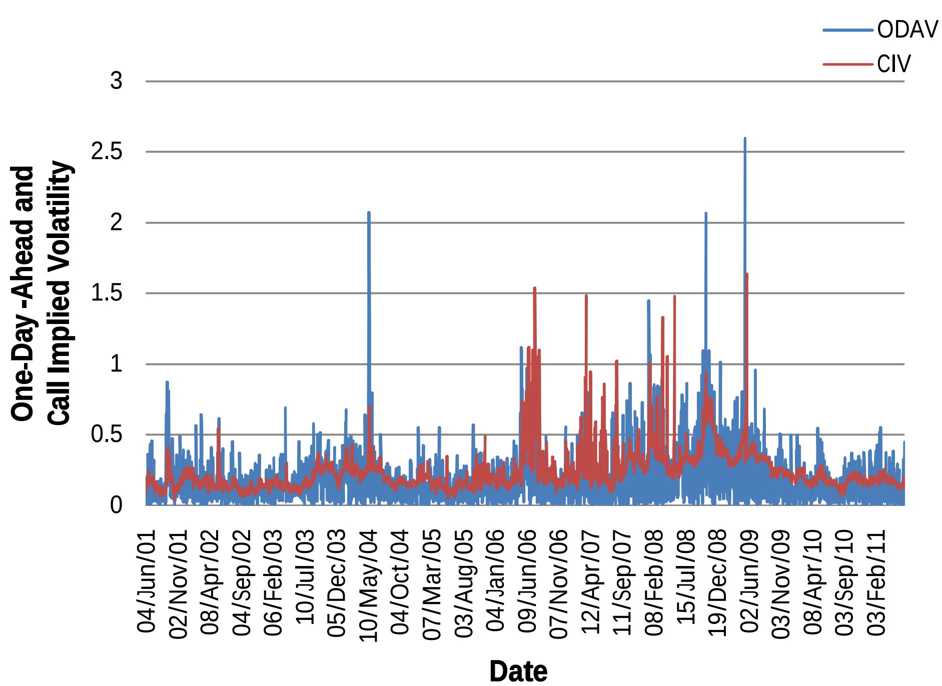


Fig-4.12: Comparison between One-Day-Ahead and Put Implied Volatility

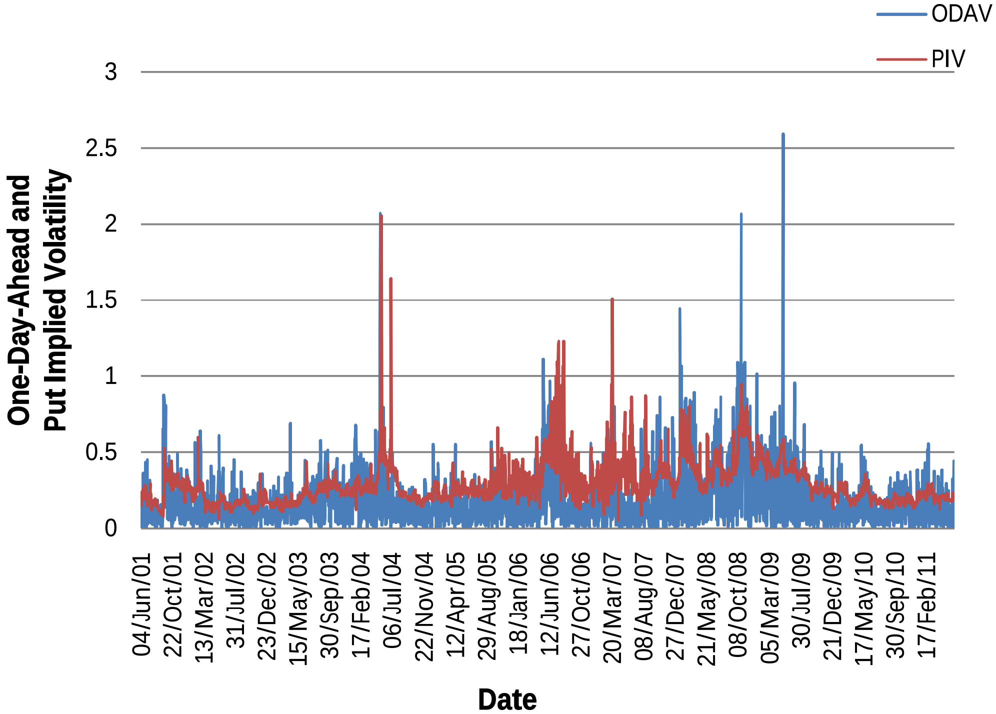


Fig-4.13: Comparison between One-Day-Ahead and MA (20) Volatility

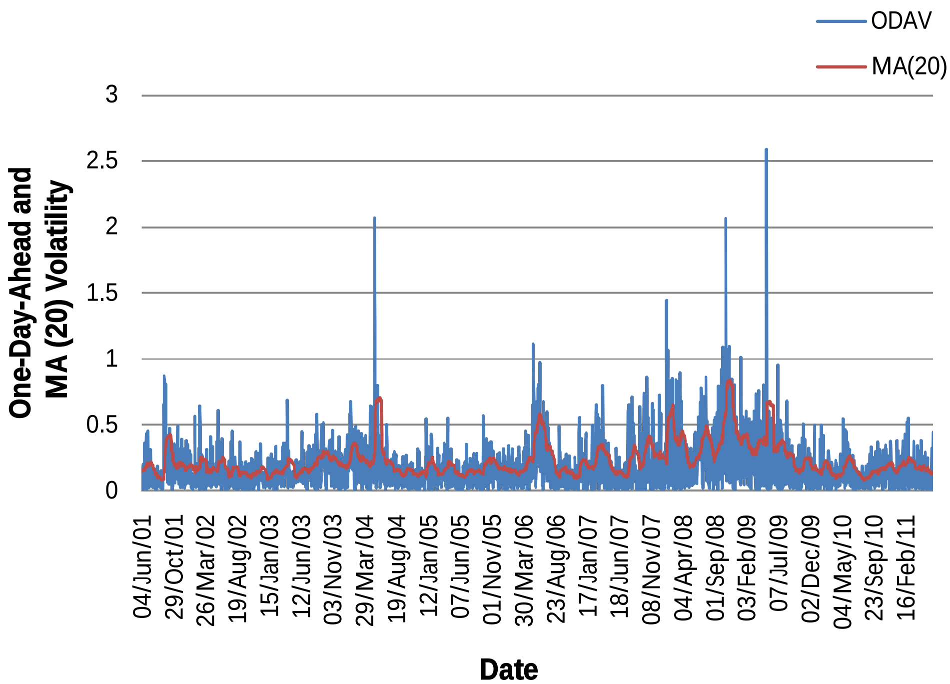


Fig-4.14: Comparison between One-Day-Ahead and EWMA Volatility

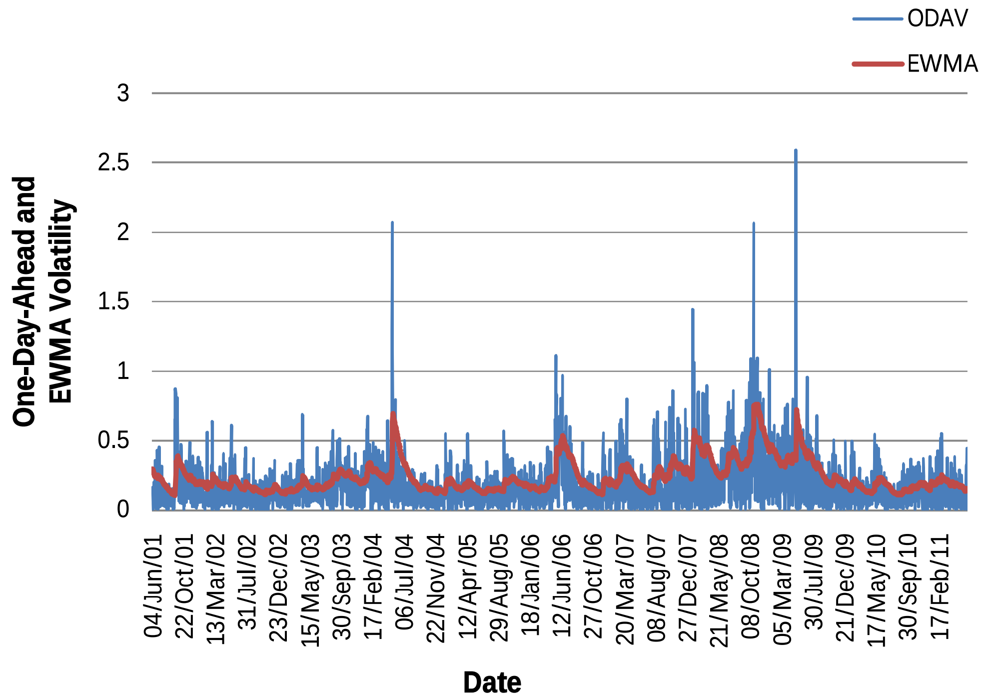


Fig-4.15: Comparison between One-Day-Ahead and GARCH (1, 1) Volatility

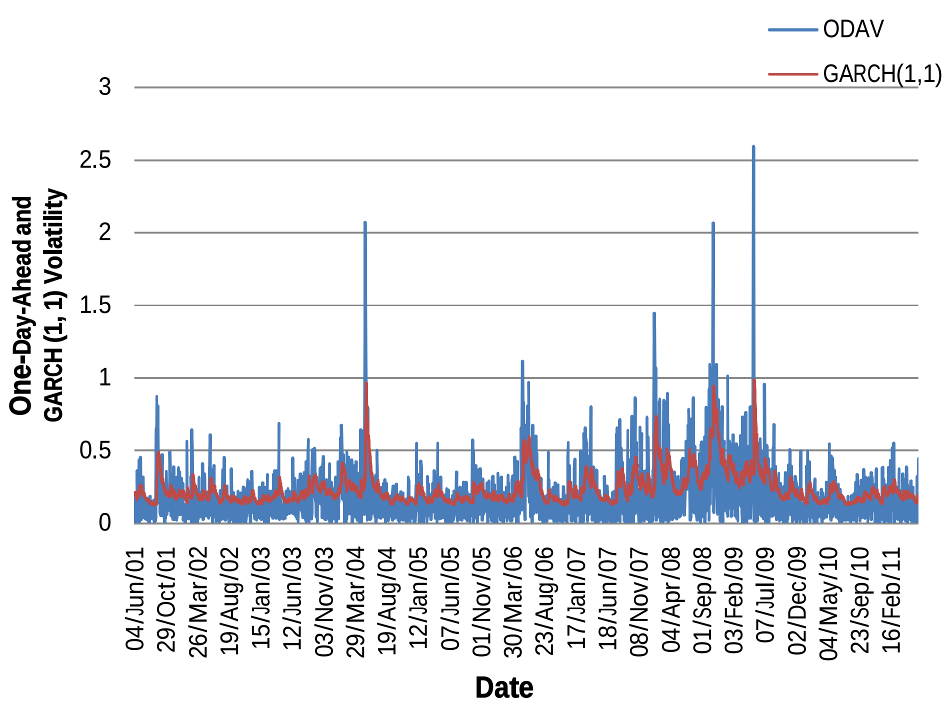


Fig-4.16: Comparison between One-Day-Ahead and EGARCH (1, 1) Volatility

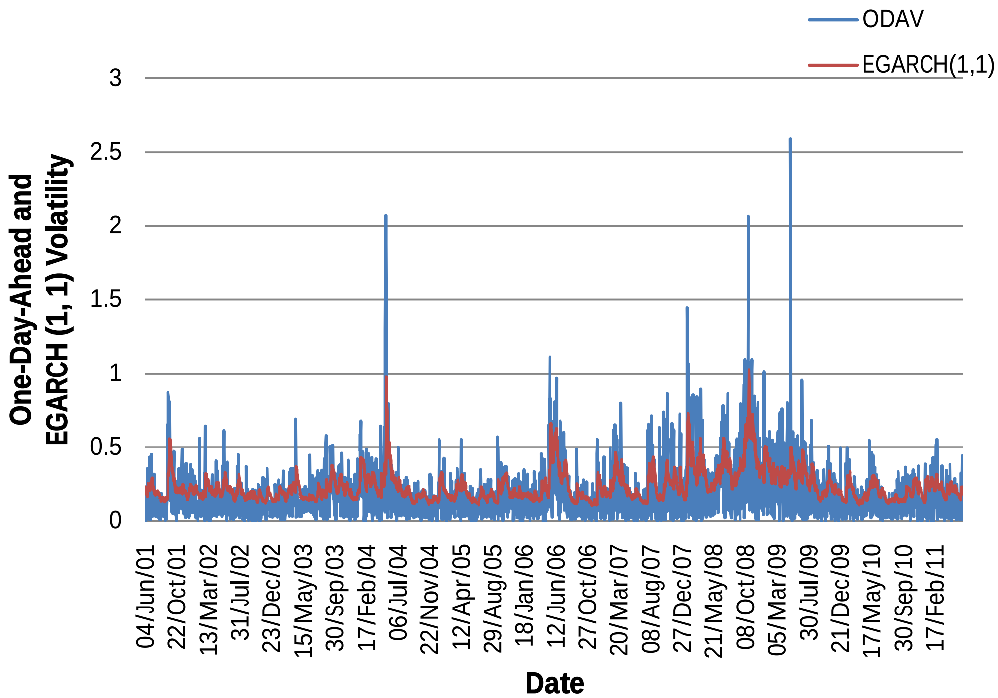


Table-4.5: Descriptive Statistics

	$\sqrt{R_{t,t+1}^2 \times 252}$	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$
Mean	0.18	0.244	0.29	0.23	0.23	0.23	0.23
Max	2.59	1.63	2.05	0.84	0.76	0.98	1.02
Min	0	0.03	0.05	0.07	0.10	0.12	0.10
Std. Dev.	0.18	0.15	0.15	0.12	0.11	0.11	0.10
Skewness	3.24	3.28	2.75	2.04	1.75	2.47	2.14
Kurtosis	25.13	20.076	18.91	8.02	6.42	11.413	10.05
Jarque-Bera	55710.11	35042.07	29706.03	4403.44	2522.98	9979.55	7132.11
Probability	0.0000	0.000	0.000	0.000	0.000	0.000	0.000

Note: $\sqrt{R_{t,t+1}^2 \times 252}$ is One-Day-Ahead volatility, $\sigma_{t,CIV}$ as call implied volatility, $\sigma_{t,PIV}$ as put implied volatility, $\sigma_{t,GARCH}$ as GARCH (1,1), $\sigma_{t,EGARCH}$ as EGARCH (1,1) volatility, and $\sigma_{t,EWMA}$ as Exponential weighted Moving Average Volatility and $\sigma_{t,MA(20)}$ is the Moving average volatility.

Table 4.6: Test of Stationarity

	Without Trend			With Trend and Intercept		
	DF	ADF	PP	DF	ADF	PP
$\sqrt{R_{t,t+1}^2 \times 252}$	-37.79*	-7.13*(14)	-55.92*(33)	-38.07*	-8.74*(9)	-55.68*(33)
$\sigma_{t,CIV}$	-20.49*	-5.96*(6)	-34.05*(35)	-21.29*	-6.20*(6)	-35.47*(35)
$\sigma_{t,PIV}$	-20.12*	-5.79*(7)	-34.11*(35)	-20.58*	-5.91*(7)	-35.05*(35)
$\sigma_{t,GARCH}$	-6.57*	-7.04(4)*	-6.73*(13)	-6.67*	-7.15(4)*	-6.88*(12)
$\sigma_{t,EGARCH}$	-7.99*	-7.22*(6)	-7.84*(14)	-8.09*	-7.32*(6)	-7.96*(13)
$\sigma_{t,EWMA}$	-3.27*	-4.35*(4)	-4.16*(14)	-3.33**	-4.44*(4)	-4.25*(14)
$\sigma_{t,MA(20)}$	-3.66*	-5.57*(5)	-5.22*(25)	-3.66**	-5.65*(5)	-5.28*(25)

Note: *: Reject the null hypothesis of a unit root with 99% confidence; **: Reject the null hypothesis of a unit root with 95% confidence, Figures in the brackets against ADF statistics are the numbers of lags used to obtain white noise residuals, and these lags are selected using AIC. In PP test figures in the brackets are bandwidth selected using the Newey-West method.

Information Content Regressions

$$\sqrt{R_{t,t+1}^2 \times 252} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t+1}$$

Where $\sqrt{R_{t,t+1}^2 \times 252}$ is the next day annualized volatility, is regressed against the volatility forecast $\sigma_{t,i}$ .This includes the call implied, put implied, Moving Average (20), EWMA, GARCH and EGARCH.

Table-4.7-: Information Content Regressions

Part-I: Simple Information Content Regressions

α	Estimate slope coefficient of independent variable							R^2	DW	Wald Test
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	AR(1)			
0.093* (12.615)	0.37* (14.527)						0.14* (6.90)	0.13	2.02	857.38*
0.081* (9.128)		0.34* (12.779)					0.15* (7.61)	0.12	2.03	1329.81*
0.054* (6.313)			0.55* (16.944)				0.15* (7.94)	0.16	2.02	380.20*
0.033* (3.798)				0.63* (18.636)			0.08* (4.92)	0.16	2.01	334.10*
0.022* (2.421)					0.67* (19.306)		0.12* (6.39)	0.17	1.99	321.96*
0.00 (-0.002)						0.77* (21.710)	0.09* (4.73)	0.19	1.99	257.52*

Note:*: 1% level of Significance, t-statistic is provided in parenthesis and Autocorrelation are corrected by using the AR(1)

Part-II: Multiple Information Content Regressions

$$\sqrt{R^2_{t,t+1} \times 252} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t+1}$$

$$\sqrt{R^2_{t,t+1} \times 252} = \alpha + \beta_1 \sigma_{t,PIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t+1}$$

Where $\sqrt{R^2_{t,t+1} \times 252}$ is the next day annualized volatility, is regressed against call or put implied volatility and the volatility forecast $\sigma_{t,i}$,which includes the Moving Average (20), EWMA, GARCH or EGARCH.

α	**Estimate slope coefficient of independent variables**							**R^2**	**DW**	**Wald Test**
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	AR(1)			
0.043* (5.15)	0.18* (5.72)		0.41* (10.42)				0.12* (6.35)	0.17	2.01	1022.320*
0.029* 3.36	0.15* 4.91			0.49* (11.03)			0.08* (4.35)	0.17	2.00	1078.416*
0.017** (1.97)	0.14* (4.61)				0.55* (12.56)		0.10* (5.42)	0.18	1.99	1102.119*
-0.003 (-0.43)	0.13* (4.47)					0.66* (15.04)	0.07* (3.97)	0.20	1.99	1212.956*
0.039* (4.23)		0.13* (4.002)	0.45* (11.32)				0.13* (6.83)	0.16	2.01	1567.868*
0.025* (2.77)		0.10* (2.97)		0.54* (12.02)			0.09* (4.63)	0.16	2.00	1690.584*
0.012 (1.32)		0.10* (3.23)			0.59* (13.59)		0.11* (5.71)	0.18	1.99	1698.594*
-0.008 (-0.907)		0.09* (3.10)				0.70* (15.99)	0.08* (4.21)	0.20	1.99	1869.444*

Note: *:1% level of Significance;**: 5% level of Significance and t-statistic is provided in parenthesis and Autocorrelation are corrected byusing the AR(1)

Part-III

$$\sqrt{R_{t,t+1}^2 \times 252} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,PIV} + \varepsilon_{t+1}$$

Where $\sqrt{R_{t,t+1}^2 \times 252}$ is the next day annualized volatility, is regressed against the call implied volatility ($\sigma_{t,CIV}$) and put implied volatility ($\sigma_{t,PIV}$)

α	**Estimate slope coefficient of independent variables**							**R^2**	**DW**	**Wald Test**
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	AR(1)			
0.067* (7.79)	0.26* (7.88)	0.17* (5.08)					0.12* (6.08)	0.14	2.01	910.893*

Note:*: 1% level of Significance and t-statistic is provided in parenthesis and Autocorrelation are corrected byusing the AR(1)

Table-4.8: OLS Estimation

α	**Estimate slope coefficient of independent variable**						**R^2**	**DW**
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$		
0.082* (12.437)	0.41* (18.181)						0.11	1.74
0.065* (8.247)		0.39* (16.788)					0.10	1.71
0.053* (7.293)			0.55* (16.944)				0.13	1.685
0.029* (3.649)				0.64* (21.42)			0.15	1.80
0.020* (2.521)					0.68* (22.078)		0.16	1.74
-0.002 (-0.0254)						0.78* (24.097)	0.18	1.81

Note:*: 1% level of Significance, t-statistic is provided in parenthesis

CHAPTER-5

Predictability of Volatility: Forward vs. Backward Looking Volatility Measures

5.0. Introduction

In the previous chapter, we have comapred the information content power of implied volatility with back ward looking volatility forecasting models. The implied volatilityis represented as theaverage volatility of the remaining life of the contract period. This chapter will discuss whether implied volatility has better predictability for the average future volatility compared to other backward looking volatility measures.

Implied volatility are considered to be 'the markets' forecast of future realized volatility during the life time of the options contracts. There are two schools of thought: one major thought is that implied volatility is an unbiased and efficient forecaster of future realized volatility, which is not captured by time series volatility model. The other thought highlights that, implied volatility is a biased and inefficient forecaster of realized volatility.

Jorion (1995) studies the options on currency futures traded on the Chicago Mercantile Exchange. He finds that implied volatility is upward biased estimator of future realized volatility, but in in terms of information content it outclassed standard time series models. Xu and Taylor (1995) achieve a parallel conclusion for four currency options (Pound, Mark, Yen and Franc) traded on the Philadelphia stock exchange. Taylor and Xu (1997) acknowledged that time series models offered incremental information to implied volatilities and vice versa in a five minutes high frequency data. Amin and Ng (1997) focuses short term forward rates(Eurodollar) options on theChicago Mercantile Exchange market.They concluded that, implied volatilities contains more information about future realized volatility than time series models. Fleming (1998) concludes that implied volatilities of S&P 100 equity index are upward-biased predictors of realized volatility. Christensen and Prabhala (1998) use the data of OEX option from November 1983 through May 1995 find that after the 1987 stock market crash, the implied volatility is an unbiased and efficient forecast of future realized volatility.

Martens and Zein (2002) find that implied volatility provides better r forecaster of future realized volatility compared to GARCH models in stock, exchange rate and oil. Ederington and Guan (2002) examine the implied volatility of S&P500 futures options data and conclude that “implied volatility has strong predictive power and generally subsumes the information in historical volatility”. J Christensen and C.H. Hansen (2002) compare both call implied volatility, put implied volatility and historical volatility through OLS method.OLS results indicate that call implied volatility is a better forecastability than put implied volatility.

In conclusion,most of the literature shows that implied volatility is a better predictor of future volatility compare to “backward-looking” volatilities. In this chapter, the study will examine whether implied volatilities calculated from call and put “at-the-money” index option has a better predictive power in an in-the-sample and out-of-the sample framework or not.

5.1. Empirical analysis

5.1.1. In the sample analysis

In the sample analysis cover the data from 1^{st} June, 2001 to 24^{th} Jun 2011 for cash market and 4^{th} June, 2001 to 23^{rd} June, 2011 for option market. For calculating both backward and “forward-looking” volatility we have used the same method and same data set which we have used in Chapter - 4. The extra variables, that is to be analyzed here is the realized volatility. As we have mentioned, our objective in this chapter is different from Chapter - 4. Here we are going to compare the the predictive power of “forward-looking” and “backward-looking” volatility. We have mentioned earlier that for any time series analysis, it is better for the analyzer to analyze the variables through their trend, descriptive statistics and stationarity.

5.1.1.1. Graphical Analysis

The trend and comparison of realized volatility and other forecasted volatility is presented here. The individual trend of both backward as well as forward looking volatility is not explained as it is already explained in Chapter-4. Fig-5.1 shows the trend of realized volatility and Fig-5.2 to 5.7 shows the comparison of all forecasting volatility models with realized volatility. The graphs shows that all forecasted volatilities are moving in the same direction as realized volatility

5.1.1.2. Descriptive Statistics and Unit Root Tests

Table-5.1 presents the descriptive statistics of all forecasted volatility, including realized volatility. The statistics show that, except put implied volatility all volatility moves in a same range as realized volatility. All the volatility has the significant Jarque-Bera test which shows that the variables are not from a normal distribution. To test the stationarity we have carried DF, ADF and PP test for all variables. Given that the tests are already done in the context of all backward and forward looking volatility in Chapter-4 except realized volatility, the result for unit root test of realized volatility is presented in Table-5.2. The result shows that realized volatility is stationary at its level. The study has use AIC (Akaike Information Criterion) and SC (Schwarz criterion) for choosing the optimum lag length in the case of ADF and PP

5.1.1.3. Simple Predictability Regressions

The result of simple predictability regression is analyzed in this section. Wald test is used for testing the null hypothesis of unbiasedness (α=0 and β=1) in the regression (Chapter-3, Equation-3.28).As the dependent variable is overlapping, we have selected the GMM estimation for the analysis. Table 5.3, part-I, shows all the regressions results where each of the volatility forecast models put separetly as an independent variables. By putting Call Implied Volatility (CIV) as the independent variable in the resgression shows that its coefficient vaule is not only significant at one percent level but also its has a higher coefficient vaule i.e., 0.54, than the information content regression coefficent. (Chapter-4). The R^2 statistics is recorded at 0.19.

Putting Put Implied Volatility (PIV) as independent variable in the simple regression shows a coefficient value of 0.53 at one percent significance level. The value ofR^2 statistics is 0.17. In both the cases, the null hypothesis of the Wald test statistics is rejected at one percent level of significance.

Puting MA (20) as independent variable in the simple predictability regession shows that the coefficient value is significant at one percent level, with a higher R^2 statistic of 0.25. EWMA as independent variable performes in the same manner as MA(20) with a coefficient value of 0.62 with a high R^2 statistic of 0.29. Its coefficient value is significant and higher than CIV, PIV and MA(20).

GARCH (1, 1) as independent variables in the simple regression displays a higher significant coefficient value 0.65 than all other forecasting models except EGARCH (1, 1). Which shows that GARCH (1, 1) not only predict the future volatility well compare to simple historical models(MA(20) and EWMA) but also it has predict better than implied volatilities.

EGARCH (1, 1) as an exogenous variable in the simple regression has shown a coefficient value of 0.70 at one percent significant level. Looking at the coefficient value we can see that it is the best forecasting model among all models for the prediction of future realized volatility. It has not only a high significant coefficient value, but also has a high R^2value among all predictability regression.

A comparison of coefficients across all the six regressions highlights following points. First, the EGARCH (1, 1) has the conatin additional information for the next day volatility compare to other volatility forecasting models. Second, Call implied volatility outclass MA (20) and Put Implied volatility for conating more information for the one day ahead volatility. Third, the simple moving avarge and implied volatility are the worst performer for containing information. Forth, the null hypothesis of reported Wald test statistics of unbiased ness is rejected in all the six information content regressions at one percent significance level.

5.1.1.4. Multiple Predictability Regressions

Multiple regressions were estimated in line with the information content tests in Chapter-4 and also used a Wald test for unbiasedness of the estimator. The results of these regressions appear in Table-5.3, Part-II. The result of the multiple regressions that involves CIV as one of the explanatory variable are as follows;

In the multiple regression by putting CIV and MA(20) as an independent variable. The results show that the coefficient of CIV has a higher significant value compare to MA(20). Which implies that the MA (20) has less predictive power compare to CIV.The study has found this results by comparing the coefficient value. MA(20) has a coefficient value of 0.25 which is less than the coefficient vaule of CIV which is 0.35. These results are different from the information content regression (Chapter-4, Table 4.7, Part-II). In the information content regression the coefficient of MA (20) was not only positive and significant, but the coefficient was higher than CIV also. In the predictability regression the vaule of The R^2 is higher compare to information content regression

In the multiple regression by putting CIV and EWMA as an independent variable. The results show that the coefficient of EWMA has a higher significant coefficient value compare to CIV. In the information content regression (Chapter-4, Table 4.7, Part-II), the EWMA was also performed in the same manner. It has a high coefficient value which is higher than CIV but the recorded R^2 statistics is seen to be higher than the information content regression.

Multiple regession containing CIV and GARCH (1,1) as an independent variables shows that GARCH (1, 1) outclassed the call implied volatility. The coefficient vaule of GARCH (1, 1) is significant at the one percent level and compared to CIV it has a high coefficient value of 0.40. Though CIV has a positive coeffient value, but not only it is lower coefficient value but also corresponding t-statistic is also low compare to GARCH (1,1).

In Chapter-4 the study has found that EGARCH(1,1) model has conatin more information for the next day volatility compare to other volatility methods. In simple predictability regression also it is the top-notch model. By comparing with CIV it has got a highly significant coefficient vaule of 0.43. It is not only beat the CIV in respect to predictability but also it has got a high coefficient value compare to MA(20), EWMA, GARCH(1,1). These results are similar to the information content regression (Chapter-4, Table 4.7-Part-II). In the information content, the EGARCH (1, 1) model is significant and has better explanatory power than CIV model.

The above results show that except MA(20), CIV has a less predictability of realized volatility compare to EWMA,GARCH(1,1) and EGARCH(1,1). In the next part of this section the study has explained the predictability of PIV.

In the multiple predictability regression where PIV and MA (20) as an independent variable show that PIV has a high coefficient vaule of 0.31 compare to the coefficient vaule of MA(20). Both the coefficient value are siginificant at the one percent level. Here the value of R^2 is recorded at 0.27. However the current results which the study has got is totally opposite to the results yield in an information content regression (Chapter-4, Table 4.7-Part-II). In the information content regression model the MA (20) has a high significant coefficient compare to PIV.

Comparing the results with EWMA model shows that the results are almost same as in CIV model. Like CIV here also PIV has a low coefficient value compare to EWMA. The coefficient value of EWMA is 0.42 at the one percent level of significance. If we compare the performances with CIV the only difference is that it has a coefficient vaule of 0.22 which is siginfiant at five percent. Compared to the similar regression in Chapter-4, Table 4.7, Part-II where the coefficient of EWMA is significant and better than PIV.

In Contrast with GARCH (1, 1), the PIV model is a weaker predictor of realized volatility.It is showing significant coefficient value of 0.23 but its too low compare to information content regesssion coefficient of PIV.

As we know that PIV is the worst performer in all forms of analysis till now. Now the question arises whether the same performance is continue for PIV in a multiple regression frame. Here also the results is same PIV has a significant coefficient value 0.26 at the one percent levelbut unable to beat EGARCH (1,1).

Form the above discussion the study has found that the ARCH class of model perform better than implied and historical volatility methods. Which signifies that they are the better predictor of the realized volatility than implied volatility.However, the study wants to find out among these implied volailties which is the worst performer. The result in Table 5.3, Part-III, show as per the regression Equation (3.31) CIV is a better forecaster of realized volatility compare to PIV. If we compare the coefficient value the study found that CIV has a coefficient vaule of 0.36 and PIV has a vaule of 0.21. Both the cofficent are significant. The results are quite similar to those in information content regression that is discussed in Chapter-4. In both simple and multiple regression analysis, the null hypothesis of unbiasedness is rejected at one percent level of significance.

The reported wald test statistics shows that the null hypothesis of unbiasedness is rejected in all predictability regressions. The results also show that both the implied volatilities are downside biased and inefficient.

5.1.2. Out of sample analysis

After examining the predictability of implied volatility in the "in-the-sample" frame work the study is now going to examine the predictive power of implied volatility in the "out-of-sample" frame work. We have used the method explain in Chapter-3,Section 3.5.2.2. For comparison purpose we have estimated all the volatilities for out of the sample framework which is explained in (Chapter-3, section-3.5.2.2). Here the GARCH forecasted model is explained more elaborately. The study has taken AR (1)-GARCH (1, 1) and AR (1)-EGARCH (1, 1) because there are generally found to be the most appropriate model for this analysis.

Both the models are estimated with an underlying GED distribution (Chapter-4, section-4.3). The two models are as follows

GARCH(1,1): $\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (5.1)

Where, $\alpha > 0, \alpha_1 \geq 0, \beta_1 \geq 0$

EGARCH (1,1): $\ln\sigma_t^2 = \omega + \beta_1 \ln\sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$ (5.2)

(Using the procedure shown below)

For GARCH (1, 1),

$$\sigma_{t+1}^2 = \omega_0 + \beta_1 u_t^2 + \alpha_1 \sigma_t^2$$

$$\sigma_{t+2}^2 = \omega_0 + \beta_1 u_{t+1}^2 + \alpha_1 \sigma_{t+1}^2$$

- - - -

- - - -

$$\sigma_{t+30}^{2}=\omega_{0}+\beta_{1}u_{t+29}^{2}+\alpha_{1}\sigma_{t+29}^{2}$$

For EGARCH (1, 1),

$$\ln\sigma_{t+1}^{2}=\omega+\beta_{1}\ln\sigma_{t}^{2}+\alpha_{1}|z_{t}|+\theta_{1}z_{t}$$

$$\ln\sigma_{t+2}^{2}=\omega+\beta_{1}\ln\sigma_{t+1}^{2}+\alpha_{1}|z_{t+1}|+\theta_{1}z_{t+1}$$

- - - - -

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$$\ln\sigma_{t+30}^{2}=\omega+\beta_{1}\ln\sigma_{t+29}^{2}+\alpha_{1}|z_{t+29}|+\theta_{1}z_{t+29}$$

In the process of evaluating all the forecasting volatility we construct a 30 days non overlapping horizon window for all foreasting models. Fig-5.8 shows the comparison of all forecasted volatility with realized volatilities.

The study has taken the MA (20), EWMA, CIV and PIV volatilities on the day where there are approximately 30 days left to expiry the option contract. The period for this calculation is from 31st May 2006 to 30th June 2011.For generating out of smple data for GARCH and EGARCH the study has taken data from 1st June 2001 to 31st May 2006, and estimated the GARCH (1, 1) GED and EGARCH (1, 1) GED models. Based on the estimated parameters we genragted the out of sample forecasting value for GARCH and EGARCH.

In case of out-of-sample, the study has construct 61 one month forecast value for each specified model. On each forecast point, the update GARCH (1, 1) and EGARCH (1, 1) forecast σ_{T}^{GARCH} and σ_{T}^{EGARCH} (Equation (5.1) and (5.2)) are created using the parameters estimated over the previous 1255 trading days by adding approximately latest 22 observations and deleting approximately first 22 observations in the previous sample each time. The process is iterated for 61 times to generate 61 forecast values of GARCH and EGARCH. Fig-5.8 plots all the six forecasted volatility models against realized volatility.

The results presented in table-5.4 shows the four error statistics for all forecasting models. Table-5.4 surmised that out of six forecast models, the ARCH family model is the best performer in the out of sample frame work. MSE statistics shows that the GARCH (1, 1) is the best method among all. After GARCH (1, 1), the next best is EWMA followed by EGARCH (1, 1), MA, CIV and PIV. The predictability supremacy of the time series volatility methods are shown here. Similarly, the results derived from some of the other methods also highlights the same thing which is presented in the below paragraph.

In case of MAE statistics, EGARCH (1, 1) is the best model, followed by EWMA,GARCH (1, 1), MA, CIV and PIV. Whereas, in the case of RMSE statistics, GARCH (1, 1) is a better predictor of realized volatility than the other models and is also better than EGARCH (1, 1). MAPE repeats the result of MAE statistics in the respect of EGARCH (1, 1) and EWMA. It shows that EGARCH (1, 1) is the best one among all. But here MA volatility measure is better than GARCH (1, 1). After EGARCH (1, 1) and EWMA, MA is the next best followed by,GARCH (1, 1), CIV, and PIV.

A closer look at the results indicate that the EGARCH (1, 1) and GARCH (1, 1) model outperforms the other volatility forecasting models in four error statistics. In MAE and MAPE, EGARCH (1, 1) is the best. In Mean Square Error and RMSE, GARCH (1, 1) is the best. ARCH family model EWMA volatility is the next best to predict realized volatility in an out-of-sample framework. It is also observed that implied volatility fails to predict the realized volatility.

5.2. Conclusion

In this chapter the study has examined whether implied volatility has a better predicticability of the future realized volatility comapre to "backward-looking" volatilities. As suggested by literature the study has used simple regression with GMM to deal with overlapping data problem. In this chapter the results show that EGARCH (1,1) is the best model compare to all other forecasting models in a simple predictability regression. The study also shows that Put implied volatility is the worst performer in the simple predictability regression. The ARCH family model provide more informative for the future volatility than MA (20), EWMA and implied volatility. Among both the implied volatilities, put implied volatility has less predictability power in explaining the future volatilities. The study shows that implied volatility are biased and inefficient forecaster of future realized volatility. The biasedness occurs because of in two possible reasons, firstly, the “error in variables” and secondly, Indian option market is not efficient enough. The underlying asset is the cash market, but when market participants are hedging their option positions then they use futures to hedge because there is a restriction of short selling in India and there is no traded option on futures contract. In case of “out-of-sample” analysis, ARCH family models outclassed all other volatility forecast models in respect to forecasting 30 days ahead volatility.

Fig-5.1: Trends in Realized Volatility

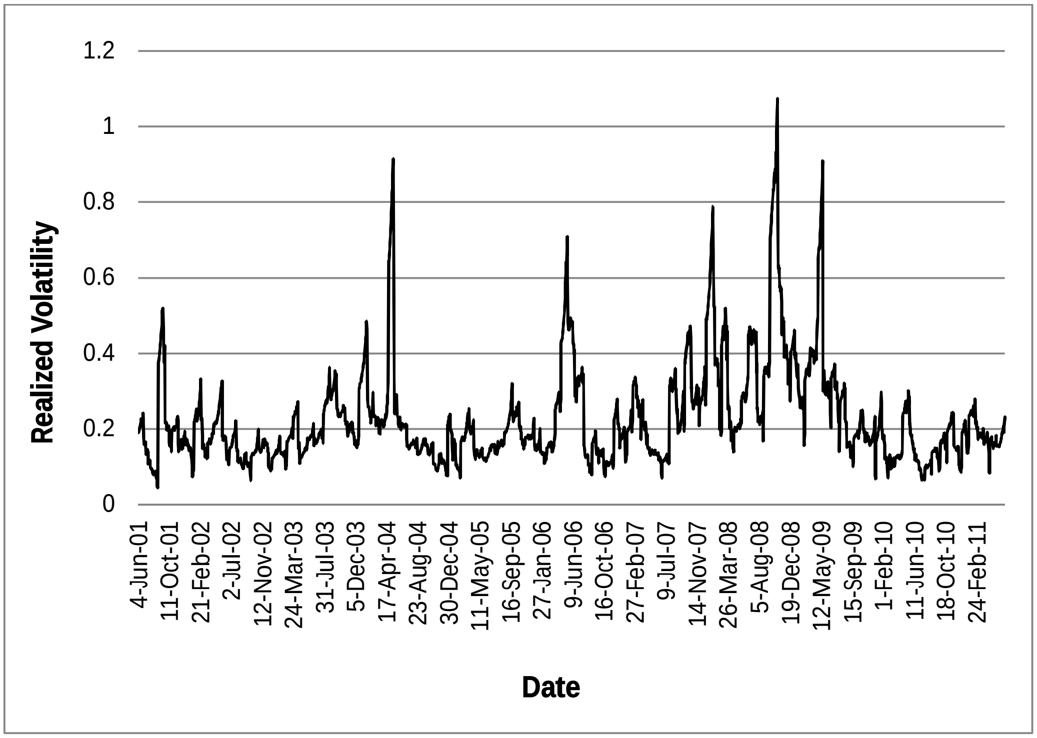

Fig-5.2: Comparison Between Realized and Call Implied Volatility

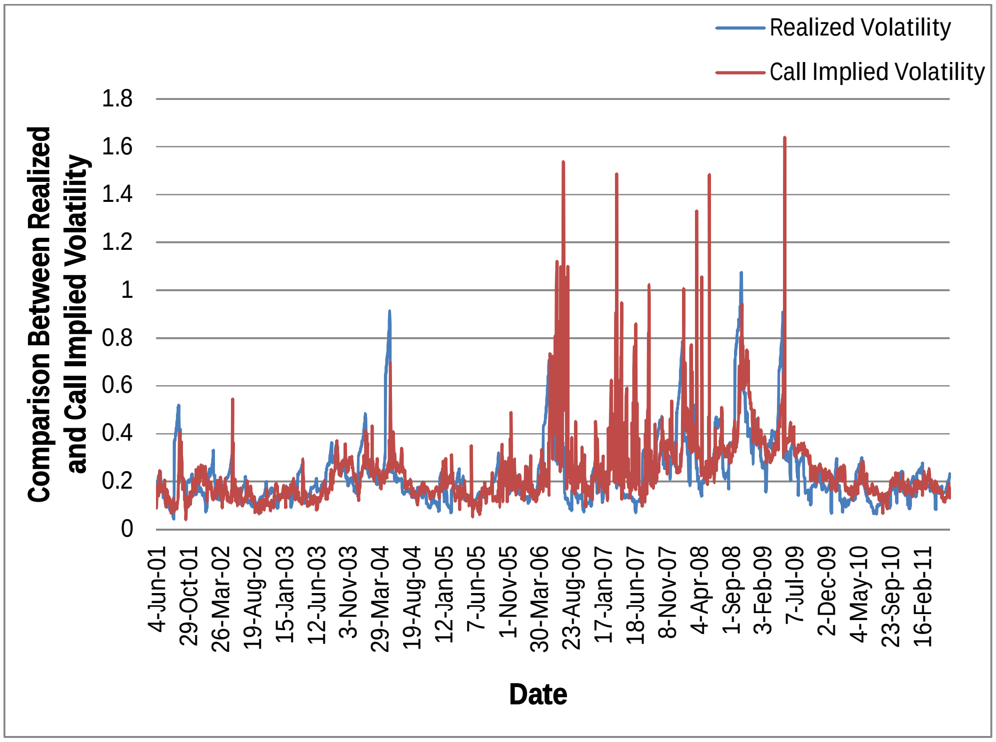

Fig-5.3: Comparison between Realized and Put Implied Volatility

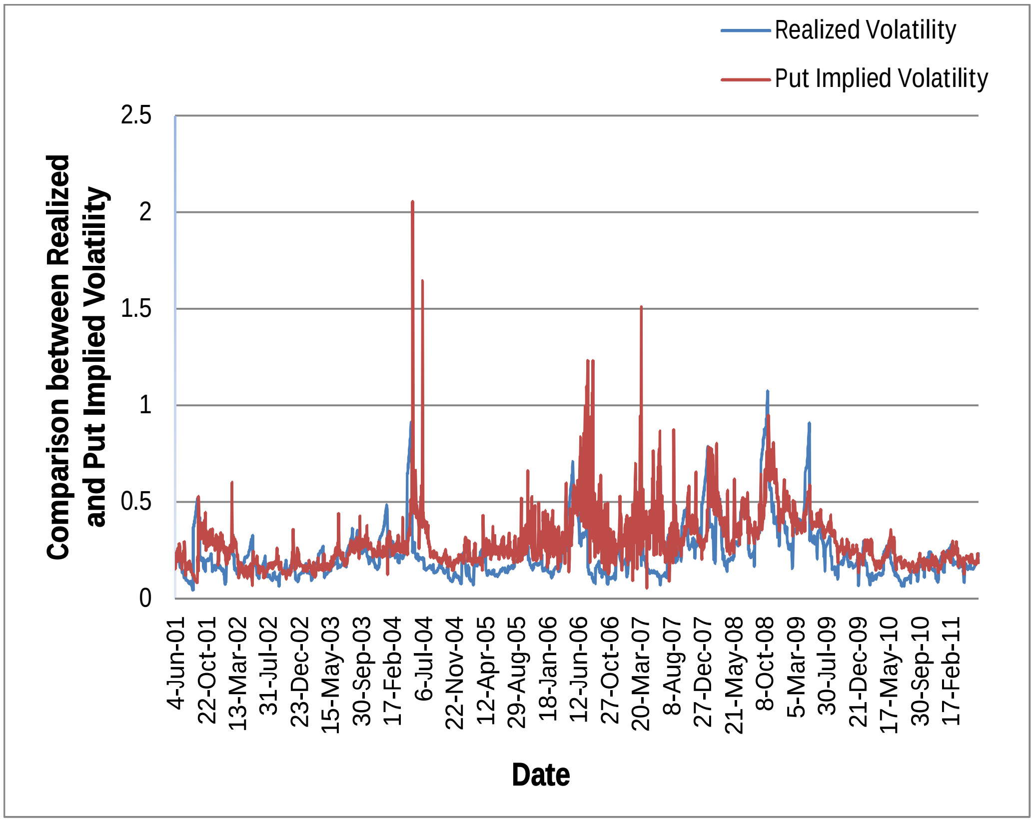

Fig-5.4: Comparison between Realized and MA (20) Volatility

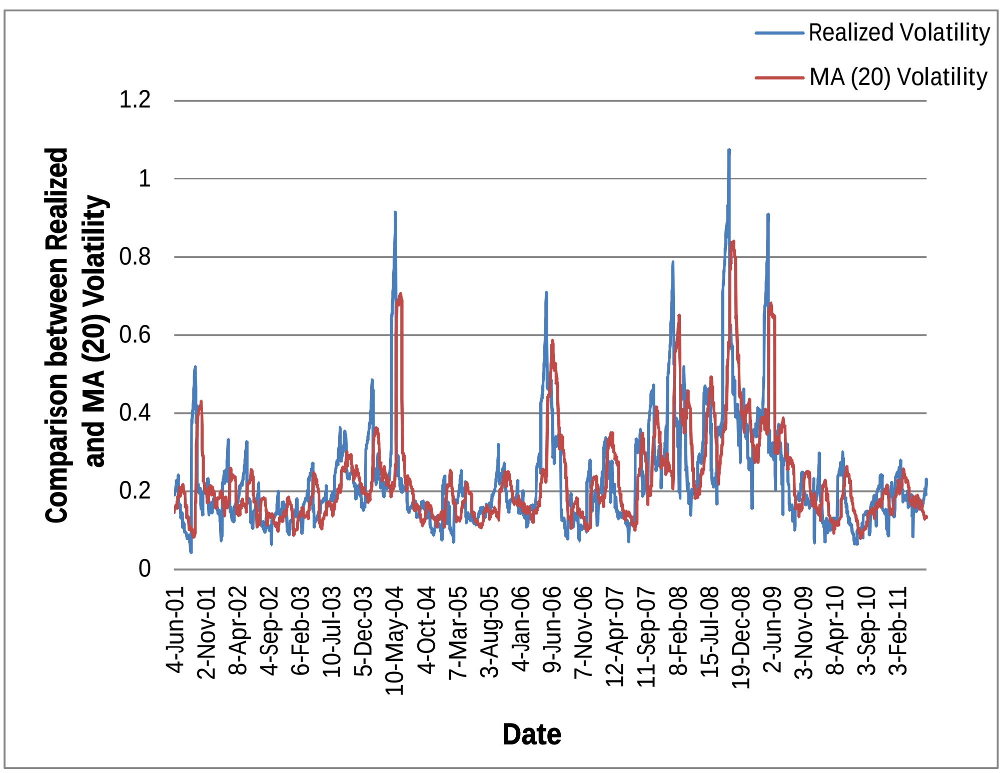

Fig-5.5: Comparison between Realized and EWMA Volatility

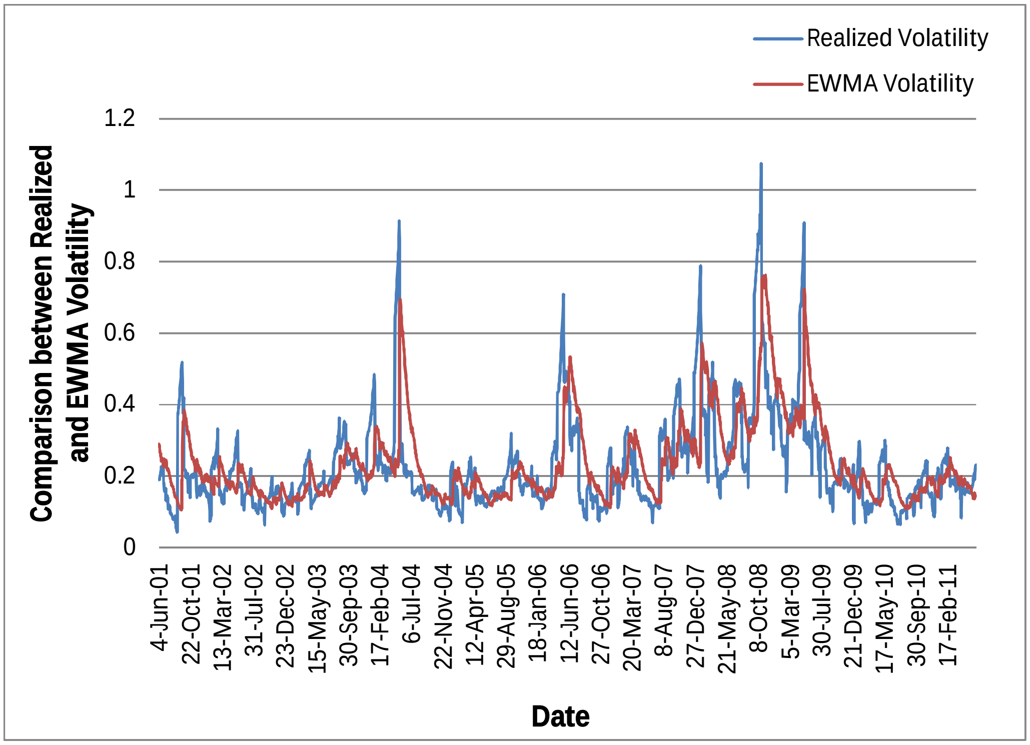

Fig-5.6: Comparison between Realized and GARCH (1, 1) Volatility

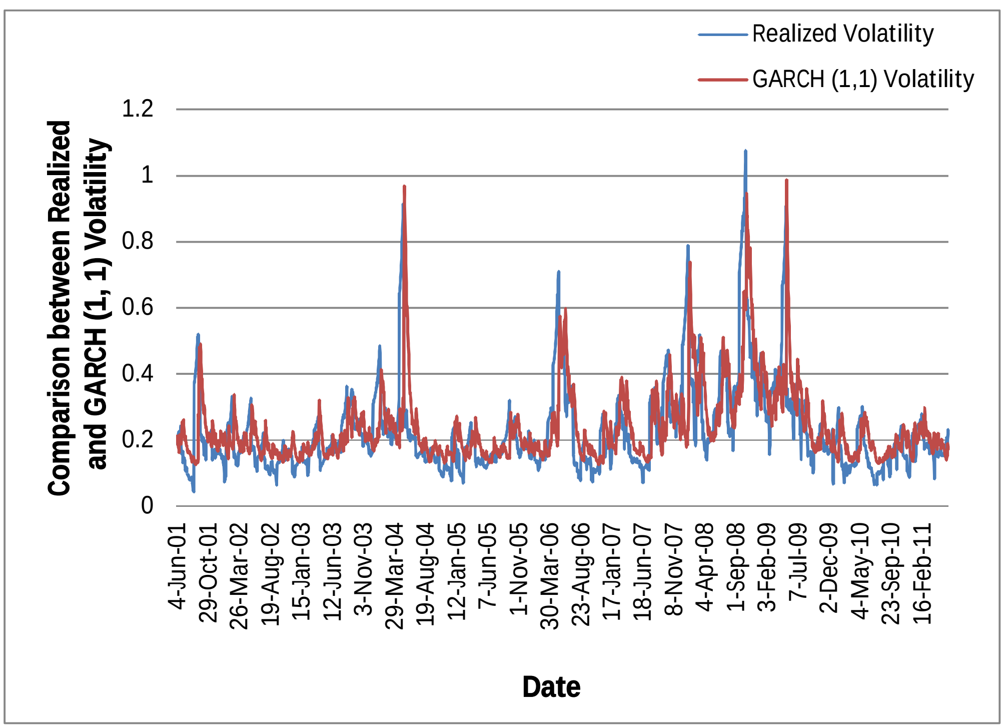

Fig-5.7: Comparison between Realized and EGARCH (1, 1) Volatility

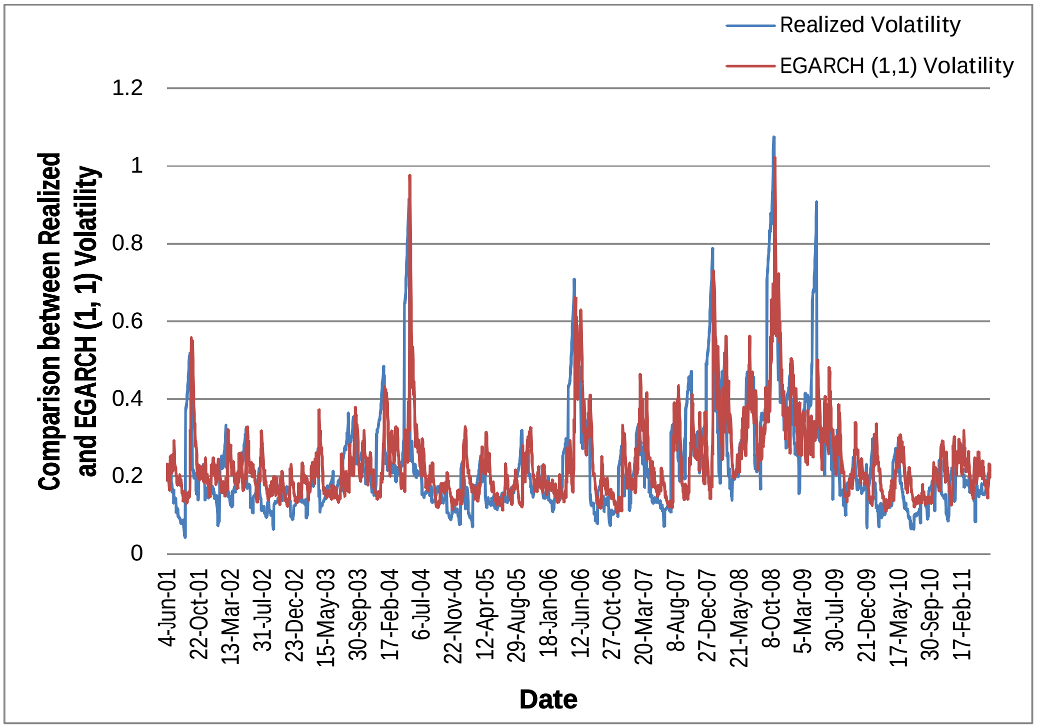

Table-5.1: Descriptive Statistics

	$\sigma_{t,T}$	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	$\sigma_{t,EWMA}$	$\sigma_{t,MA(20)}$
Mean	0.22	0.24	0.29	0.23	0.23	0.23	0.23
Maximum	1.07	1.63	2.05	0.98	1.02	0.76	0.84
Minimum	0.04	0.03	0.05	0.12	0.10	0.10	0.07
Std. Dev.	0.13	0.15	0.15	0.11	0.10	0.11	0.12
Skewness	2.26	3.28	2.75	2.47	2.14	1.75	2.04
Kurtosis	9.81	20.07	18.91	11.41	10.05	6.42	8.02
Jarque-Bera	7011.39	35042.07	29706.03	9979.55	7132.11	2522.98	4403.44
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: $\sigma_{t,T}$ Is realized volatility, $\sigma_{t,CIV}$ as call implied volatility, $\sigma_{t,PIV}$ as put implied volatility, $\sigma_{t,GARCH}$ as GARCH (1, 1), $\sigma_{t,EGARCH}$ as EGARCH (1, 1) volatility, and $\sigma_{t,EWMA}$ as Exponential weighted Moving Average Volatility and $\sigma_{t,MA(20)}$ is the Moving average volatility.

Table 5.2: Test of Stationarity

	Without Trend			With Trend		
	DF	ADF	PP	DF	ADF	PP
$\sigma_{t,T}$	-5.774*	-6.324*(4)	-6.319*(10)	-5.841*	-6.407*(4)	-6.401*(8)

Note: * Reject the null hypothesis of a unit root with 99% confidenceFigures in the brackets against ADF statistics are the numbers of lags used to obtain white noise residuals, and these lags are selected using AIC. In PP test we used bandwidth10. This optimal bandwidth is selected using the Newey-West method. $\sigma_{t,T}$ is the realized volatility.

Predictability of Regressions

$$\sigma_{t,T} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t,T}$$

Where $\sigma_{t,T}$, the volatility over the remaning life of the option, is regressed against the volatility forecast $\sigma_{t,i}$, which includes the call implied, put implied, Moving Average (20), EWMA, GARCH and EGARCH.

Table-5.3-: Predictability Regressions

Part-I: Simple Predictability Regressions

α	**Estimate slope coefficient of independent variable**						R^2	**Wald Test**
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$		
0.10* (5.33)	0.54* (6.34)						0.19	30.157*
0.071* (3.56)		0.53* (6.79)					0.17	109.342*
0.105* (7.75)			0.53* (8.01)				0.25	60.191*
0.080* (5.83)				0.62* (9.48)			0.29	35.246*
0.073* (4.13)					0.65* (8.02)		0.29	18.880*
0.063* (3.51)						0.70* (8.62)	0.29	13.799*

Note: * 1% level of Significance and the GMM estimation of Hansen (1982) along with Newey-West (1987) variance and covariance estimation is used

Part-II: Multiple Predictability Regressions

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t,T}$$

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,PIV} + \beta_2 \sigma_{t,i} + \varepsilon_{t,T}$$

Where $\sigma_{t,T}$, the volatility over the remaining life of the option, is regressed against the volatility forecast $\sigma_{t,i}$, which includes the Moving Average (20), EWMA, GARCH or EGARCH and the call and put implied volatility respectively.

α	**Estimate slope coefficient of independent variables**							
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	R^2	**Wald Test**
0.084* (5.76)	0.35* (2.97)		0.25* (2.67)				0.27	39.932*
0.074* (5.31)	0.28* (2.26)			0.36* (3.28)			0.30	44.475*
0.066* (4.12)	0.27* (2.48)				0.40* (3.30)		0.30	52.563*
0.057* (3.44)	0.28* (2.71)					0.43* (3.65)	0.31	58.011*
0.068* (3.92)		0.31* (2.93)	0.29* (3.20)				0.27	122.825*
0.063* (3.77)		0.22** (1.96)		0.42* (3.91)			0.30	129.675*
0.053* (2.99)		0.23* (2.47)			0.44* (3.77)		0.30	148.490*
0.043** (2.31)		0.26* (2.89)				0.46* (3.90)	0.31	52.365*

Note: *: 1% level of Significance; **: 5% level of Significance and the GMM estimation of Hansen (1982) along with Newey-West (1987) variance and covariance estimation is used

Part-III

$$\sigma_{t,T} = \alpha + \beta_1 \sigma_{t,CIV} + \beta_2 \sigma_{t,PIV} + \varepsilon_{t,T}$$

Where $\sigma_{t,T}$, the volatility over the remaning life of the option is regressed against the call implied volatility ($\sigma_{t,CIV}$) and put implied volatility ($\sigma_{t,PIV}$)

α	**Estimate slope coefficient of independent variables**						R^2	**Wald Test**
	$\sigma_{t,CIV}$	$\sigma_{t,PIV}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$		
0.077* (3.99)	0.36* (2.93)	0.21** (1.88)					0.22	36.323*

Note: * 1% level of Significance, ** 5% level of Significance and the GMM estimation of Hansen (1982) along with Newey-West (1987) variance and covariance estimation is used

Fig-5.8: Comparison of Out-of-Sample Forecast with Realized Volatility: A one Month Forecast

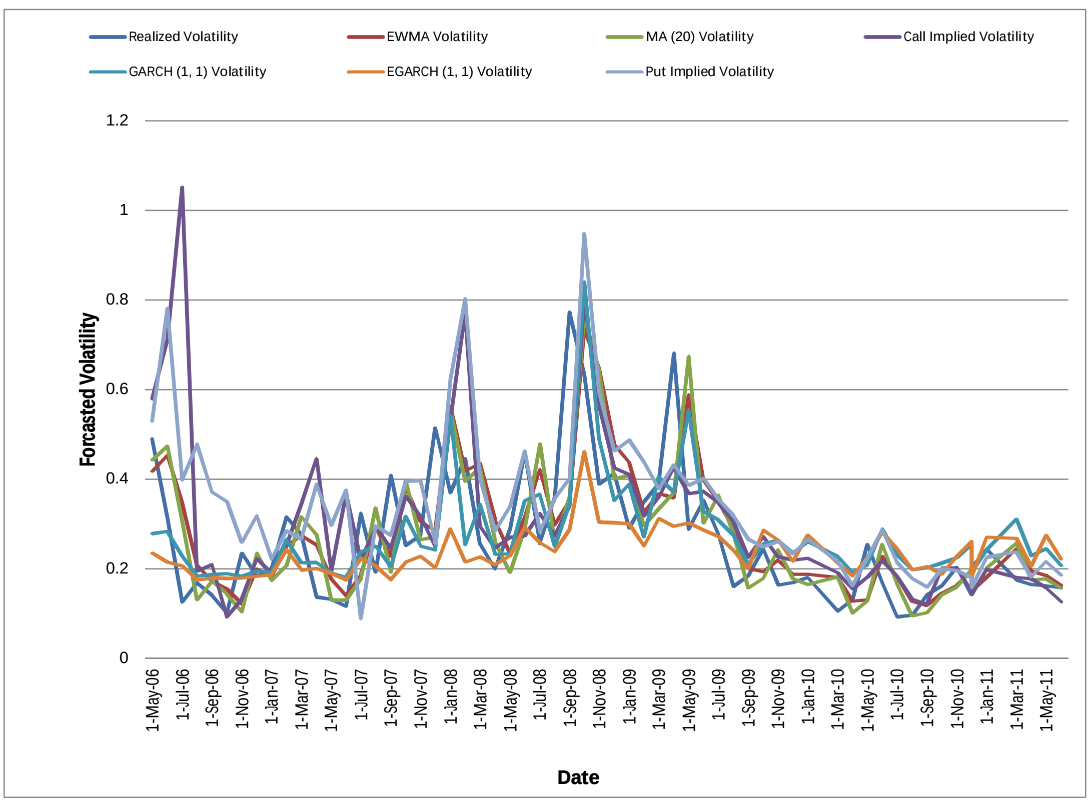

Table-5.4: Comparison of out of sample forecasts with realized volatility

Error	σ_T^{EWMA}	σ_T^{MA}	σ_T^{CIV}	σ_T^{GARCH}	σ_T^{EGARCH}	σ_T^{PIV}
MSE	0.015	0.017	0.031	0.014	0.016	0.026
MAE	0.090	0.097	0.106	0.092	0.089	0.121
RMSE	0.124	0.132	0.178	0.122	0.126	0.163
MAPE	35.856	37.354	48.592	39.155	35.840	56.908

Note: $\sigma_{t,T}$ is the realized volatility, σ_T^{CIV} as call implied volatility, σ_T^{PIV} as put implied volatility, σ_T^{GARCH} as GARCH (1,1), σ_T^{EGARCH} as EGARCH (1,1) volatility, and σ_T^{EWMA} as Exponential weighted Moving Average Volatility and σ_T^{MA} is the Moving average volatility in an out of sample frame work.. All the volatilities are 22 day's ahead volatility. MSE is Mean square error, MAE is Mean Absolute Error, RMSE is the Root Mean Square Error and MAPE is the Mean Absolute Percentage Error.

CHAPTER-6

Implied Volatility in ARCH Class of Models: An Analysis of S& P CNX Nifty in India

6.0. Introduction

The last two chapters have assessed the information content of the volatility forecasts for the next day and the predictability of forecasted volatility over the expiry date by using regression framework. The literature advocates another way to measuring the information content power of implied volatility by putting lagged implied volatility as an other independent variable in the conditional variance frame work.Day and Lewis (1992), Lamoureux and Lastrapes (1993), Xu and Taylor (1995) consider lagged implied volatility as an additional independent variable in the variance equation of GARCH (1,1) model. They are examining the information content power of variables (lagged implied, past GARCH variance) by comparing its statistical significance.

With this background, the objective of this chapter is to compare the information content power of implied volatilities from call and put options on the S&P CNX Nifty index in India by using GARCH and EGARCH models of conditional volatility.

6.1. Empirical Analysis

Here, the study attempts to get the information content power of implied volatility in a GARCH and EGARCH framework. Nevertheless, there is a minor difference in the data sample in comparison to Chapter-4 and 5. For our investigation, we use the daily closing prices of the S&P CNX Nifty index spanning from the period of 1st June 2001 to 24th June 2011 and the corresponding closing price and strike price of both call and put options on the S&P CNX Nifty index, that is from 4th June, 2001 to 23rd June, 2011.

For conditional variance estimation, we converted the closing price of S&P CNX Nifty index into a continuously compounded rate of return (R_t) by taking the first difference of the natural logarithmic of closing prices, i.e. $R_t = \ln (S_t)-\ln(S_{t-1})$. This return series is being annualized by multiplying it with 252 trading days. The logic backed by the conversion of annualized return is justified as we are comparing this return with the implied volatility that is in an annualized form. The volatility models that are estimated in this section are anticipated to capture the conditional variance of the stochastic components of the return series over the time as mentioned in the methodology section in Chapter-3, we have followed the celebrated ARCH class of models such as GARCH and EGARCH methodologies to test the information content power of implied volatility. The logic as to why these models are used to explore the impact of implied volatility in conditional volatility models has been discussed in the Chapter 3.

To estimate the GARCH and EGARCH models, the study has used the maximum likelihood estimation by using Berndt-Hall-Hall-Hausman (1974) algorithm. "This form of model is useful in examining the information content of implied volatilities since it permits the relation between changes in expected returns and changes in market volatility to be incorporated in the estimation procedure"[16]. The additional benefit is that the conditional variance is a function of implied volatility and its own lagged.

There is no significant difference in the summary statistics of the closing price of the S&P CNX Nifty index as reported in Chapters 4 and 5. Hence, a discussion of the descriptive statistics of the concerned variables is skipped. Fig-6.1 shows that the annualized daily returns of the S&P CNX Nifty index, which has a fatter tail in comparison to a normal distribution. This is evident from summary statistics as reported in Table-6.1 where value of the kurtosis and skewness figures clearly explains the fact. This is further supported by Jarque-Bera test of normality. Given the non-normality nature of the return series, the study has employed a GED distribution which is also used in Chapters-4 and 5. To eliminate the first degree auto correlation among the returns the study has fit AR model. Among the different auto regressive orders, the AR(1) is found to be the best fitted model of the return series as per the convenient statistical level of significance. For further analysis we have to test whether there is an autocorrelation among residual and square residual or not.

[16] Day and Lewis (1992)

To test whether there is presence of autocorrelation among residual and square residual we are doing a Ljung Box-Q statistics test.The test statistics based on the null hypothesis of ‘No Autocorrelation’ against the alternative of the presence of autocorrelation, are reported in Table-6.2. From this results, it summarized that that the null hypothesis is strongly rejected in the case of residual and squared residuals. The rejection of null hypothesis allows us to apply GARCH and EGARCH models. Before proceeding towards the further analysis, we have tested the ARCH effect on the mean equation of the return series. We use a Lagrange Multiplier (LM) test. The result show that the null hypothesis of "No ARCH Effect" is strongly rejected in the S&P CNX Nifty index returnwith anone percent level of significance as reported in Table-6.2.

At the outset in Table-6.3, the estimation result of AR(1)-GARCH(1,1) andAR(1)-EGARCH (1,1) models are presented. In the conditional volatility framework, both the GARCH and EGARCH model is estimated by considering with and without lagged implied volatility as an extraindependent variable in the variance equation.The same analysis is performed both for the call and put implied volatility separately. The GARCH(1,1) and EGARCH (1, 1) model is represented by the following specifications:

AR (1): $R_t = c + \tau R_{t-1} + u_t$ (6.1)

Where, R_t is the annualized return of S&P CNX-Nifty index at time period t, ‘c’ is the intercept, ‘R_{t-1} ’is the previous period annualized return at the time period t-1 and ‘u_t ’ is the white noise error term. The above equation specifies that the return on daily stock index closing prices are a function of past returns of the index and a residual. .

GARCH (1,1)-IV Method

For Call option

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 \quad (6.2)$$

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 + \psi \sigma_{t-1,CIV}^2 \quad (6.3)$$

For Put option

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 \quad (6.4)$$

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 + \psi \sigma_{t-1,PIV}^2 \quad (6.5)$$

Where, $\omega > 0$, $\beta_1 \geq 0$, $\alpha_1 \geq 0$. Equation (6.2) and (6.4) are the same as it represent GARCH (1, 1) model where the conditional variance σ_t^2 is a function of mean 'ω'. News about volatility from the previous period is measured as the lag of the squared residual from the mean equation u_{t-1}^2, and last period's forecast variance σ_{t-1}^2. In Equation (6.3) and (6.5), the conditional variance is a function of mean, lagged squared error, last period variance and an extra variable the squared of the lagged call implied volatility $\sigma_{t-1,CIV}^2$ for the analysis of call option and put implied volatility $\sigma_{t-1,PIV}^2$ for the analysis of put option respectively in both the equations. The EGARCH (1, 1) model is represented as follows.

EGARCH (1,1)-IV Method

For Call option

$$\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} \quad (6.6)$$

$$\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} + \psi \ln(\sigma_{t-1,CIV}^2) \quad (6.7)$$

For Put option

$$\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} \quad (6.8)$$

$$\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} + \psi \ln(\sigma_{t-1,PIV}^2) \quad (6.9)$$

The above equations show the EGARCH (1, 1) model. In these equations, $\ln \sigma_t^2$ is the natural logarithmic of conditional variance because of that it constrains the volatility to be positive. 'ω' is the constant level of volatility. 'β_1' Explains the consistency parameter. 'α_1' measures the response of volatility to change in news. It is crucial to note that, the modulus values of the residual series measures the relation with respect to positive news.'θ_1' explains the relationship of volatility to both positive and negative news as the modulus of the series is not taken into account. The coefficient 'ψ' is used toassess if lagged implied volatilities (both call and put) provides any additional incremental information compare to historical lagged conditional variance in Equation (6.7) and (6.9).

In the above equations, we can interpret that the coefficients of ψ in Equation (6.3) and (6.7) for call option, and (6.5) and (6.9)) for put option measure the incremental informative power of implied volatility (both for call and put) to contribute to the changes in the conditional variance of return (S&P CNX Nifty Index) over time. Therefore, the hypothesis for the analysis is that whether the lagged implied volatility (call or put) options contributes significantly more to determine the conditional variance of the stock index return series or the lagged conditional variance. The null hypothesis that implied volatilities do not contain any information is tested through Wald test. The study uses Wald test based on the hypothesis as ω=0, $\beta_1 = 0$, $\alpha_1 = 0$ and ψ=1 and in the Equation (6.3) and (6.5) and, ω=0, $\beta_1 = 0$, $\alpha_1 = 0$, θ_1=0 and ψ=1 in the Equation (6.7) and (6.9). The unrestricted model in Equation (6.3) and (6.7) for the call option, and (6.5) and (6.9) for put option, allows implied volatility to have information content. Where as in Equation (6.2) and (6.6) conditional future volatility depends only on past volatility and past shocks to the return.

The results for this analysis is reported in Table-6.3. The results show that the coefficient of mean equation in each specification[17] is significant at one percent level. The conditional variance Equation (6.2) implies that the estimated significant value of β_1 and α_1 are 0.136 and 0.839, respectively with t-statistics of 8.426 and 48.843. Equation (6.3) and (6.5) included one period lagged call and put implied volatility respectively in GARCH specification of conditional volatility. Putting lagged call implied volatility in the GARCH specification, we have seen that the coefficient of lagged call implied volatility is significant with coefficient value of 0.10 and there is an improvement in the value of log likelihood from a simple GARCH model. But the

[17] Specification-1: AR(1)-GARCH(1,1)or EGARCH(1,1) , Specification-2: AR(1)-GARCH(1,1) or EGARCH(1,1)+Lagged Call Implied volatility and Specification-3: AR(1)-GARCH(1,1)or EGARCH(1,1)+Lagged put Implied Volatility

coefficient value of lagged call implied volatility is smaller than lagged conditional variance. The lagged conditional variance is significant at a coefficient value of 0.68. The same thing happened in case of lagged put implied volatility. Lagged put implied volatility as an independent variable in the variance equation of GARCH specification shows low coefficient value i.e., 0.006. It not only has a low coefficient but also has an insignificant statistics. Whereas, lagged conditional variance has been significant at one percent level with a coefficient value of 0.82. The lagged put implied volatility also contain less information about the conditional variance than the square of the lagged residuals, which is not happened in the call implied volatility specification. The same outcomes have shown in the Wald test. In both the specifications, the null hypothesis is rejected (ω=0, β_1=0, α_1=0 and ψ=1) at one percent level of significance. The lagged implied volatilities do not contain information about the past conditional variance, could be due to the presence of measurement error.

We have already discussed the basis on which the EGARCH model is selected as it incorporates the sign of the residuals in the volatility equation and thus it distinguishes between bad and good news. The estimation of EGARCH models with implied volatilities as an independent variable in the variance equation are presented in Table-6.4. The table presents the results for the return series that consists of with asymmetric effects of positive and negative shocks on conditional volatility. The result of the test for the information contain of lagged implied volatilities are similar to the results presented in Table - 6.3. Here also, the coefficients of mean equations in all specifications are significant at one percent level. It is interesting to observe that in all specifications, the coefficient associated with the asymmetric term θ_1 is negative and significant at one percent level. We can say that the downward movements in the market are followed by higher volatilities than upward movements of the same magnitude. Here also the same results repeat as on GARCH model. Result shows that both the lagged call and put implied volatilities do not contains information above the lagged conditional variance. The coefficients are better than GARCH frame work. The call implied volatility is significant at one percent level with coefficient value of 0.21. Whereas, put lagged implied volatility has a coefficient value of 0.22 with one percent level of significance. More over rejection of null hypothesis (ω=0, β_1=0, α_1=0, θ_1=0and ψ=1) suggests that Black-Scholes implied volatilities are inefficient to predict the conditional volatility. After estimating the models we validate whether there is still an ARCH effect in residuals and square residuals or not. The result show that we accept the null hypothesis of ARCH effect in both GARCH and EGARCH model.

6.2. Conclusion

This chapter makes an attempt to compare the information content power of implied volatilities from call and put options on S&P CNX Nifty index to GARCH and EGARCH models of conditional volatility. The study is based on daily return of S&P CNX Nifty and the data of option markets from the period 1st June 2001 to 24th June 2011. For the analysis of comparison, we have added the lagged implied volatilities both call and put to the conditional variance equation as indepnednt variables. To check the information content power the study has used by the Wald test. The study has estimated GARCH and EGARCH with GED distribution because it has the ability to capture the fat tailed distribution. To summarize the results, it is seen that lagged conditional volatility contains more information than the lagged implied volatilities in both GARCH and EGARCH models. The finding of the study also concludes that the null hypothesis is rejected, which shows that implied volatilities are biased and inefficient. This might be due to the presence of measurement error such as specification error, mismatch error and jump in prices.

Fig-6.1:Histogram showing the distribution of Annualized Return Series

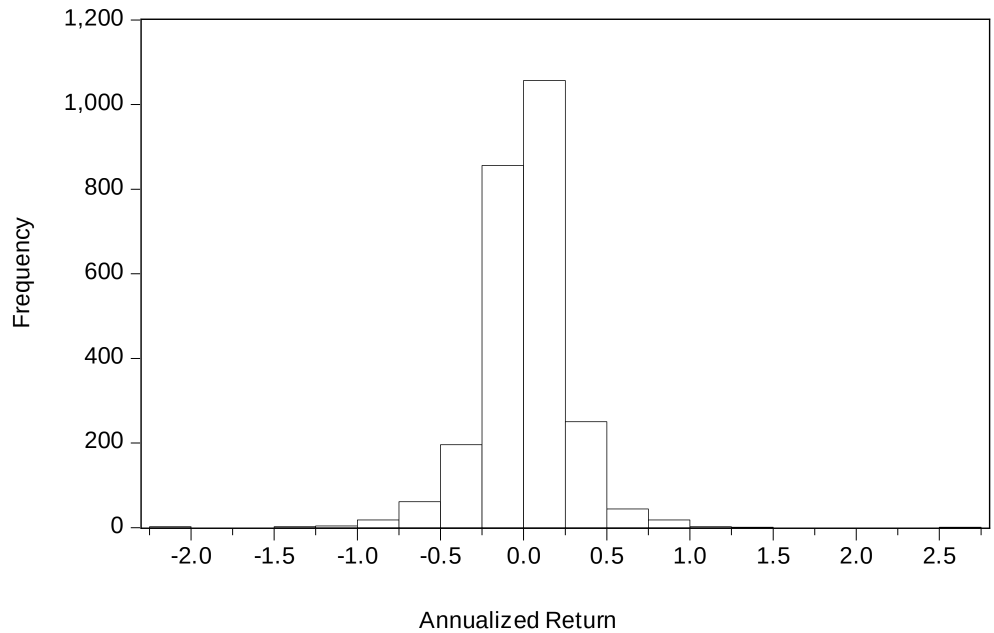

Table-6.1: Basic statistics of Annualized Return

Variable	Mean	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	J-B
Annualized Closing Price Return	0.0096	2.592	-2.07	0.26	-0.28	11.84	8213.98*(0.01)

NOTE: * Indicates the rejection of the null hypothesis of normal distribution in J-B test.

Table-6.2: Estimated Test Statistics for ARCH Effect

	Q^2 (5)	Q^2 (10)	Q^2 (20)	LM (4)
Squared Residual of AR (1) Model	353.81*	523.86*	696.04*	211.69* (57.68)
	Q(5)	Q(10)	Q (20)	
Annualised Return of S&P CNX Nifty	18.96*	33.456*	58.093*	
Squared Annualised Return of S&P CNX Nifty	331.63*	498.94*	658.82*	

Note :*: 1% level of Significance, Q and Q^2 are the LB Q statistics for the return and squared return, and square residuals of AR(1) respectively. The selection of lag length of LB Q test and LM test are 5, 10, 20 and 4 respectively.F-statistic is in parenthesis

Table -6.3: Implied Volatility in GRCH Model

$$R_t = c + \tau R_{t-1} + u_t, \quad u_t \sim \text{GED}(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2$$

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 + \psi \sigma_{t-1,CIV}^2$$

$$\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 + \psi \sigma_{t-1,PIV}^2$$

Where R_t is defined as the annualized return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Model	GARCH(1,1)	GARCH(1,1)-CIV	GARCH(1,1)-PIV
Mean Equation			
C	0.02* (5.24)	0.018* (4.54)	0.020* (5.179)
R_{t-1}	0.07* (3.46)	0.084* (3.88)	0.075* (3.531)
Variance Equation			
ω	0.001* (4.87)	0.003* (4.20)	0.001* (4.55)
u_{t-1}^2	0.13* (8.42)	0.147* (6.67)	0.142* (8.14)
σ_{t-1}^2	0.839* (48.84)	0.68* (15.21)	0.82* (37.71)
$\sigma_{t-1,CIV}^2$		0.10* (4.08)	
$\sigma_{t-1,PIV}^2$			0.006 (1.18)
GED Parameter	1.443* (34.79)	1.491* (30.62)	1.449* (34.12)
Log likelihood	265.424	271.13	265.784
AIC	-0.20	-0.21	-0.20
SC	-0.19	-0.19	-0.18
DW	1.99	2.02	2
LM (4)	2.72 (0.67)	3.54 (0.88)	2.527 (0.63)
Wald test		1922.895* (480.714)	68564.45* (17141.11)

Notes: :*: 1% level of Significance, Asymptotic t-statistic are in parenthesis and LM (4) represents LaGrange Multiplier statistic to test the presence of additional ARCH effect in the residuals from AR(1)-GARCH(1,1). The F-statistics for LM test is also in parenthesis.

Table-6.4: Implied Volatility in EGRCH Model

$R_t = c + \tau R_{t-1} + \varepsilon_t$, $\varepsilon_t \sim GED(0, \sigma_t^2)$

$$\ln\sigma_t = \omega + \beta_1 \ln\sigma_{t-1} + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$$

$$\ln\sigma_t = \omega + \beta_1 \ln\sigma_{t-1} + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} + \psi\sigma^2_{t-1,CIV}$$

$$\ln\sigma_t = \omega + \beta_1 \ln\sigma_{t-1} + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1} + \psi\sigma^2_{t-1,PIV}$$

Where R_t is defined as the annualized return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Model	EGARCH(1,1)	EGARCH(1,1)-CIV	EGARCH(1,1)-PIV
Mean Equation			
C	0.01* (3.91)	0.014* (3.72)	0.014* (3.761)
R_{t-1}	0.08* (4.18)	0.09* (4.22)	0.09* (4.232)
Variance Equation			
ω	-0.34* (-9.74)	-0.44* (7.88)	-0.45* (7.808)
Ln σ^2_{t-1}	0.95* (133.15)	0.92* (69.09)	0.92* (69.603)
$\|z_{t-1}\|$	0.26* (9.64)	0.26* (9.00)	0.26* (8.946)
z_{t-1}	-0.12* -(7.30)	-0.13* (-7.56)	-0.13* (-7.644)
$\sigma^2_{t-1,CIV}$		0.21* (2.49)	
$\sigma^2_{t-1,PIV}$			0.22* (2.511)
GED Parameter	1.46* (35.77)	1.47* (33.35)	1.48 (20.336)
Log Likelihood	283.38	287.70	287.90
AIC	-0.22	-0.22	-0.22
SC	-0.20	-0.20	-0.20
DW	2.03	2.03	2.03
LM (4)	2.39 (0.68)	2.76 (0.68)	3.17 (0.52)

Notes: :*: 1% level of Significance, Asymptotic t-statistic are in parenthesis and LM (4) represents LaGrange Multiplier statistic to test the presence of additional ARCH effect in the residuals from AR(1)-EGARCH(1,1). The F-statistics for LM test is also in parenthesis.

CHAPTER-7

Predictive Ability of VIX for Volatility

7.0. Introduction

Recent market turmoil, along with tougher regulatoryrestrictions, has led investors and asset managers, to cautiously monitor the volatility and downside risk of their equity holdings in the financial market. In this context, market participants have shown an increasing interest in volatility indices. These indices are used not only as sentiment indicators, but also serve as underlying instruments for a number of derivatives contracts which can be used for hedging the volatility of the market.Such measures canbe feasible in those occasions where there is liquidity in the existing option market. It has been argued that exchanges should introduced these indices for trading. In 2008, the National Stock Exchange (NSE) launched the VIX index in the derivatives segment and provide the data of VIX from 2nd March 2009 to till date.The Black-Scholes implied volatility that we have used in previous chapters has considered only the near-the-money option for the calculation. Whereas VIX replaced the multitude of Black-Scholes implied volatility measures with a single value obtained as a weighted average across all observed option prices with appropriate time to maturity. Nevertheless, we want to know whether VIX has a better predictive ability for volatility compared to other backward looking volatility methods.Here in this chapter we have depicted the predictability using non overlapping data set for one month. In this chapter our analysis is different from last three chapters in two aspects.First, the VIX index of India is expected market volatility over the succeeding 30 calendar days. In this chapter, we have used average monthly volatility of all backward looking volatility for this reason. Second, we have not used 'out of the sampling' analysis framework like we have used in Chapter-5 because the number of observations are very small. Pierre Giot (2002) found that VIX/VXN indices contained more information both in forecasting volatility and risk assessment. Blair, Poon, and Taylor (2001) also show that VIX index contain much more information compare to volatility calculated from historical returns of S&P100 index.

Chung et al (2011) find that VIX index has the ability to hold the incremental information regarding the future behavior of S&P 500 index. Ming Jing Yang (2012) found that Taiwan stock index options (TVIX)contains more information coapre to both historical volatility and GARCH volatility models.

Based on this review, in this chapter, we examine whether VIX has a good forecastability than backward looking models. In the previous chapters, we found that implied volatility is a biased forecaster of realized volatility because of an error in variables and inefficiency in Indian option market. Another aspect was that in the Chapter-5, we have used an overlapping data. However, in this chapter we are looking at VIX, which is a model free volatility measures and we are using a non- overlapping data set.The present study varies from past work from two perspectives. Firstly, the study compare VIX with "backward looking" volatility of S&P CNX Nifty index option. Secondly, the study has used a non-overlapping sample for this analysis.

7.1. Empirical Analysis

For the empirical analysis the study has taken the data of VIX from 2nd March 2009 to 31st Dec 2013. By convention, VIX index is the expected market volatility over the succeeding 30 calendar days. That's why we have recorded all the volatilities on the last Friday of the month that immediately follows the expiration of the contract. As the near month contract will expire on the last Thursday of the month, middle month contract will become the near month contract. If Friday is a holiday, then we have considered the next business day. For the ARCH family model we have used the return series (R_t)**.** The time series trend analysis, behavior of closing price and its corresponding returns are presented in Fig-7.1 and Fig- 7.2. The calculation methodof MA (20) and EWMA has already explained in Chapter-3. Hence, we are not making an attempt to repeat these here. For Calculation of ARCH family model we use the same procedure as in Chapter-4. Among the different auto regressive orders, the ARMA (1,1) is found to be the best fitted model of the return series as per the convenient statistical level of significance. To test whether there is presence of autocorrelation among residual and square residual we are doing Ljung Box-Q statistics test.The test statistics based on the null hypothesis of "No Autocorrelation" against the alternative of the presence of autocorrelation, are reported in Table-7.2. From this results, it summarized that that the null hypothesis is strongly rejected in the case of residual and squared residuals. The reject of null hypothesis agree us to apply GARCH and EGARCH models. Before proceeding towards the further analysis, we have tested the ARCH effect on the mean equation of the return series. We use a Lagrange Multiplier (LM) test to check whether there is a presence of ARCH effect in the data set or not and, the result revealed that the null hypothesis of 'No ARCH Effect' is strongly rejected in the S&P CNX Nifty index return at 6days lagwith a one percent level of significance as reported in Table-7.2.

The estimated results of ARMA(1, 1)-GARCH (1, 1) and ARMA(1, 1)-EGARCH (1, 1) models are shown in Table-7.3 and 7.4. We have used the ARMA(1,1) in the mean equation of GARCH and EGARCH because it has found to be the best fit model for this data set. Apart from this, we have already discussed the basis on which we have selected the EGARCH model as it incorporates the sign of the residuals in the volatility equation and thus it distinguishes between bad and good news separately. The both GARH (1, 1) and EGARCH (1, 1) models are as follows.

Mean Equation:

ARMA (1,1): $R_t = c + \tau_1 R_{t-1} + \tau_2 u_{t-1} + u_t, \quad u_t \sim GED(0, \sigma_t^2)$ (7.1)

Variance Equations:

GARCH (1, 1): $\sigma_t^2 = \omega_0 + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2$ (7.2)

EGARCH (1, 1): $\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$ (7.3)

Through the above equation, we got the conditional volatility for S&P CNX nifty Index option. To match with the VIX we average the conditional volatility based on the expiry date (Approximately 30 days). The same procedure is also applied on MA(20) and EWMA. By that we will get 57 monthly volatilities for all backward looking measures. We have plotted realized volatility, VIX and all backward looking volatility in Fig- 7.4. It shows that all forecasted volatilities are moving in a same range. However, from this plot it is very difficult to find out which one is the best among all.To understand the best forecaster of the futureindex price we explain our analysis in the next section. Before proceeding with our further analysis of results, it is better to focus on the descriptive statistics and stationary of the all the volatility series.

7.1.1. Descriptive Statistics and Unit Root Tests

Table-7.5presents the descriptive statistics of VIX with all other forecasted volatility. Except EGARCH (1, 1) all other volatilities are of low ranges. To examine further, the unit root test is conducted at all the variables as per the requirement of time series analysis. This is because, when the data have unit root characteristics, such analysis may lead to spurious results and misleading conclusion. Hence, the time series result is reported in Table-7.6. From the DF, ADF and PP test, it is concluded that all the variables are stationary. The study has use AIC (Akaike Information Criterion) and SC (Schwarz criterion) for choosing the optimum lag length in the case of ADF and PP tests.

7.1.2. Simple and Multiple Predictable Regressions for VIX

In this section, we are using two regressions, one is simple predictability and another is multiple predictability regression. In the simple predictability regression for testing the null hypothesis of unbiasedness (α=0 and β=1) in the regression (Chapter-3, Equation-3.45), we have used a Wald test. For multiple regression the Wald test with a null hypothesis (α=0, β1=1 and β_2=0) for VIX as an efficient and unbiased estimator for realized volatility (Chapter-3, Equation-3.46). We first test the predictability of VIX compare to the other backward looking measure with the regression equation (Chapter-3, Equation-3.45). Results are presented in Table-7.7, with one part deals with individual performances and part two deals with comparing performances. Since the dependent variable is based on non-overlap, standard error is computed by OLS. In the part-I of the table show that EGARCH (1, 1) contain substantial amount of predictability for realized volatility. The slope coefficient is 0.99 and highly significant. Forecasting with other backward looking volatility model also produces a significant result. The slope of the MA (20) is 0.78 with R^2 value 0.72. Incase of EWMA, the coefficient of EWMA is significant, but the coefficient value is 0.76 which is less than MA (20) coefficient. The GARCH (1, 1) 0.88 with a one percent level of significance for the CNX nifty Index option. The results are consistenct with the conclusion of the previous chapters that implied volatility is not performing well compared to backward looking volatility.

Table 7.7, Part-II, shows the predictability regression where the study has used multiple independent variables. All these OLS regression VIX as one of the independent variables along with one of the backward looking volatility such as MA(20), EWMA, GARCH (1, 1) and EGARCH (1, 1). Here we have also used a Wald test with a null hypothesis (α=0, β_1=1 and β_2=0) VIX as an efficient and unbiased estimator for realized volatility.

Now let start our discussion by comparing VIX with other volatility forecasting models. In comparison with MA (20), the VIX has a negative insignificant coefficient value of -0.046. The MA (20) has a high significant coefficient value 0.821. This regression shows a high R^2 value of 0.72. Similarly, the EWMA significantly outperformed VIX. The coefficient of EWMA is at 0.84 and it is statistically significant at the one percent level. Whereas, VIX has a lower negative insignificant coefficient value of -0.10. The estimation result also shows the value of R^2 as 0.70.

In relation with GARCH (1, 1) model, the VIX performed very weakly with a coefficient value of -0.052. The GARCH (1, 1) has a better coefficient value in comparison to the coefficient value of MA (20) and EWMA, in the regression which involves VIX as one of the independent variables. However, in the EGARCH (1, 1) specification, as per the Chapter-3, Equation-3.46, the VIX has a low coefficient value, -0.036 and is insignificant in comparison to the conditional variance series (σ_{EGARCH}). The coefficient of σ_{EGARCH} is highly statistically significant at the one percent level with a coefficient of higher magnitude of 1.012.

Further, the result shows that (Table-7.7, Part-II) study has rejected the null hypothesis of wald test ((α=0, β_1=1 and β_2=0) in all five multiple regesssion. The Wald tests are statistically significant in each individual regression at the one percent level. The VIX is not performing well because of two major reasons. Firstly NSEE is not allowed VIX to trade. Secondly the sample size for this analysis is too small.

The results are in similar line with Chapter-4, 5 and 6 because of two reason: (i) sample size is very less it is only 57 observation and (ii) inefficiency of the Indian option market.

7.2. Conclusion

This chapterexamines whether VIX is a better predictor of the future volatility or the backward looking volatilities. For this analysis, the study has used simple OLS with AR(1) model. For the analysis, the study has taken the daily return of S&P CNX Nifty from 2nd March 2009 to 31st Dec 2013 and VIX index data from the period 2nd March 2009 to 31st Dec 2013. Based on the analysis the key conclusions that aredrawn from this chapter. Firstly, in simple predictability regression for 30 calendar days VIX model underperformed compared to all other “backward-looking” volatility. Secondly, GARCH and EGARCH model contain more information of the expected average 30 day volatility. Thirdly, the multiple predictability regressions results show that VIX provides an inferior forecaster than “backward-looking” volatility. Fourth, VIX is biased estimator of the average 30 days. Finally, the biasedness may arise because of small sample size and inefficiency of the option market.

Fig-7.1: Trends in S&P CNX Nifty Index Closing Price

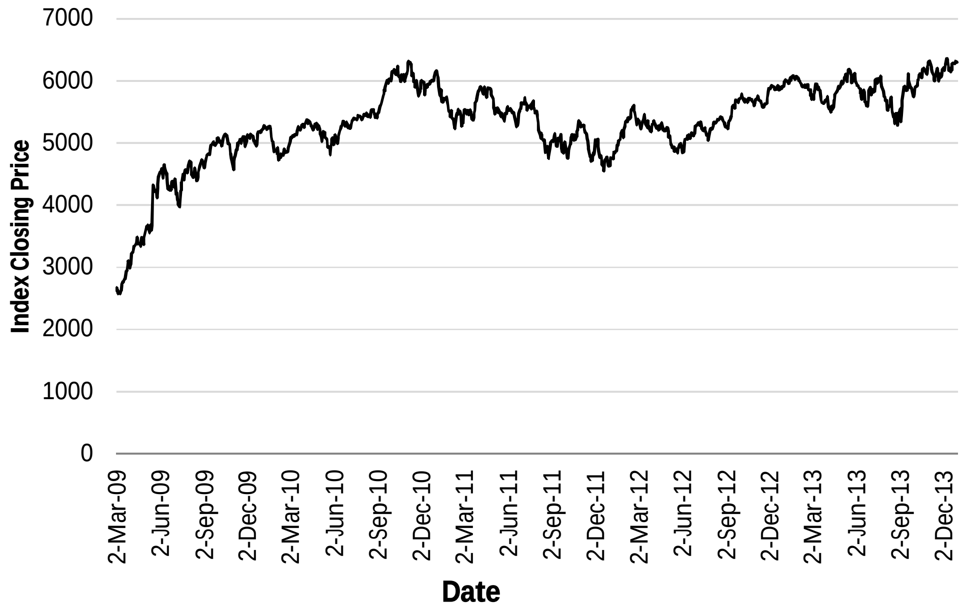

Fig-7.2: Trends in S&P CNX Nifty Return

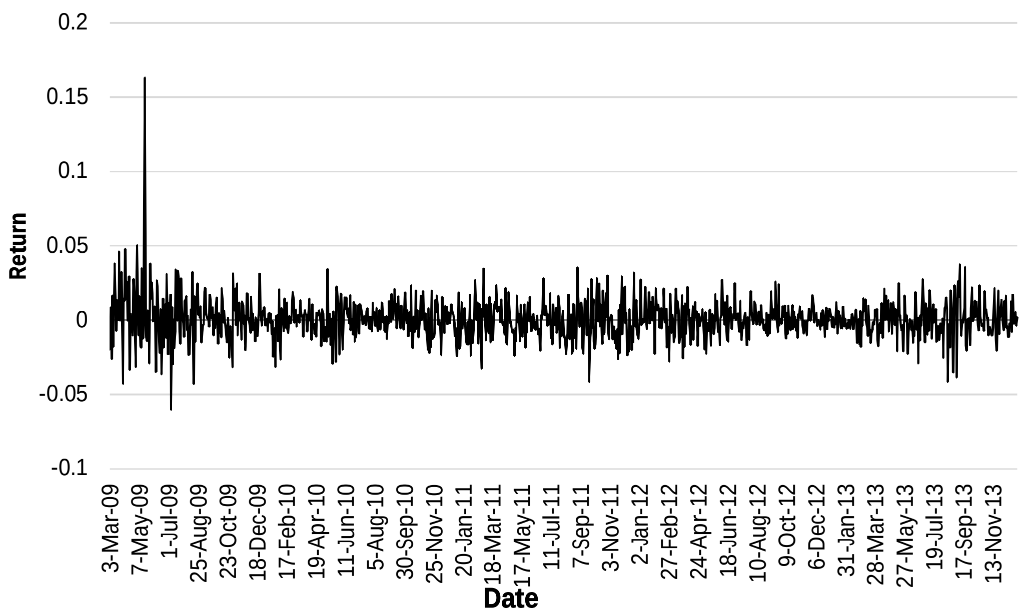

Table-7.1: Basic statistics of closing Price and its return of S&P CNX Nifty Index

Variable	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	J-B
Closing Price	5318.50	6363.90	2573.15	644.72	-1.43	6.43	974.43(0.01)
Closing Price Return	0.0007	0.16	-0.06	0.013	1.48	21.46	17532.90*

Note: * Indicates the rejection of null hypothesis of normal distribution in J-B test at 1%.

Fig-7.3: Histogram of the Return Series

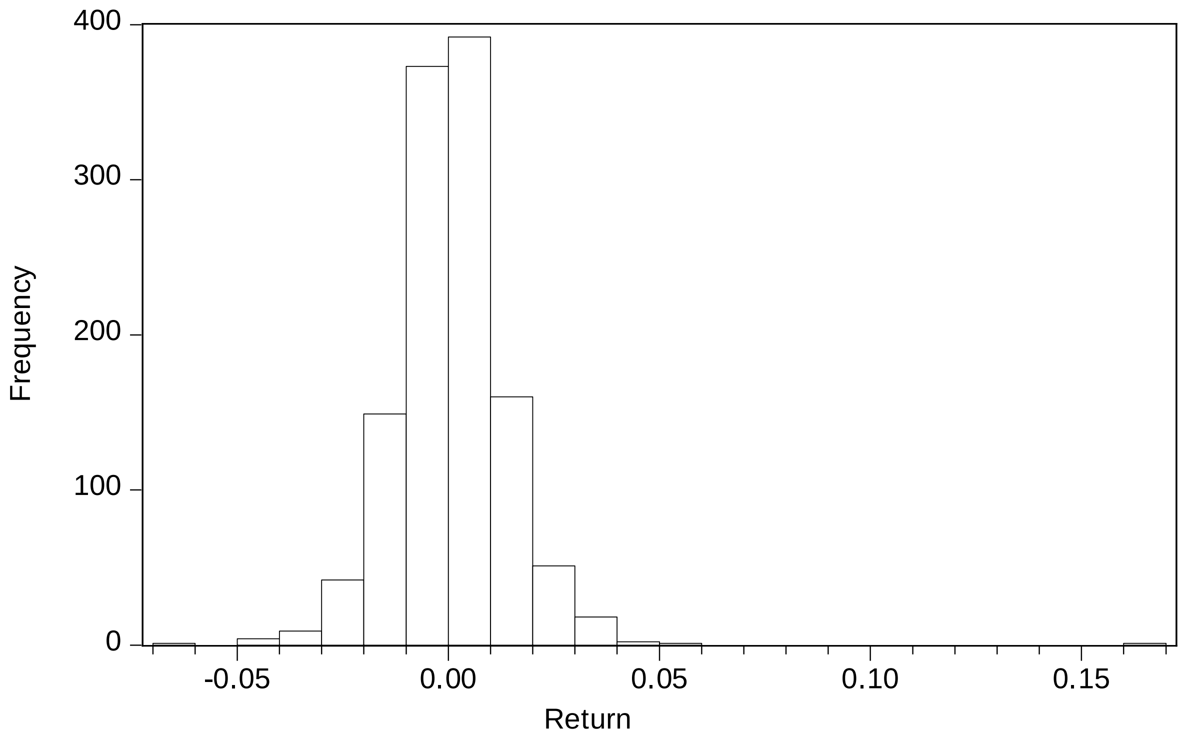

Table-7.2: Estimated Test Statistics for ARCH Effect

	Q^2 (7)	Q^2 (10)	Q^2 (20)	LM (6)
Squared Residual of ARMA(1,1) Model	11.63* (0.00)	22.95* (0.00)	38.60* (0.00)	13.30* (0.01)
	Q (7)	Q (10)	Q (20)	
Annualised Return of S&P CNX Nifty	13.38** (0.05)	19.35** (0.05)	31.77** (0.03)	
Squared Annualised Return of S&P CNX Nifty	11.86*** (0.09)	25.57* (0.00)	41.04** (0.03)	

Note :*: 1% level of Significance; **:5% level of Significance;***: 10% level of Significance, Q and Q^2 are the LB Q statistics for the return and squared return, and square residuals of ARMA(1,1) respectively. The selection of lag length of LB Q test and LM test are 7, 10, 20 and 6 respectivel. p- value are in parenthesis.

Estimation Of GRACH(1,1) Process

ARMA(1,1): $R_t = c + \tau_1 R_{t-1} + \tau_2 u_{t-1} + u_t$, u_t~GED $(0,\sigma_t^2)$

GARC(1,1): $\sigma_t^2 = \omega + \beta_1 u_{t-1}^2 + \alpha_1 \sigma_{t-1}^2$

Where, R_t is defined as the return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Table-7.3: Parameter estimates of the GARCH (1, 1) model

Model-GARCH(1,1)	
Mean Equation	
C	0.0005* (1.55)
R_{t-1}	0.23* (0.54)
u_{t-1}	-0.17* (-0.41)
Variance Equation	
ω	0.000** (1.93)
u_{t-1}^2	0.05* (3.76)
σ_{t-1}^2	0.93* (55.84)
GED Parameter	1.44* (24.01)
Log likelihood	3632.85
AIC	-6.03
SC	-6.003
DW	2.01
LM (6)	3.19 (0.78)

Notes:*: 1% level of Significance; **:5% level of Significance, Asymptotic t-statistic are in parenthesis and LM (6) represents LaGrange Multiplier statistic to test the presence of additional ARCH effect in the residuals from ARMA(1,1)-GARCH(1,1). The F-statistics for LM test is also in parenthesis.

Estimation Of EGRACH(1,1) Process

ARMA (1,1): $R_t = c + \tau_1 R_{t-1} + \tau_2 u_{t-1} + u_t$, $u_t \sim GED(0, \sigma_t^2)$

EGARCH (1,1): $\ln \sigma_t^2 = \omega + \beta_1 \ln \sigma_{t-1}^2 + \alpha_1 |z_{t-1}| + \theta_1 z_{t-1}$

Where, R_t is defined as the return on S&P CNX Nifty Index and σ_t^2 is the conditional variance of the innovations.

Table-7.4: Parameter estimates of the EGARCH (1,1) model

Model-EGARCH (1, 1)	
Mean Equation	
C	0.0002* (0.90)
R_{t-1}	0.30* (0.82)
u_{t-1}	-0.251* (-0.65)
Variance Equation	
ω	-0.18* (-2.59)
Ln σ_{t-1}^2	0.99* (172.69)
$\|z_{t-1}\|$	0.13* (4.72)
z_{t-1}	-0.06* (-3.71)
GED Parameter	1.45* (23.09)
Log Likelihood	3643.10
AIC	-6.04
SC	-6.01
DW	2.014
LM (6)	23.09 (0.77)

Notes: :*: 1% level of Significance, Asymptotic t-statistic are in parenthesis and LM (6) represents LaGrange Multiplier statistic to test the presence of additional ARCH effect in the residuals from ARMA(1,1)-EGARCH(1,1). The F-statistics for LM test is also in parenthesis.

Table-7.5: Descriptive Statistics

	$\sigma_{t,T}$	$\sigma_{t,VIX}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$	$\sigma_{t,EWMA}$	$\sigma_{t,MA(20)}$
Mean	0.18	0.22	0.19	0.19	0.19	0.19
Maximum	0.69	0.51	0.47	0.34	0.51	0.51
Minimum	0.08	0.13	0.10	0.10	0.08	0.07
Std. Dev.	0.08	0.07	0.06	0.05	0.08	0.08
Skewness	3.35	1.47	2.39	0.74	2.23	2.18
Kurtosis	19.29	5.71	9.73	3.37	9.08	9.06
Jarque-Bera	725.21	37.56	159.35	5.47	133.14	130.30
Probability	0	0	0	0	0	0

Note: $\sigma_{t,T}$ is realized volatility, $\sigma_{t,VIX}$ as the Volatility Index, $\sigma_{t,CIV}$ as call implied volatility, $\sigma_{t,PIV}$ as put implied volatility, $\sigma_{t,GARCH}$ as GARCH (1,1), $\sigma_{t,EGARCH}$ as EGARCH (1,1) volatility, and $\sigma_{t,EWMA}$ as Exponential weighted Moving Average Volatility and $\sigma_{t,MA(20)}$ is the Moving average volatility.

Table 7.6: Test of Stationarity

	Without Trend			With Trend and Intercept		
	DF	ADF	PP	DF	ADF	PP
$\sigma_{t,T}$	-8.77*	-8.77*(0)	-8.53*(3)	-8.51*	-8.51*(0)	-8.23*(3)
$\sigma_{t,VIX}$	-4.59*	-3.77*(3)	4.72*(4)	-4.66*	-2.83(3)	-4.65*(4)
$\sigma_{t,GARCH}$	-5.001*	-5.001*(0)	-5.04*(2)	-4.39*	-4.39*(0)	-4.43*(2)
$\sigma_{t,EGARCH}$	-3.34*	-3.34*(0)	-3.29*(2)	-3.23**	-3.23**(0)	-3.28**(2)
$\sigma_{t,EWMA}$	-4.96*	-5.20*(1)	-4.84*(1)	-4.31*	-3.78*(3)	-4.24*(1)
$\sigma_{t,MA(20)}$	-4.54*	-4.54*(0)	-4.60*(1)	-4.20*	-4.20*(0)	4.22*(1)

Note: * Reject the null hypothesis of a unit root with 99% confidence. Figures in the parathesis against ADF statistics are the numbers of lags used to obtain white noise residuals, and these lags are selected using AIC. In PP test figures in the brackets are bandwidth selected using the Newey-West method.

Fig-7.4: Comparison of VIX with "Backward-Looking" Volatility

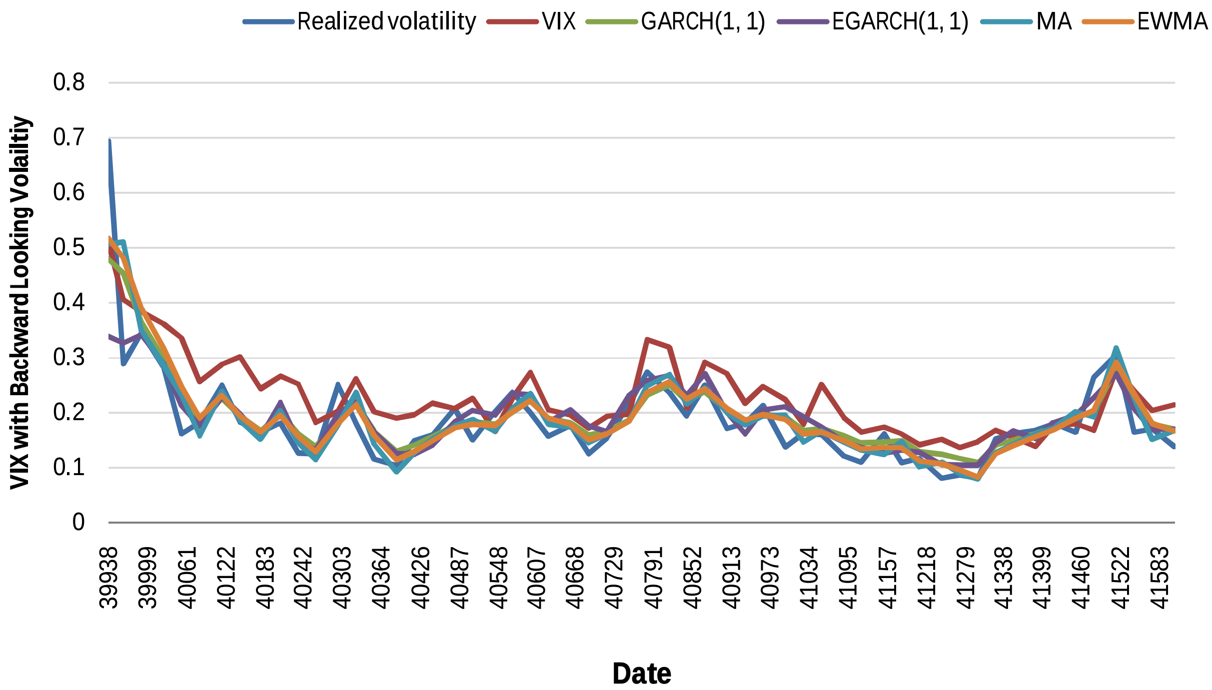

Table-7.7: One Month predictability Regressions

$$\sigma_{t,T} = \alpha + \beta\sigma_{t,i} + \varepsilon_{t,T}$$

Where $\sigma_{t,T}$, the average realized volatility, is regressed against the volatility forecast $\sigma_{t,i}$ .This includes the Moving Average (20), EWMA, GARCH or EGARCH and VIX.

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<u>Part-I</u>: Simple One Month predictability Regressions

α	Estimate slope coefficient of independent variable					R^2	Wald Test
	$\sigma_{t,VIX}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$		
0.04*** (1.68)	0.57* (4.63)					0.49	20.70*
0.03* 3.52		0.78* (15.66)				0.72	74.11*
0.03* (3.10)			0.76* (12.83)			0.70	48.97*
0.01 (0.81)				0.88* (12.54)		0.69	9.37*
-0.009 (-0.71)					0.99* (13.86)	0.79	13.63*

Note:*: 1% level of Significance, * *:5% level of Significance, * **:10% level of Significance, t-statistic are in parenthesis and Autocorrelation are corrected using the AR(1)

$$\sigma_{t,T} = \alpha + \beta_1\sigma_{t,VIX} + \beta_2\sigma_{t,i} + \varepsilon_{t,T}$$

Where, $\sigma_{t,T}$, the average realized volatility, is regressed against VIX and the volatility forecast $\sigma_{t,i}$, which includes the MA (20), EWMA, GARCH or EGARCH.

<u>Part-II</u>: Multiple One Month predictability Regressions

α	Estimate slope coefficient of independent variables					R^2	Wald Test
	$\sigma_{t,VIX}$	$\sigma_{t,MA(20)}$	$\sigma_{t,EWMA}$	$\sigma_{t,GARCH}$	$\sigma_{t,EGARCH}$		
0.03* (3.06)	-0.04 (-0.46)	0.82* (8.84)				0.72	356.48*
0.04* (3.00)	-0.10 (-0.87)		0.84* (7.480)			0.70	268.93*
0.01 (0.90)	-0.05 (-0.43)			0.93* (7.04)		0.69	251.95*
-0.00 (-0.53)	-0.03 (-0.37)				1.02* (9.072)	0.79	304.36*

Note:* 1% level of Significance, and Autocorrelation were corrected using the AR(1)

CHAPTER-8

Summary and Conclusion

8.0. Approach of the study:

Volatility forecasts are vital for taking financial decisions that involve implementation and evaluation of asset pricing and risk management. Most pricing models measure risk in terms of market volatility, and the degree of volatility affects the expected returnsof all financial assets. A number of mathematical and statistical models have been proposed to characterize the dynamic behavior of market volatility, such as“forward-looking” and backward-looking volatility methods. Each of these approaches delivers a different volatility estimate. This study seeks to compare the predictive power of “forward-looking” with “backward-looking” volatility. To do this, we have compiled data and estimatesthat are both backward and forward-looking in nature. We examined the data points and the predictive power of implied volatility and compared these with “backward-looking” volatility of S&P CNX Nifty spot and options indices traded in the NSE of India for the period May 31, 2001 to June 30, 2011.

The study begins by reviewing the literature on this subject to identify a framework within which the data can be analyzedin order to make volatility forecasts both forward and “backward-looking” a month in advance. The broader argument is that whether implied volatility (forward-looking) is an unbiased and efficient forecaster of realized volatility. One side of the argument is that in financial markets the current market contain all the information.. Hence, implied volatility may be the best forecaster of future volatility. On the other hand, another school of thought is that“forward-looking” volatility is a biased estimator of future volatility. Against this backdrop, our study examines the predictability of implied volatility in the context of the emerging Indian options market.

8.1. Objectives of the Study:

The objectives of present study are:

1. To investigate the information content of implied volatility against the “backward-looking” volatility of S&P CNX Nifty index option in India.

2. To investigate the predictive power of implied volatility against the "backward-looking" volatility of S&P CNX Nifty index option in India.
3. To examine whether implied volatility provides a superior monthly ahead volatility forecast for S&P CNX Nifty index compared to other "backward-looking" volatilities.
4. To compare the information content of the implied volatility from call and put options on the S&P CNX Nifty index in the conditional volatility framework.
5. To assess the "backward-looking" volatility in the context of the newly emerged volatility Index, i.e. (VIX) as constructed byNSE in India.

8.2. Major Findings of the study:

This study endeavors to examine the data points of implied volatility for one-day-ahead volatility in comparison to "backward-looking" volatility, based on information content regressions, in three forms in Chaptrt-4: First, a multiplesimple regression which squares off the one-day-ahead returns in an annualized form that represents the dependent variable, and the various measures of volatility serve as independent variables. Second, the square of the one-day-ahead returns in an annualized form acts as a dependent variable, and call-implied volatility or put-implied volatility represents one of the independent variables and other forecast volatilities as other independent variables. In the third regression, both call- and put-implied volatilities are used as independent variables. The study also analyzed the predictive power of implied volatility. Chapter5 attempts to investigate the predictability of implied volatility compare to "backward-looking" volatility both in "in the sample" and "out of the sample" data structures. In the sample analysis, we run three types of predictability regressions. In the first type, we run all six individual forecast volatilities separately in each regression with realized volatility as a dependent variable which was calculated by using the average daily return over the remaining life of the option. In the second, the study used call-implied volatility or put-implied volatility as one of the independent variables and other forecast volatilities as other independent variables. In the third regression, the study used both call- and put-implied volatilities as independent variables. Both in Chapter-4 and 5,the Wald test has been used to check the unbiasedness of the coefficient. Further, the study has used lag of the implied volatilities as an independent variable in thevariance equation of the ARCH calss of model. In Chapter 6, we first estimated the conditional volatility model without the lagged implied volatility as an independent variable and then with the lagged implied volatility. The study also looked at the predictability of implied volatility using VIX data. We compared “backward-looking” volatility with VIX predictability in Chapter7 using a simple OLS estimation. Based on the above analysis, we infer the key findings of the study as below:

- The analysis has revealed that “backward-looking” volatility contains incremental information for the next day volatility as compared to “forward-looking” volatility. Among all the “backward-looking” volatilities, EGARCH(1,1) model was estimated to carry more information for the next day volatility.
- Put-implied volatility has completely failed to explain one-day-ahead volatility. Its performance was worse than MA (20) historical volatility model and call-implied volatility.
- Further, ARCH family model contain more information about realized volatility compare to MA(20), EWMA and implied volatility.
- Betweencall- and put-implied volatility,the former has more predictability power than the latter.
- Implied volatilities are biased and inefficient estimators of the future realized volatility.
- GARCH(1,1) and EGARCH(1,1) models provide the best monthly ahead volatility forecast for the S&P CNX Nifty index compared to implied volatility.
- Implied volatility in a conditional volatility framework is not showing impressive results. Both lagged GARCH and EGARCH models contain more information than the lagged implied volatility.
- From the point of view of information content and predictability, implied volatility is a biased predictor. The bias arises due to errors in variable problem. The reasons for bias could be the following: First, the errors in variables problem, i.e., (i) Options model with constraints creates a specification error, (ii) presence of nonsynchronous trading in Indian option market, and (iii) jump in S&P CNX nifty spot and option index prices.

Second, the inefficiency in the Indian option market due to non-availability of appropriate data on option price for hedging because of restrictions on short selling in India and there is no traded option on futures contract the investor is forced to use spot price instead.

- The newly emerged VIX underperformed in predicting 30-day volatility compared to other volatility forecasting models. VIX is also an inferior forecaster than “backward-looking” volatility.

8.3. Policy Implications of the Study:

Implied volatility could be useful for an option trader if it is an efficient forecaster. Otherwise, it will cost the investor if he/she trades in the market. Based on our findings, the following policy suggestions may be in order:

In the Indian contest, the traders, financial managers and investors use Black-Scholes and Black-Scholes-Merton models to calculate the implied volatility. According to an NSE notification, the exchange uses these models for calculating the base price of an option. However,this study highlights that the above forecasting modelshave certain limitations: (1) transaction costs and taxes are not considered, and are assumed to be zero; (2) one of the assumptions of the Black-Scholes model is that stock price follows a continuous time Geometric Brownian Motion, i.e., the price is log-normally distributed which is found to be not true; (3) these models assume a constant risk-free interest for the whole contract period; and (4) these models assume that there is no arbitrage opportunity in the market.Therefore, this study proposes that NSE should implement a model that addresses the above issues. This should be in line with the best practices followed in the developed financial markets.

There are restrictions on short-selling in the Indian cash market. Due to this, many investors hedge their positions of options with futuresnot with cash. Therefore, it is desirable that the NSE should introduce an option contract with underlying futures, rather than cash. Such facility is already available in developed country derivatives markets. The NSE has recently introduced a Volatility index for the S&P CNX NIFTY. But, so far NSE has not permitted the traders to trade on the VIX. Allowing trading options on the VIX can help improve the functioning of financial markets. When the options market started in India, there was less liquidity in the market, which probably is one of the reasons why implied volatility does not have good predictability of future volatility. But the scenario changed after 2006 trading volumes have increased manifold and the market is quite vibrant. This calls for educating the public about options trading by conducting seminars and workshops.

8.4. Implications for Further Research:

Based on this study, some implications for further research may be in order. As we have noticed, some of the existing studies have focused on an options pricing model while others are related to the options market. However, both these categories are limited in number and there is need for further in-depth analysis in both the segments. Future research may focus on the following aspects to understand the implied volatility behavior of the Indian financial marketbetter:

1. There is need for developing alternative option pricing models for analyzing implied volatility.
2. Predictability of implied volatility should be tested using high frequency data.
3. Since the volume of the stock option is increasing considerably by the day, there is need for further research on the predictive power of stock option-implied volatility.
4. Further analysis of call-put parity with respect to implied volatility is also very much needed.

8.5. Limitations of the Study:

This study has exclusively focused on the information content and predictability of implied volatility compared to "backward-looking" volatility. But, there are a few limitations of this study. The major limitation of this study is that it dealt with the liquidity of the Indian options market only. Although it would be interesting to extend the study to other indices, this could not be done due to less liquidity of other indices. Methodologically, the study is only restricted to Black-Scholes model. But, there are other sophisticated models in the literature., which could not be covered in this study. Broader issues like behavior of foreign institutional investment, foreign direct investment and global meltdown in 2008, which might have created structural breaks on India's financial market, also could not be addressed in this study.

In this study, for calculating implied volatility, we have taken only ‘at the money’ near month contract, but there are other weighted methods like ‘deep out of the money’ and ‘deep in the money’ contracts in the literature. Compared to developed option markets like the US and Europe, until now there is less liquidity in the ‘deep in the money’ and ‘deep out of the money’ contracts for both call and put options in India. If you compare the option volume (combination of index and stock options) of 2002, it is just 0.04% of the volume of 2011. In 2005, the volume was only 1.5% of 2011. Due to this low volume, itis not possible to consider ‘deep out of the money’ and ‘deep in the money’ for our analysis. With little liquidity in the market, the analysis may not be very useful.

As far as econometric techniques are concerned, there is always scope for further improvement. First, it must be mentioned that the models and the equation used in our analysis for predicting VIX are not fully comparable to the ones used by other analysts. This is due to the shortness of the VIX series. Second, while comparing the conditional volatility with implied volatility, some researchers have used averaging conditional variance methods in “in the sample” framework to match option expiry. We avoided this for comparability with the “backward-looking” volatility methods. Therefore, the information content and predictability of implied volatility analysis can be extended in many directions with the improvement in techniques and increase in sample size for the Indian options market.

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Website

www.nseindia.com

www.google.com

www.ivolatility.com

APPENDIX

Appendix-1

Key Contract Specifications for S&P CNX Nifty Options

Underlying Index	S&P CNX Nifty Index is a market capitalization-weighted index of 50 component stocks listed on the National stock Exchange
Contract Size	Permitted lot size shall be 200 and multiples thereof (minimum value Rs.2 lakh)
Trading cycle	&P CNX Nifty options contracts have 3 consecutive monthly contracts, additionally 3 quarterly months of the cycle March / June / September / December and 5 following semi-annual months of the cycle June / December would be available, so that at any point in time there would be options contracts with atleast 3 year tenure available. On expiry of the near month contract, new contracts (monthly/quarterly/ half yearly contracts as applicable) are introduced at new strike prices for both call and put options, on the trading day following the expiry of the near month contract.
Minimum Price Fluctuation	The price step in respect of S&P CNX Nifty options contracts is Re.0.05
Base Prices	Base price of the options contracts, on introduction of new contracts, would be the theoretical value of the options contract arrived at based on Black-Scholes model of calculation of options premiums.
Expiry day	S&P CNX Nifty options contracts expire on the last Thursday of the expiry month. If the last Thursday is a trading holiday, the contracts expire on the previous trading day.
Settlement basis	Cash settlement on T+1 basis
Style of option	European
Strike price interval	Rs.20
Daily settlement price	Premium value(net)
Final settlement price	Closing value of the index on the last trading day

Appendix-2

Base Price & operating ranges applicable to Options contracts.

Circular No. NSE/F&O/0040/2002 October 31, 2002

1. Base price of the Options Contracts on introduction of new contracts shall be the theoretical price of the options contract, based on Black-Scholes model. The formula for calculation of theoretical base price as per Black-Scholes model.

2: On subsequent trading days, if the contract has traded, the base price of the contract for the next trading day shall be the closing price of the contract. The closing price shall be calculated as follows:

> 2.1 If the contract is traded in the last half an hour, the closing price shall be the last half an hour weighted average price.
>
> 2.2 If the contract is not traded in the last half an hour, but traded during any time of the day, then the closing price will be the last traded price (LTP) of the contract.

3: If the contract is not traded for the day, the base price of the contract for the next trading day shall be the theoretical price of the options contract arrived at based on Black-Scholes model of calculation of options premiums.

Appendix-3

Box-1- Historical Events in Financial Derivatives in India

Year	Progress of Financial Derivatives
1952	Enactment of the forward contracts (Regulation) Act.
1953	Setting up of the forward market commission.
1956	Enactment of SCRA.
1969	Prohibition of all forms of forward trading under section 16 of SCRA.
1972	Informal carry forward trades between two settlement cycles began on BSE.
1980	Khuso Committee recommends reintroduction of futures in most commodities.
1983	Govt. ammends bye-laws of exchange of Bombay, Calcutta and Ahmadabad and introduced carry forward trading in specified shares.
1992	Enactment of the SEBI Act.
1993	SEBI Prohibits carries forward transactions.
1994	Kabra Committee recommends futures trading in 9 commodities.
1995	G.S. Patel Committee recommends revised carry forward system.
14th Dec 1995	NSE asked SEBI for permission to trade index futures.
1996	Revised system restarted on BSE.
18th Nov 1996	SEBI setup LC Gupta committee to draft frame work for index futures.
11th May 1998	LC Gupta committee submitted report.
1st June 1999	Interest rate swaps/forward rate agreements allowed at BSE.
7th July 1999	RBI gave permission to OTC for interest rate swaps/forward rate agreements.
24th May 2000	SIMEX chose Nifty for trading futures and options on an Indian index.
25th May 2000	SEBI gave permission to NSE & BSE to do index futures trading.
9th June 2000	Equity derivatives introduced at BSE.
12th June 2000	Commencement of derivatives trading (index futures) at NSE.

31st Aug 2000	Commencement of trading futures & options on Nifty at SIMEX.
1st June 2001	Index option launched at BSE.
4th June 2001	Trading on equity index options at NSE.
2nd July 2001	Trading at stock options at NSE.
9th July 2001	Stock options launched at BSE.
July 2001	Commencement of trading in options on individual securities.
1st Nov 2001	Stock futures launched at BSE.
9th Nov 2001	Trading on Stock options commences on the NSE.
9th Nov 2002	Trading of Single stock futures at BSE.
June 2003	Trading of Interest rate futures at NSE.
Aug 2003	Launch of futures & options in CNX IT Index.
13th Sep 2004	Weekly options of BSE.
June 2005	Launch of futures & options in Bank Nifty Index.
Dec 2006	'Derivative Exchange of the Year by Asia risk magazine.
June 2007	NSE launches derivatives on Nifty Junior & CNX 100.
Oct 2007	NSE launches derivatives on Nifty Midcap -50.
1st Jan 2008	Trading of Chhota (Mini) Sensex at BSE.
1st Jan 2008	Trading of mini index futures & options at NSE.
3rd March 2009	Long term options contracts on S&P CNX Nifty Index.
29th Aug 2008	Trading of currency futures at NSE.
Aug 2008	Launch of interest rate futures.
1st Oct 2008	Currency derivative introduced at BSE.
10th Dec 2008	S&P CNX Defty futures & options at NSE.
Aug 2009	Launch of interest rate futures at NSE.
7th Aug 2009	BSE-USE form alliance to develop currency & interest rate derivative markets.
18th Dec 2009	BSE's new derivatives rate to lower transaction costs for all.
Feb 2010	Launch of currency future on additional currency pairs at NSE.
April 2010	Financial derivatives exchange award of the year by Asian Banker to NSE.
July 2010	Commencement trading of S&P CNX Nifty futures on CME at NSE.
28th Oct 2010	Introduction of European style stock option at NSE.

29th Oct 2010	Introduction of Currency options on USD INR by NSE.
July 2011	Commencement of 91 day GOI trading Bill futures by NSE.
Aug 2011	Launch of derivative on Global Indices at NSE.
Sep 2011	Launch of derivative on CNX PSE & CNX infrastructure Indices at NSE.
30th March 2012	BSE launched trading in BRICSMART index derivatives.

Source: NSE and BSE

Appendix-4

4.1. What is a Derivative?

A derivative security is a financial contract whose value is derived from the value of underlying assets such as equity, equity index, fixed income instrument, foreign currencies, commodities, weather, credit events, etc. The Securities Contracts (Regulation) Act 1956 of India defines "derivative" under section 2(ac). As per this,the term "Derivative" includes

(i) "a security derived from a debt instrument, share, loan whether secured or unsecured, risk instrument or contract for differences or any other form of security."

(ii) "a contract which derived its value from the price, or index of prices at underlying securities."

4.2. Types of Derivatives Market Instruments

The most commonly used derivatives contracts are forwards, futures, options and swaps. Here we take a brief look at the various derivatives contracts that are trading in the world derivatives market.

4.2.1. Option Contracts

Option is a contract between two parties – the buyer and the seller, that gives the buyer of the option the right but not the obligation to buy (sell), and the seller the obligation and not the right to sell (buy)(as the case may be, depending on the type of option) the underlying asset at a later (prespecified) date at a pre-decided price which is fixed on today (time of writing the contract).

In an exchange traded option the option buyer pays some amount of money to the option seller called as premium, which is decided by the exchange. And the option seller pays the margin. There are basically two types of options – a call option and a put option. A call option is an option which gives the holder the right to buy the underlying asset on (by) a fixed date, and for a fixed price. A put option is an option which gives the holder the right to sell the underlying asset on (by) a fixed date for a fixed price. The price specified in the contract is known as the strike price or the exercise price; the date of exercise of option is known as the expiration date or maturity date. Depending upon the expiration procedure there are two types of option

– American and European. American options can be exercised at any time up to the expiration date and European options can be exercised only on the expiration date.

Although options trade in an organized market, a large amount of options trading is conducted privately between two parties who find that contracting with each other may be preferable to a public transaction on the exchange. This type of market, called over-the-counter market, was actually first type of market. But after an organized option exchange came into being in 1973, the interest of over-the-counter market started declining.However, subsequently, over-the-counter market has been revived and is now very large and widely used, mostly by corporations and financial institutions. In this study we focus on option that are traded on an organized options exchange that is NSE (National Stock Exchange of India).

4.2.2. Forward Contracts

A forward is a contract negotiated between two parities the buyer and the seller to buy or sell a commodity or financial asset at a later date at a price agreed upon today. One of the parties in a forward transaction takes a long position that means he has agreed to buy the underlying asset on a fixed future date for a fixed price. The other party assumes a short position that means he has agreed to sell the underlying asset on a fixed future date for a fixed price. A forward contract may appear like an option contract but an option buyer carries the rights, not the obligation, to go through with the transaction. If the price of the underlying asset change and it is unfavorable for him on maturity date, the option holder may decide to forgo buying (selling) at the fixed price. On the other hand in the case of forward contact, the two parties incur the obligation to ultimately buy and sell the asset. They cannot forgo buying and selling.

Forward markets for foreign exchange have existed for many years. According to the Bank of International Settlements the volume of forward transactions is around $475 billion per day. Forward contracts on physical commodities are also commonly observable. Forward contracts on both foreign exchange market and physical commodity market involve physical settlement at the maturity. That means on the final settlement the seller has to deliver the asset physically. Many forward contacts are however cash settled forward contracts. At the maturity of such contacts, the long position holder receives a cash payment if on the expiry date the spot price of the underlying asset is above the purchase price specified in the contract. If on the expiry date the spot price of the underlying asset is below the purchase price specified in the contract, then the long position holder makes cash payment.

4.2.3. Futures Contracts

Like a forward contract, a futures contract is also a contract between two parties a buyer and seller to buy/sell something at a future date at a price agreed upon today. Futures contracts evolved out of forward contracts and possess many of the same characteristics. In real meaning, they are like the liquid forward contracts which are traded on an organized market.

Futures contracts differ from forward contracts on the basis of the daily settlement procedure. In the daily settlement, investors or traders, who incur losses, pay the losses every day to the investors or traders who make profits. In the field of financial derivatives it is called as mark to market. By daily fluctuations of futures contracts, buyers and sellers attempt both to profit from these price changes and to lower the risk of transacting in the underlying assets. Another major difference is that a futures contract is a standardized contract, traded on a futures exchange, to buy or sell a certain underlying asset at a certain date in the future, at a specified price. There is an interesting contract on futures, that is the option futures. An option on futures contract gives the buyer the right to buy or sell a futures contract at a later date at a price agreed upon today. It is the most versatile of risk management contracts. These contracts can be used to protect against an adverse price movements in equity, commodity, fixed income and foreign exchange market. Whether they are traded for the purpose of hedging or speculation, the risk involved can be limited to the amount of up front premium for the option. Because of these characteristics they are popular as a hedging vehicle, and have been used by corporates, treasury, banks, farmers and equity portfolio managers etc throughout the world.

4.2.4. SWAP Contracts

Options, forwards and futures compose the set of basic instruments of the derivatives market. Yet, there are many more combinations and variety of derivatives contracts. One of the most popular derivatives contract is called a swap. A swap is a contract where two parties agree to exchange two different streams of cash flows at specified intervals over a specified period of time. The swap payments are based on an agreed principal amount, which is called as notional amount. There is no intermediate payment of money and hence, the swap agreement itself provides no new funds to either party. In standard contract, a swap contract could call for the exchange of anything. In current practice however, most swaps involve the exchange of returns interest rates, commodities, currencies or securities.

4.3. Importance of Derivatives Market

There is a future risk associated with the market; derivatives market provides a range of benefits for minimizing that risk. Not only can the businesses around the world effectively use derivatives to hedge risks by reducing uncertainty about future prices, thederivatives also encourage investments, since investors can achieve better returns at a lower cost. The derivatives also fulfill a significant function in the price discovery of assets.

4.3.1. Protection against Risk

Derivatives play a critical role in the financial market by enabling businesses, government, financial institutions, and institutional investors to effectively manage various risks associated with their business activities or business assets. For example, market participants use derivatives to hedge against market risk. Market risk may be arising from events such as fluctuation in the relative value of foreign currencies, bankruptcy, or by changes in the interest rate. Derivatives contract not only counter the market risk, but also the counterparty risk. Counterparty risk arises by the possible default of a contract. Derivatives contract performs this function better than the other risk management tools because they are liquid with low transaction costs, have a sizeable depth of the market, and are more readily accessible as compared with other financial products.

4.3.2. Price Discovery

For efficient economic system, discovering of present and future price of any asset class plays a crucial role. Derivatives as financial instruments do that efficiently. The prices of any asset class tend to move up or down depending upon the market participant expectations on the market. Hence, the price in the futures market reveals the demand – supply expectation in the future and thus undertakes the process of price discovery in the spot market. That is why the prices of derivatives converge with the prices of the underlying asset at the expiration of the derivatives contracts.

4.3.3. Speculation Activities

Speculators, due to their volume of activity, drive prices in one direction and then in the other, thus causing upward and downward movements in prices.What drives the price is not always the fundament factors, but often it is the sentiment of the market. There are mainly two types of speculators: one is rational and other one is irrational. An irrational speculator may lose in the process of speculation by an uneven jump in the market without knowing much about the market. But, the rational speculators would jump in and take a position on any mispricing in the market and this will result in the price being brought back to equilibrium. For example, if a speculator thinks that an asset in the derivatives market is overpriced and hence its price may fall, he would immediately jump in and sell the derivatives contract. The masses follow the trend and that results in a large sell off in the market and thereby it brings the contract back to its actual worth. They also add liquidity to the markets. So, speculative activity is required to maintain that balance in the derivatives market.

4.4. Players in Derivatives Market

Number of participants in derivatives market have been seeing increases. Participants exhibit different kinds of behavior when they are trading in the derivatives market. Depending on the purpose of participation, there are mainly three types of players in the derivatives market: hedgers, speculators, and arbitrageurs. Hedgers use futures, forwards, options, and swaps to reduce the risk that they face from uneven future price movement in the market. Speculators are those who bet on the future movement of the asset price. They are never interested in actually owning the asset. They will just buy from one end and sell it to the other in expectation of future price movements. Arbitrageurs are those who take advantage of discrepancy between prices in two different markets.

4.4.1. Hedgers

The word hedge means protection. The dictionary states that hedge is " a contract entered into or asset held as a protection against possible financial loss". That means hedgers use the derivatives markets to protect their losses due to unfavorable movements in the price. In futures trading environment the hedger is counterbalancing his transaction involving a position in the futures market that is opposite of the position in the cash market. Since the cash market price and futures market price of an asset are likely to be correlated, any loss or gain in the cash market will be roughly offset or counterbalanced in the futures market. In the option market there is concept called delta[18] hedging. In delta hedging the hedger establishes a delta equivalent long (short) position in the underlying reference against a short (long) position in the option.

4.4.2. Speculator

Speculators facilitate hedgers by providing liquidity in the market. The speculators are those participants who have the ability to enter and exit the market quickly, easily and efficiently. These traders are day traders who are attracted by the opportunity to realize a profit if they prove to be correct in anticipating the direction and timing of price changes. These speculators may be part of the general public or they may be professional traders, including members of an exchange trading either on the electronic platform or on the trading floor. Some exchange members are noted for their willingness to buy and sell on even the smallest of price changes.

They speculate on the price movements during a single trading day, thus open and close positions many times a day, but do not carry any position at the end of the day. They are also called jobbers. They monitor the prices continuously and generally attempt to make profit from just a few ticks per trade. Yet, all the speculators are not jobbers – some are traders who take a position for a longer time period, may be for a few days, weeks or even months to make a profit. For price prediction, they use fundamental analysis, technical analysis and other information available in the market.

4.4.3. Arbitrage

An arbitraguer is always attempting to earn a risk free profit by simultaneous purchase and sell of a commodity or asset in different markets with the sole intent to

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[18] Delta= $\frac{\Delta C}{\Delta S}$ where C is option price and S is spot price

make profit from the difference in buying and selling prices. The arbitraguer is an important intermediary that helps in the price discovery mechanism in all markets, be it equity, fixed income, forex or derivatives. In a security market, the arbitrage traders will simultaneously buy and sell the same or closely related securities. They take advantage of the price differences in two separate markets such as the NSE and the BSE. If the security market is perfect, then there would never be any arbitrage traders or trades. Since the securities markets are not perfect when news or other information comes into the market, at that time the movement in the security or index prices are temporally unequal in two different markets for the same security or index. If the markets were perfect, all identical securities would trade at the same price in each market they were traded on. Another opportunity to make gains by arbitrage is taken advantage of by observing the cost of carry. Let us say the cash price of a stock is ahead of its futures price. Atthat point of time an arbitrage trader will sell the stock on the cash market and buy the futures. The arbitrage ends up with the same or closely related investment but they have just made profit by taking the difference in the prices from the two separate markets.

In India there is also a group of traders who are doing an arbitrage between India and international market. For example, crude futures traded in MCX (Multi commodity Exchange) whose final settlement price is taken from NYMEX(New York Mercantile Exchange). Thus, arbitraguers may make gains by taking a long or short position in MCX and taking the opposite position in NYMEX (New York Mercantile Exchange). They also simultaneously take a position in currency futures to hedge the currency risk. With the above function over the past 25 years, the financial market has seen strong growth and innovation, and derivatives have contributed substantially to this impressive growth and increase the efficiency of the world financial market.