MODELLING VOLATILITY IN EQUITY MARKET IN INDIA: AN EMPIRICAL STUDY

Thesis submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

In

COMMERCE

to the

GOA UNIVERSITY

By

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V. V. M.’s Shree Damodar College of Commerce and Economics

Margao-Goa.

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Under the Guidance of

Dr. Y. V. Reddy

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DECLARATION

I, Ms. Keni Ganga alias Maithili / Maithili Sankalp Naik, hereby declare that the work reported in this thesis titled “Modelling Volatility in Equity Market in India: An empirical study” submitted to Goa University in partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy in Commerce is an authentic record of my work carried out under the supervision of Dr. Y. V. Reddy, Registrar, Goa University.

This work has not previously formed the basis for the award of any Degree, Diploma or Certificate of this or any other university. The references made to the previous works of other authors have been clearly indicated and duly acknowledged in the list of references.

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CERTIFICATE

This is to certify that the work reported in the PhD thesis titled "Modelling Volatility in Equity Market in India: An Empirical Study" submitted by Keni Ganga alias Maithili /Maithili Sankalp Naik to Goa University for the degree of Doctor of Philosophy in Commerce is a bonafide record of original work carried out by her under my supervision and guidance.

This work has neither been submitted in part nor in full to any university or institution of learning for the award of any degree or diploma.

PROF. Y. V. REDDY

Registrar

Goa University

Date:

Place: Goa University, Taleigao-Goa.

A life that touches others goes on forever……

Dedicated

To My Late Father

Shri. Girish A. Keni

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LIST OF ABBREVIATIONS

ABBREVIATION	FULL FORM
ACF	Auto Correlation Function
ADF	Augmented Dickey Fuller
AIC	Akaike Information Criteria
ARCH	Autoregressive Conditional Heteroskedastic
LM	Lagrange's Multiplier
AR	Autoregressive
ARMA	Autoregressive Moving Average
BoP	Balance of Payment
BPM5	Balance of Payment Manual, 5th Edition
BRIC	Brazil Russia India China
BS	Black Scholes
BSE	Bombay Stock exchange
CBOE	Chicago Board of Options Exchange
CPI	Consumer Price Index
CRR	Cash Reserve Ratio
CSO	Central Statistics Office
CURBAL	Current Account Balance
DCC	Dynamic Conditional Correlation
DEF	Deficite
DGE&T	Director General of Employment and Training
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedastic
EMH	Efficient Market Hypothesis
EMPY	Employment
EWMA	Exponentially Weighted Moving Average
F&O	Futures and Options
FII	Foreign Institutional Investors
FOMC	Federal Open Market Committee
GARCH	Generalized Autoregressive Conditional Heteroskedastic

GDP	Gross Domestic Product
GJR	Golsten,Jagannathan and Runkle
HQIC	Hannan-Quinn Information Criteria
IGARCH	Integrated Generalised Autoregressive Conditional Heteroskedasticity
IIP	Index of Industrial Production
IMF	International Monetary Fund
INF	Inflation
IRF	Impulse Response Function
ISD	Implied Standard Deviation
IVIX	India Volatility Index
JB	Jarque Bera
KPSS	Kwiatkowski Phillips Schmidt Shin
LBQ	Ljung-Box Q
LIFFE	London International Financial futures Exchange
LR	Likelihood ratio
MAE	Mean Absolute Error
MAPE	Mean Absolute Percent Error
MAT	Minimum Alternate Tax
MCIR	Monetary Credit Information Review
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedastic
MI	Monetary Information
MIDAS	Mixed Data Sampling
MONEP	Marche des options Negociables
NSE	National Stock Exchange
NSSO	National Sample Survey Organisation
OLS	Ordinary Least Square
OMO	Open Market Operations
OTC	Over The Counter
PACF	Partial Auto Correlation Function
PGARCH	Power Generalized Autoregressive Conditional

	Heteroskedastic
PP	Philip-Perron
PPI	Producer price Index
RBI	Reserve Bank of India
RMSE	Root Mean Square error
S&P	Standard and Poor's
SDDS	Special Data Dissemination Standards
SEBI	Securities and Exchange Board of India
SIC	Schwarz Information Criteria
SPA	Superior Predictive Ability
SV	Stochastic Volatility
TGARCH	Threshhold Generalized Autoregressive Conditional Heteroskedastic
VAEX	Volatility Index for Amsterdam Exchange Index
VaR	Value at Risk
VAR	Vector Auto regressive
VCAC	Volatility Index for Cotation Assistee en Continu
VDA	Variance Decomposition Analysis
VDAX	Volatility Index for DAX
VIX	Volatility Index
VKOSPI	Volatility Index for Korea Composite Stock Price Index
VXD	Dow Jones Industrial Average Volatility Index
VXN	Nasdaq Market Volatility Index
WPI	Wholesale Price Index
WSE	Warsaw Stock Exchange

INTRODUCTION

1.1 VOLATILITY AND FINANCIAL RISK MANAGEMENT:

The etymology of the word *"Volatile"* can be traced back to the Latin verb "*volare*", which means "to fly". By the end of the 16th century, it was used as an adjective for things that were so light they seemed ready to fly. The adjective was soon extended to vapors and gases, and by the early 17th century, *volatile* was being applied to individuals or things that were prone to sudden change. In recent years, the word *volatile* is used aggressively in financial, political, and technical contexts. Volatility mainly indicates the spread of all outcomes of a variable that is uncertain. Versatility, inconsistency or unsteadiness of something can be expressed as volatility. Volatility could simply be defined as sudden movements or variations in financial asset prices. A variable demonstrating very high increase or decrease based on its mean value may be considered volatile. Such patterns are commonly observed in stock prices, exchange rate, inflation rate and other similar variables.

Return volatility, is of course, central to financial economics. It is synchronized with the concept of risk and uncertainty. And sometimes these terms are used interchangeably. But even though volatility is related to risk, it is not exactly the same (Ladokhin, 2009). Risk is associated with the uncertainty of a negative outcome of a variable, whereas spread of outcomes is measured by volatility. This could include positive, as well as, negative results. In financial risk management, volatility it is a vital parameter used in options and derivative pricing models. The Black Scholes model and Binomial Tree model of pricing are extensively used approaches in evaluation of major class of derivatives like

Options, Futures/Forwards and Swaps. But all these approaches lay great emphasis on volatility in pricing of the above products. Volatility forecasting also finds its use in financial ratios like Sharpe's ratio that helps in comparing investment performance and also in risk management applications like Value at Risk (VaR). Financial theories, like the Modern Portfolio Theory, use volatility to compute an optimal portfolio that maximises and diversifies risk. Thus volatility finds its use in many applications of financial management.

In financial markets, volatility presents a strange puzzle to policy makers, market participants, and academicians as without sufficient volatility in the market superior returns cannot be earned. But if the volatility is "high" it leads to substantial losses for the market participants, as well as, to the overall economy. Therefore volatility estimation is an essential part in most finance decisions be it asset allocation, derivative pricing or risk management (Eryllmaz, 2015). Volatility of a variable is measured using standard deviation. The basic formula used is

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \mu)^2}$$

Where, r_t represents the returns of an asset over period *t*, and μ is the average returns over period T. The other measure of volatility is the variance σ^2. Beta coefficient is also considered an indicator of volatility or risk. It determines the variations in stock returns in comparison to market returns. Understanding and measuring volatility is of great significance to players in financial markets. Because high levels of volatility in financial market prices (returns) have the ability to create negative effects on risk averse investors. Besides, such changes in volatility also affect the consumption patterns, corporate capital, leverage ratio, business measures and macroeconomic variables.

1.2 STYLIZED FACTS OF VOLATILITY:

Certain properties of volatility have emerged which make it forecastable

1.2.1 Volatility Clustering: Volatility clustering means that the large variations of financial returns are followed by large changes and small changes tend to be immediately followed by small changes. Thus volatility does not remain constant over time and clusters of volatility are formed. Volatility clustering happens as a result of investor inertia, which is caused by investor threshold to the incorporation of new information (Ladokhin, 2009). This leads to a delay in financial returns to move back to the mean levels.

1.2.2 Leverage Effect: Leverage Effect indicates the negative asymmetric relations between volatility and asset returns. This means that volatility is higher in a falling market. The volatility of stock prices rise when they drop.

1.2.3 Mean Reversion: Another important stylized fact of volatility is that it reverts back to its mean levels over time. A period of high volatility will eventually be followed by a period of normal volatility and a period of low volatility will be followed by a rise in volatility.

1.2.4 Fat Tails: It is well documented that asset returns exhibit fatter/heavy tails in comparison to normal distribution. This results in higher Kurtosis values ranging between 4 and 50. Thus indicating extreme non-normality.

1.3 TYPES OF VOLATILITY:

While there are several methods for measuring volatility, **Historical Volatility** and **Implied Volatility** are two important metrics applied by options traders.

Historical volatility, gauges the variations of underlying securities by measuring price changes over predetermined periods of time. It is often referred to as realized volatility. Fluctuations in asset returns are measured based on intraday changes or based on the change from one closing price to the next. Historical volatility may be measured for periods ranging from 10 to 180 trading days, depending on the intended duration of trade of the investors. They can gain insights on relative values for the intended time frames of their options trades by comparing the percentage changes over longer periods of time. Volatility is almost always expressed in annual terms, regardless of the lookback period.

On the other hand, implied volatility measures the expected variations of an underlying stock or index over a specific period of time. It cannot be computed from historical prices of the stock, but rather is a by-product of an option pricing model. In the simplest terms, implied volatility can be referred to as the market's expectation of the future volatility of the stock price between now and the option's expiration. Like historical volatility, implied volatility is always expressed as an annualized percentage to make comparison of values more straightforward.

As historical volatility measures past metrics, investors tend to combine this data with implied volatility, which takes forward-looking readings on option premiums at the time of the trade. The relationship between historical and implied volatility is such that, historical volatility reading serves as the baseline, while fluctuations in implied volatility define the relative values of option premiums. When the two measures represent similar values, options premiums are generally considered to be fairly valued, based on historical norms. Options traders seek the deviations from this state of equilibrium to take advantage of overvalued or undervalued option premiums.

1.4 MACROECONOMIC CONDITIONS AND VOLATILITY:

The stock market volatility is significantly influenced by macroeconomic factors. The key macroeconomic reasons for volatility are listed below:

1.4.1 Foreign Institutional Investors (FIIs): The Indian Stock market opened up for Foreign Institutional Investors in the year 1993. FIIs are Investment, Insurance, Mutual Funds, Pension Fund Companies and Charitable Institutions that invest in the Indian equity market, but are incorporated outside India. The FII inflow is a prime source of funds for stock markets worldwide. In India, SEBI monitors the activities of the FIIs and lays down eligibility, investment, and taxation parameters. The FIIs have to compulsorily register with SEBI if they want to invest in the Indian stock market. In addition to this, mandatory approval from the RBI has to be obtained while converting the rupee to foreign currency transactions from FII accounts. At present, the guidelines for FII holding is set at 40% in any listed company for equities. FII investment has tremendous advantage in the form of improvement in market efficiency, reduction in capital investment cost, strengthening the corporate sector, and so on. FII inflows also represent “investor sentiments”. A sudden FII outflow, directly affects the investor sentiments and therefore affects the overall market speculation.

1.4.2 Impact of Global Economy: The domestic markets are largely affected by developments/events in the global markets. Any positive or negative news in the global market such as economic slowdown, crises, crude oil prices, rise in commodity prices give rise to volatility in local market. Indian economy has reported a strong economic growth in the last few years and investment inflows into the Indian market is on the rise. As discussed earlier, the foreign investors (FIIs) are large entities and their entry and exit in the market results in large volatility in stock markets. The funds are mostly influenced by the foreign markets. As a result, global events and global market movements reflect in our own stock markets. Therefore, negative news from an overseas market, triggers a short-term avalanche in the Indian markets. With the introduction of market liberalization policies, the share of Indian trade in the global market is on the rise. The contribution of the revenue by the Indian companies coming from the foreign markets is also on the rise every fiscal year. Therefore, share price of these companies is more likely to grow, as noticeable revenue is coming from out-shore business. With the growth of international market integration, the domestic market becomes vulnerable to the risks as and when there are developments in the world economy.

1.4.3 Inflation: Inflation indicates the rate of change in the price of goods and services. Inflation is measured with the help of Consumer Price Index (CPI). It is the average price of a basket of goods and services purchased by households. With the rise in inflation there is an erosion in the purchasing power of money, as each unit of currency buys fewer things. Inflation is often considered a culprit for stock market volatility.

Implications of high inflation are that it leads to a decline in the real value of currency and other monetary avenues over time. High inflation levels leads to shortage of goods and uncertainty over future inflation discourages investment and savings. High inflation, if left unchecked, could lead to increase in unemployment and a recessionary trend in the business cycle. Thus investors consider inflation as a warning of a slowdown in the market. Economists favour a steady level of inflation as a steady inflation rate helps in mitigating economic recession and stabilizes the economy by reducing the real level of debt.

1.4.4 RBI Policy: The Reserve Bank of India (RBI) is India's central bank which formulates the monetary policy. Through the monetary policy, the RBI controls the money supply in the economy. The Open Market Operations (OMO), altering benchmark rates, and changing reserve requirements of the banks, are some methods employed by the RBI to control inflation and interest rates which are the key parameters for economic growth. The impact of monetary policy is mainly three folds. Firstly, it affects the liquidity of the market. Whenever there is a change in the benchmark rate (Repo Rate) hike or rate cut, there will be a gush of liquidity inflow or outflow in terms of FII inflow or outflow in the market. Secondly, monetary policy will have implications on the cost of borrowing for individuals, as well as corporates. And lastly, the changes in benchmark interest rates will affect the valuation of companies, thus leading to adjustment in company stock prices whenever there is a monetary policy change. Apart from the above there are investor sentiments (expectations, anticipation of RBI’s next move, etc) that affect the stock market volatility.

1.4.5 Government Policies: Amendments in government policies lead to volatility in stock markets. In recent times the markets have reacted sharply to key government decisions like demonitisation, the implementation of Goods and Service Tax, passing of the Land Acquisition Act, etc. But slower-than-expected recovery in the economy and corporate earnings was also noticed due to unnecessary and avoidable moves of the government like the demand notices issued to Foreign Institutional Investors (FII) levying the Minimum Alternate Tax (MAT) with retrospective effect.

1.4.6 Other Factors: Apart from the factors discussed above there are certain external factors which can lead to a volatile market. Some of them are namely,

- Political Instability: This can be regarded as the single most major reason for a crash in the stock market. No investors will prefer to invest in an unstable political scenario and will definitely look for profit elsewhere. Turmoil in politics has no explanation for an impact on the growth of companies. However, stock markets always negatively respond to political instability.
- Negative news: Havoc is bound to be created in stock markets when markets start to rise unexpectedly within a short time, thus creating negative news. Markets negative news like rise in crude prices, dollar appreciation, fed rate cut, and US visa restrictions had showed slowdown in economic growth.

- Economic growth: High growth sectors for economic growth are primarily the capital goods and power sectors which also leads to a volatile market.
- Profit booking: Investors sometimes book profits just before every crash whether it was in 2000, 2006, or 2008. However, there is an equal number of investors losing money in every crash.

1.5 MEASURES TO CONTROL VOLATILITY:

The following measures have been adopted to control volatility:

1.5.1 Circuit Breakers: As discussed earlier, stock prices can move in either direction due to various reasons, such as, investments, government policies, market conditions, etc. Adversely, they also respond radically due to manipulation, greed by speculators, and investor's fear. In order to control such harmful and extreme movements of price fluctuations, there is a dependable system in the stock exchanges, called the 'circuit breakers'. When the exchange triggers the circuit breakers nationwide, the complete equity and derivative markets trading is halted. In July 2001, the NSE implemented index based market-wide circuit breakers to ensure safety of the investors. SEBI has partially revised the earlier guidelines on September 03, 2013. According to the revised guidelines, the index-based market-wide circuit breaker system is applicable at three check points of the index movement: 10%; 15%; and 20% respectively. The index-based market-wide circuit breakers are triggered by movement of any of the BSE Sensex or the NSE Nifty, whichever is breached earlier. The trigger of circuit limits also depends on the time at which it occurs. The circuit breakers operate as follows:

10% movement in either direction

- If the movement is before 1 pm - 45 minutes halt

- If the movement is after 1 pm but before 2:30 pm - 15 minutes halt
- If the movement is after 2.30 pm - no halt

15% movement in either direction after the above mentioned halts, trading starts again. If the market hits 10% again, there will not be any halts, but if it breaches 15%, circuit limits comes to play again.

- If the movement is before 1 pm – 1 hour 45 minutes halt
- If the movement is after 1 pm but before 2 pm - 45 minutes halt
- If the movement is after 2 pm - remainder of the day

20% movement in either direction on resumption – if the market hits 20%, trading will be halted for the remainder of the day. The above percentage is calculated on the closing value of the Sensex or the Nifty on the last day of the immediate preceding quarter.

1.5.2 Pre Open Session: In 2010, SEBI introduced the pre trading/pre open session to settle on an agreeable opening price. The Pre-Open session was a necessary move introduced to reduce volatility due to an abrupt opening of the market and to channelize the liquidity. The opening price reflects the overnight news in securities and an equilibrium price is reached which is the result of the demand and supply of the assets and is not based on the opening trade price. The pre-open session is scheduled for 15 minutes starting from 9 am and lasting up to 9:15 am. The duration of the session is sub divided into three parts: First, 8 minutes for order entry, modification, cancellation. Next 4 minutes is allowed for order matching and trade confirmation and remaining 3 minutes are allotted as buffer for trade transition. All BSE Sensex and NSE Nifty securities form a part of the pre-trading session.

1.5.3 Increase in Market timings: Global markets have a profound influence on the Indian stock market. The information that flows from other parts of world has an influence on securities' prices. The Asian markets open before the Indian stock market due to a difference in time zone, whereas, the European and American markets have extended market timings. An increase in market timings helps in readily assimilating the information from these global markets. This acts as risk hedging that might arise due to global information flow. This has a considerable advantage as the increase in market timings helps in readily assimilating the information from markets, reduces volatility and its impact cost. There is an advantage of trading positions over a longer time window responding to the market movements overseas. Presently, the exchange-traded equity derivatives market is open from 9:55 am to 3:30 pm. While exchange-traded currency derivatives market operates from 9:00 am to 5:00 pm, exchange-traded commodity futures market operates from 8:00 am till 11:30 pm.

1.5.4 Market Surveillance: SEBI set up the Market Surveillance division in July 1995. It plays a crucial role of ensuring market safety and integrity by monitoring the activities of the stock exchanges. SEBI provides the market surveillance on movements and trends, and further analyses the same. When reported about any specific complaints regarding inside trading, preliminary inquiries are conducted to determine events of market manipulation, insider dealing, or any other suspicious activity. In cases of confirmatory reporting of the trading misuse, the client details and records are obtained from the stock brokers, and necessary actions are initiated. There is a provision of risk containment which ensures safety of market as a system. All the stock exchanges have an elaborate margining system in the stock market i.e. by mark to market margins, daily margins, and adding limits to intraday trading.

1.6 IMPLIED VOLATILITY AND OPTION PRICING:

Implied volatility is one of the deciding factors in the pricing of options. Options, which give the buyer the opportunity to buy or sell an asset at a specific price during a pre-determined period of time, have higher premiums with high levels of implied volatility, and vice versa. The option value, C, is usually defined as a function of five factors, known as the direct determinants of an option value in the Option Pricing Theory such as the Black-Scholes Theory:

$$c = f(s_t, K, T - t, r, \sigma)$$

Where, S_t is the underlying asset price at time t, K indicates the strike price of the option, r the risk-free interest rate, T-t the time to maturity of the option, and σ denotes the volatility of the underlying asset returns over the remaining life of the option. In the Black–Scholes framework, of these five direct determinants explained, barring volatility, all others are observable in the market. But it is possible to find the volatility value if the market price of an option is known. Thus σ_{iv}, can be expressed as, $\sigma_{iv=} f^{-1}(C_t)$, It is obtained by inverting the pricing function, where f^{-1} is the inverse function of *f*. This volatility estimate is the market's assessment of the future volatility over the remaining life of the option. The volatility value which is derived by inverting the option pricing model is called implied volatility and it is given by

$$\sigma_{isd} = f^{-1}(C_t, S_t, K, T - t, r)$$

where, f^{-1} is the inverse function of f. In 1979, Merton showed that Implied volatility is the market's expectation of the underlying asset's average return volatility over the remaining life of the option in the deterministic volatility case. By equating the market price of an index option to its model value and solving for volatility, we identify the implied (by the option price) volatility. This implied volatility is the market's "best" assessment of the expected volatility of the underlying asset (in this case, a stock index) over the remaining life of the option.

It is important to remember that implied volatility is all probability. It is only an estimate of future prices, rather than an indication of them. Even though investors take implied volatility into account when making investment decisions, and this dependence inevitably has some impact on the prices themselves, there is no guarantee that an option's price will follow the predicted pattern. However, when considering an investment, it does help to consider the actions other investors are taking in relation to the option, and implied volatility is directly correlated with market opinion, which does in turn affect option pricing. Another important thing to note is that implied volatility does not predict the direction in which the price change will go. For example, high volatility means a large price swing, but the price could swing very high or very low or both. Low volatility means that the price most likely won't make broad, unpredictable changes.

1.7 IMPLIED VOLATILITY INDEX:

Gastineau, in 1977, was the first academician to propose a volatility Index based on option market prices. This was a few years after the Chicago Board of Options Exchange (CBOE) introduced the trading of the first option contract in 1973. Several researchers tried to follow Gastineau's model, but it was the seminal work of Robert Whaley (1993) that paved the way for indices based on implied volatility. Robert Whaley, in 1993, developed an innovative model-free methodology of calculating an implied volatility index. It was based on index options, instead of individual stock options, both call and put options were used in its computation, thus making it more efficient to capture information content. Soon the CBOE adopted this methodology and became the first organized exchange to officially introduce an implied volatility index called the VIX. The VIX gained popularity and today is considered the benchmark risk measure of the US equity market.

In understanding VIX, it is significant to highlight that it is forward-looking, measuring the volatility that investors expect to see. Like the Dow Jones Index, the VIX is also computed on a real-time basis throughout each trading day. The only significant difference is that the VIX measures volatility and not price. The VIX is more of a barometer of investors' sentiments. An implied volatility index is often referred to as the "investors' fear gauge" (Whaley, Understanding VIX, 2009) as the level of VIX indicates the consensus view on the expected future realized stock index volatility. A rise in the level of volatility index leads to an increase in insecurity and fear in the market; alternatively, a decline in the level of volatility index is an indication of optimism and triggers run-ups in the daily stock index prices. Additionally, the VIX levels also indicates the degree of willingness of market participants to pay in terms of volatility in order to hedge the downside risk of their portfolios with put options, or long positions in call options with limited downside risks instead of positions in the underlying asset. The main reasons for the introduction of VIX were, firstly, to provide a benchmark to measure expected short-term market volatility, and secondly, to provide an index upon which futures and options contracts on volatility could be written. In 2003, the CBOE changed the VIX methodology. The new VIX employs Whaley's model free methodology and is based on S&P 500 options which are considered the benchmark of the US stock market.

Following the exceptional success of the US VIX, other exchanges across the world followed suit and developed their own volatility indices. The CBOE and S&P soon announced the formation of the "VIX Network", a network of exchanges across the globe with agreement on the use of CBOE's VIX methodology. The objective of this network was to provide an information-sharing platform to users of the VIX methodology and to promote it as a global measure for computing stock market volatility.

1.8 INTERNATIONAL IMPLIED VOLATILITY INDICES:

The exceptionally success of VIX paved the way for other volatility indices worldwide. In 1994, the VDAX was introduced by Deutsche. The French Marche des Options Negociables de Paris (MONEP) introduced two implied volatility indices, VX1 and VX6 in 1997. The latest addition to the world of implied volatility indices family is the UK volatility index FTSE 100 Volatility Index, which came into existence in 2008. The Australian Stock Exchange, The German Deutsche Börse, Hang Seng Indexes in Hong Kong, National Stock Exchange of India, Euronext LIFFE, Taiwan Futures Exchange, and the TMX Group in Canada have entered into an agreement with CBOE to use the VIX methodology. The US CBOE has expanded its scope by initiating VIX measure for individual stocks such as VXAPL (Apple), VXAZN (Amazon) VXGS (Goldman Sachs), VXGOG (Google), VXIBM (IBM), as well as, securities linked to commodity, foreign exchange, energy, and global equity exchange traded funds and futures contracts.

1.9 INDIA VIX:

The Global crises of 2008, re-emphasised the influence of volatility on investment portfolios and market participants started exploring newer options to hedge their portfolios against market uncertainty. This lead to the introduction of India VIX in the Indian stock market. It is a volatility index computed by National Stock Exchange, the leading stock exchange in India. Based on NIFTY Options order book, it gauges the expected short-term volatility in the market. i.e. for the next 30 calendar days. Higher the India VIX values, higher the expected volatility and vice versa. (www.nseindia.com). The NSE uses the computation methodology of the CBOE for the calculation of India VIX with suitable amendments for the Indian market. The India VIX indicates the investor's perception of the expected market volatility over the next 30 calendar days.

The formula used in the India VIX calculation is:

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

Where,

σ India VIX/100 India VIX= σ x 100

T Time to expiration

Ki Strike price of i^{th} out-of-the-money option; a call if Ki > F and a put if Ki < F

ΔKi Interval between strike prices – half the distance between the strike on either side of Ki

R Risk-free interest rate to expiration

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

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

K0 First strike below the forward index level, F.

A high India VIX value would suggest that the market expects significant changes in the Nifty, while a low India VIX value would suggest that the market expects minimal change. It has also been observed that historically, a negative correlation exists between the two. Globally, exchanges are now offering derivative products based on the volatility index. These products have become quite popular among the participants as they expand the opportunities available to participants and provide efficient means to hedge against volatility. Some studies have also shown that derivatives on volatility indices can be useful for portfolio diversification and hedging. In Feb 2014, NSE launched NVIX i.e. futures on its own volatility index India VIX. The trading symbol of the future contract is INDIAVIX.

1.10 MODELS FOR VOLATILITY:

Modelling and forecasting stock market volatility has been the subject of vast empirical and theoretical investigation over the past decade. The motivations for this line of research are numerous. Volatility is the central concept in finance. As discussed in the earlier sections, modelling and forecasting volatility holds immense significance in financial risk management. There are a number of time series volatility models to estimate volatility and to capture different properties of financial time series. According to a study done by (Poon & Granger, 2001) the models capturing the main features of volatility based on actual returns can be classified into the following three groups, namely: (i) Historical Price Models;

(ii) ARCH Class Conditional Volatility Models; and (iii) Stochastic Volatility Models.

(i) Historical Volatility: Historical volatility simply involves calculating the variance (or standard deviation) of returns in the usual way over some historical period, and this then becomes the volatility forecast for all future period. *Random Walk model* is the simplest historical price model which is given by: $\sigma_t^2 = \sigma_{t-1}^2 + \varepsilon_t$ where, σ_t^2 is a white noise series and σ_{t-1}^2 is used as a forecast for σ_t^2. Several other extensions of the Random Walk model are the *Historical Average model, the simple Moving Average model, the Exponential Smoothing method and the Exponentially Weighted Moving Average (EWMA) model.* In case of the two exponential models greater emphasis is given to more recent estimates of volatilities. In the class of historical price models we may also include the *Simple Regression model* in which volatility is expressed as a function of its past values and an error term i.e. $\sigma_t^2 = \sum_{i=1}^{t-1} \beta_i \sigma_{t-i}^2 + \varepsilon_t$

(ii) ARCH Class Conditional Volatility Models: For capturing volatility clusters in financial time series in a more sophisticated way the *Autoregressive Conditional Heteroskedastic (ARCH) and Generalized ARCH (GARCH) models* have been widely used. Engle (1982) first introduced Autoregressive Conditional Heteroscedastic (ARCH) processes which are mean zero serially uncorrelated processes with non constant variances conditional on the past, but constant unconditional variances. For *ARCH processes* recent past gives information about the one-period forecast variance. The ARCH(q) model with variance (h_t) can be represented as: $h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2, \omega > 0, \alpha_i \geq 0$ (Bollerslev, 1986) generalized the ARCH model proposed by Engle assuming that conditional on information available at time t-1, variance is a linear function of both lagged conditional variances and of squared residual returns. Following Bollerslev, the *Generalized ARCH [GARCH (p, q)]* model can be represented as $h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$, Where $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ and the sum of $\alpha_i + \beta_j < 1$ for variance to be finite.

In 1976, Black suggested that changes in volatility were found to be negatively correlated with changes in the stock prices, i.e., volatility was higher in a falling market than in a rising market. This phenomenon is known as 'leverage effect'. Though it is well known that the empirical models allowing 'leverage' effects dominate the standard GARCH specifications, but factors other than leverage behind the observed asymmetries are also recognized. Three famous GARCH formulations describing the asymmetry in financial markets are *Exponential GARCH (EGARCH)* model by Nelson; *Threshold GARCH (TGARCH or GJR GARCH) model* by Golsten, Jagannathen and Runkle; and *Power GARCH (PGARCH) model* by Ding, Granger and Engle. Nelson (1991) developed the EGARCH model in which the conditional variance is specified in logarithmic form and thus avoided the need of imposing the constraint of non-negative parameter restrictions. In the EGARCH model the innovation is so appropriately weighed that it can capture the asymmetric nature of volatility in the financial market, thus correcting the weakness of the GARCH model.

Nelson's specification for the log variances is

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

Lawrence Golsten, Ravi Jagannathan, and David Runkle (1993) developed another type of GARCH model which can capture the feature of asymmetric response of volatility in financial market, known as **Threshold GARCH model (TGARCH) or GJR GARCH** model. The variance in the TGARCH (p, q) model takes the following form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

Z. Ding, C. W. Granger, and R. F. Engle (1993) also developed a different variant of the GARCH model named Power GARCH (PGARCH) model which is capable of capturing asymmetric response of volatility to positive and negative innovations.

(iii) Stochastic Volatility Models: Stochastic Volatility models are used to evaluate volatilities of derivative securities, such as options. When volatility of the underlying price follows a stochastic process rather than being a constant, it immediately implies that the distribution of returns is fat tailed. Although due to the existence of volatility noise term the Stochastic Volatility (SV) models are relatively more flexible, yet this also resulted into nonexistence of any closed form of the SV model. Therefore, SV models cannot be estimated directly by using maximum likelihood method.

1.11 SIGNIFICANCE OF THE STUDY:

Volatility has always been an area of concern for market participants as it disrupts the smooth functioning of the stock market and creates an atmosphere of uncertainty and fear. It adversely affects the individual earnings, as well as, the country's economic progress. Volatility indicates the vulnerability of the financial market and therefore plays a key role in assessing the risk/return trade off. Thus understanding of volatility patterns become important Researchers worldwide are trying to identify the main source of volatility. Some believe that the arrival of new, unexpected information that affects expected returns on a stock (Engle and Mcfadden, 1994) leads to aggressive price movements. Others attribute volatility to changes in trading volume, practices or trends, which in turn are resolute by factors such as changes in macroeconomic policies or shifts in investor's risk appetite. In recent years, Stock exchanges worldwide have introduced a new information measure known as the volatility index. Volatility Index is a measure of the market's expectation of volatility over the near term. In India, NSE introduced its own volatility index based on the CBOE methodology. A volatility index may be considered as the best estimate of market uncertainty (Padhi, 2011) as it incorporates all the available information that is relevant for forming the expectation about the future volatility. Under the Efficient Market Hypothesis Theory (EMH), an efficient market immediately locks up all macroeconomic news. We expect stock prices to quickly adjust to fresh information and the VIX to react to inflow of news in the market. Thus examining the impact of scheduled macroeconomic news on the Indian Volatility Index (India VIX) will provide insight to investors whether to observe these news releases in their portfolio selection and management. The findings of the study will also reveal if it is essential for investors to consider the scheduled macroeconomic news in their financial planning.

In the present study we undertake the estimation of volatility in the Indian stock market by employing the GARCH family of models. We further explore the changes in volatility of returns on NSE before and after implementation of IVIX.

This will provide evidence to market participants and regulatory authorities if the introduction of volatility index has improved the speed and quality of information flowing in the Indian stock market and whether it has helped to curb spot market volatility in India.

Modelling and forecasting stock market volatility has always been an area of interest among market participants. This study will benefit the market participants as it will help them to know the most suitable model of India VIX prediction, consequently helping them to make informed investment decisions and explore the opportunities.

In recent years, the Indian stock market is highly integrated with the global markets with increased participation in terms of institutional investors. In the aftermath of the global financial crises it becomes essential to examine the volatility linkages among developed and emerging markets. Due to market integration, it is vital to know whether implied volatility spills over from one market to another, as this phenomenon will have implications for risk managers, international portfolio managers and option traders globally. They need to describe which market leads other markets and which market is a major source of implied information.

These questions will be specifically addressed through this study in the Indian context.

LITERATURE REVIEW AND RESEARCH METHODOLOGY

2.1 REVIEW OF LITERATURE

Implied volatility index is a futuristic estimate of volatility in the stock market. The interesting behaviour of the volatility index has led to an enormous amount of empirical work in this area. The usefulness of this index for the Indian market can be understood by examining its properties, behaviour, information content and information efficiency. The present study also focuses on the influence of scheduled macroeconomic announcements on the Indian volatility index, and the degree of volatility in the India stock market before and after implementation of the India VIX. In addition it intends to examine the volatility spill over phenomenon between major global indices and the India VIX. In order to get a better insight into the problem, a wide spectrum of existing literature will be reviewed before proceeding with our study. The review of available literature is categorised based on research objectives discussed later in this chapter.

2.1.1 Objective I: To study the impact of Scheduled macroeconomic announcements on Indian VIX.

Monique W. M. Donders and Ton C. F. Vorst (1996) study the Implied Volatility of options around scheduled news announcement days of the underlying stock. It is observed that the implied volatilities increases as the event day approaches and drops sharply post announcements. It gradually moves back to its long run level. The standard EGARCH Model or a Jump Diffusion Option Pricing model seem insufficient to describe this phenomena. However, an extended GARCH Model with structural breaks better describes the volatility and implications of schedule announcements.

Louis H. Ederington and Jae Ha Lee (1996) argue that the impact of news announcement on market volatility largely depends whether the news is scheduled or unscheduled. They study the impact of information releases on market uncertainty by considering the implied standard deviation from T-Bonds, Eurodollar and Deutschemark Option Markets. The scheduled macroeconomic announcements considered are employment report and producer price index. The authors observe that since the timings of the scheduled announcements are known in advance, the pre-release Implied Standard Deviations (ISDs) rise as it impounds the anticipated impact of important releases on volatility, and post release the uncertainty gets resolved and the ISDs decline. They also notice that major unscheduled announcements cause unexpectedly high volatility which causes market participants to upward their estimates of volatility over the remaining life of an option thus leading to an increase in the implied standard deviation. In addition, the authors also notice that ISDs rise on mondays and fall on fridays due to the weekly pattern of scheduled macroeconomic announcements.

John R. Nofsinger and Brian Prucyk (1999) investigate the influence of scheduled macroeconomic news on OEX Index options, as well as, on individual equity option volume. Their results indicate that announcements lead to an increase in OEX Index option volume but no change is observed in the volume of individual equity options. Announcements associated with consumer confidence and new home sales are observed to influence the highest trading response.

Antulio N. Bomfin (2000) analyses the pre-announcement and news effect on the stock market volatility. The news announcement considered is the monetary policy decision regarding target federal fund rates. The data indicates that the markets are calm before announcements i.e. the conditional volatility is abnormally low on pre-announcement day. On the news release day, the surprise element in the policy decision boosts the market volatility significantly. Positive surprises have greater impact on volatility than negative surprises.

Rohan Christie-David, Mukesh Choudhary, and Timothy W. Koch (2000) study the responses of gold and silver future prices to 23 monthly macroeconomic news release by US federal agencies. It is observed that both these metals respond strongly to the release of capacity utilization news. CPI, GDP & PPI news strongly affect gold prices whereas employment news affects both gold and silver. But, gold futures respond weekly to Federal Deficit News and Silver to CPI, hourly wages, business inventories and construction spending.

Jussi Nikkinen and Petri Sahlstrom (2001) study the impact of US macroeconomic news release on the implied volatility index of its own domestic market and also on foreign stock market i.e. the finish market. The US macroeconomic news announcements considered are PPI, CPI & Employment. The results of the research reveal that implied volatilities increase before the macroeconomic news release and falls after the announcement in the US and the finish market. This indicates that the volatility associated with the US news release is also reflected in the finish market. Of the three macroeconomic variables observed, employment news has the most impact on volatility.

Suk-Joong Kim, Micheal D. Mckenzee, and Robert W. Faff (2004) investigate the impact of scheduled government announcements relating to six different macroeconomic variables on the risk and returns of three major US financial markets (i.e. the Bond, Stock and Foreign exchange market). The authors undertake the analysis using the GARCH model. It is observed that BOT news has the greatest impact on the foreign exchange market. The news relating to GDP is found to be important in the bond market, and consumer and producer price information was found to be significant in the US stock market.

Fabio Fornari(2004) has studied the Swaption market to understand the effect of macroeconomic news announcements on implied volatility. 35 global indicators are studied, of which, 16 belong to the US, 5 to the European Union, 7 to Italy, 5 to France and 2 to Germany. The author concludes that US news releases produce significant reactions in the US as well as Euro Swaption markets. No evidence of Euro news affecting either the domestic or the US rates is found. The implied volatilities extracted from the swaption markets decline on announcement days.

Peter De Goeji and Wessel Marquering(2004) evaluate the reactions of daily stock and bond returns to macroeconomic news release pertaining to producer price index, employment and FOMC. The empirical data suggests that the mean, unconditional variance, and unconditional covarianceare all greater on announcement days. The results suggest that asymmetric volatility found in the bond market is due to misspecification of model. The author differentiates between FOMC announcements and producer price index and employment announcements. It is found that both categories of announcement are key in determining volatility dynamics.

Jussi Nikkinen, Petri Sahlstrom, Mohammed Omran, and Janne Aijo. (2006) also investigate the impact of schedule US macroeconomic news announcements on global stock markets. The authors intend to study market integration in terms of US macroeconomic announcements because of the dominant role of the US Stock market in world economy. The authors have studied the behavior of GARCH Volatilities of 35 locals stock markets grouped in 6 regions. 10 US macroeconomic announcements are considered. The results reveal that G7 countries, European countries other than G7, developed Asian countries and emerging Asian countries react to US macroeconomic news and therefore are closely integrated, whereas Latin American and transition economies do not react to US news.

Fang Cai, Hyunsoo Joo, and Zhivei Zhang (2009) use high frequency data to analyse the reaction of market rates in nine emerging markets to macroeconomic news release in the US and domestic markets. The period of study is from 2000 to 2006. The findings reveal that, except for Thailand and Turkey all other countries are affected by news realeases. It is observed that US macroeconomic news has stronger on Exchange returns and volatilities, and impact of news changes systematically with market sentiments.

George J. Jiang, Eirini Konstantinidi, and George Skiadopoulos (2010) study the role of schedule news announcements in explaining the transmission of stock market volatility across the US and European markets and within European markets. The implied volatility indices considered are VIX, VXN, VXD-US, VDAX, VCAC, VAEX, VBEL, VSMT and VSTOX-European. They have considered a set of US and European scheduled announcements. The authors have constructed event dummies as well as have tried to measure the new surprises for US and European macroeconomic announcement. The results reveal that news announcements partially explain the volatilities spillover that is reported and the surprise element of the news has a significant impact on the magnitude of volatility spillovers. The authors have used a VAR Model to understand the linkages.

Barbara Bedowska-Sojka (2011) attempts to study the reaction of German (DAX) and Polish Index (WIG20) to the US macroeconomic announcements and domestic and neighbour country announcements. The author has considered high frequency data and 10 macroeconomic announcements. The study shows that the US news impact is more profound than the domestic and neighbour country news.

Milena Suliga and Tomasz Wojtowicz (2013) inspect the impact of four indicators published in the US employment report on the Warsaw Stock Exchange. They employ the high frequency returns from Jan 2004 to Nov 2014 and analyse the impact of each indicator on price discovery process on WSE. The four employment indicators examined are unemployment rate, non-farm payroll, average hourly earnings, and average work week. Joint impact of some pair of indicators is also looked into.

Imlak Shaikh and Puja Padhi (2013) makes an attempt to link India VIX to scheduled macroeconomic announcements. The period of study taken is from November, 2007 to May, 2012. The macroeconomic variables considered are

MCIR, CPI, WPI, IIP, GDP and Employment. The findings suggests that implied volatility index rises before the release of scheduled macroeconomic announcements and the same goes normal on the day of report release and after the day of report release. It is observed that Indian investors regard announcements relating to MCIR and GDP in the valuation of financial assets. The results on GDP are found to be most statistically significant.

Imlak Shaikh and Suresh Kumar Jakhar (2013) made an attempt to establish linkages between macroeconomic communication and VIX. The findings of the study indicates that India VIX rises during the non-announcement period as there is uncertainty about the information disclosure and it drops and reverts to its normal levels after the event day as the uncertainty gets resolved. The Investors jointly consider information disclosure of employment and GDP in their financial planning.

Imlak Shaikh and Puja Padhi (2013) scrutinize the impact of scheduled macroeconomic announcements on India VIX. The authors employ a GARCH framework to understand the impact of RBI monetary policy statements, CPI, WPI, IIP employment rate and GDP on the IVIX . They conclude that on days with no announcements the IVIX increases significantly, whereas, on announcement days the IVIX declines and returns to its normal levels as the uncertainty gets resolved. The announcements on GDP and Inflation (WPI) are found to be most influential.

Barbara Bedowska-Sojka(2013) studied the reactions of two stock markets namely French and German to the release of macroeconomic news from the US and German market. The reaction of intraday returns of DAX and CAC40 to macroeconomic surprises is analysed. They observe that the US and German news cause immediate and significant reactions in the returns of the two indices. The US macroeconomic fundamentals have a stronger impact on both the markets.

Mustafa Onan, Aslinhan Salih, and Burze Yasar (2014) have analysed the impact of 23 macroeconomic announcements on high frequency data of implied volatility skew of S&P 500 and VIX. The authors report that VIX is significantly affected by these announcements whereas the implied volatility slope to a lesser extent. The study also analyses the surprise contained in the announcements. The authors find evidence that good and bad announcements significantly and asymmetrically change implied volatility slope and VIX.

Esin Cakan, Nadia Doytch, and Kamal P. Upadhyaya (2015) examine the influence of the US macroeconomic news surprises on the volatility of 12 emerging economies. The authors use the GJR-GARCH Model. They find that volatility is persistent and asymmetric and it increases with bad news on inflation in 5 out of 12 emerging economies and decreases with good news on US employment in 8 out of 12 economies. Thus, the study demonstrates the pre-dominant role played by USA in the global market as the economic and employment situation of USA has an impact on developing economies.

Sami Vahama (2015) highlights the different methodologies/approaches followed in studying the impact of scheduled macroeconomic announcements on implied volatilities. The study indicates that different approaches may lead to conflicting conclusions. He elaborates the two common approaches followed in the past. In the first approach only the impact of arrival of news on implied volatilities is studied. While in the latter the impact of news content is also analysed. It is thus concluded that, while there is no doubt that implied volatilities are affected by the arrival of scheduled macroeconomic news, but following different methodologies may yield inconsistent results on the direction of the effect.

Nicolas Boitout and Radu lupu (2015) study the market reaction to scheduled macroeconomic news announcements using two methods. Firstly, a jump detection mechanism is implemented to account for immediate consensus in market reaction; and secondly, the volatility impact is studied which indicates the market uncertainty. The study uses a set of 164 traded assets and 664 macroeconomic events. The authors further examine whether the market reaction to macroeconomic announcements have an impact on the probability of a reaction that will be caused by the next release of the same macroeconomic news. From their results it is evident that previous market reaction significantly affects the probability of a reaction for the current release.

2.1.2 Objective II: To investigate the changes in Volatility in Indian Equity market before and after implementation of India VIX.

M. T. Raju, Anurban Ghosh (2004) have studied the volatility in developed markets, as well as, emerging markets and have found that mature markets over a long period of time provide high returns with low volatility. Whereas, amongst emerging markets except India and China, all other countries exhibit low returns with high volatility. The authors reveal that the Indian markets are informationally more efficient and the intra-day volatility is very much under control compared to past years.

Harvinder Kaur (2004) has studied whether the volatility in Indian markets exhibit characteristics similar to those found in major developed stock markets. The author states that the volatility and returns are the highest in the Indian stock market in the months of February and March. Similarly, the month of December provides good opportunities to investors to make safe returns. It is also revealed that there is no conclusive evidence of consistent relationship between the US and Indian stock markets.

Madhusudan Karmarkar (2005) makes an attempt to capture the stock market volatility in India Using the GARCH (1,1) model. For the estimation of volatility two major market indices are considered, namely: S&P CNX Nifty; and BSE Sensex. Further, the author has also considered fifty individual companies included in the S&P CNX Nifty to study the heteroscedastic behaviour of the Indian stock market. The results of the study reveal the presence of time-varying volatility with volatility clustering and high persistence and predictability of volatility. The predictive ability of fitted GARCH (1,1) model is tested by comparing the out of sample volatility forecasts with true realized volatility. In addition, a regression based efficiency test has been performed. The test indicates that the GARCH (1,1) model provides a good forecast of market volatility. When looking at the 50 individual companies, it may be noted that the GARCH (1, 1) model successfully captures the volatility for most of the companies. Except for four companies, a GARCH model of a higher order may be appropriate.

Bhaskar Sinha (2005) investigates if asymmetric GARCH models can explain persistence of shock and volatility in the Indian stock market. Daily returns of the two most prominent domestic indices, i.e. BSE Sensex and NSE Nifty has been used. The GARCH (1,1), GJR-GARCH and EGARCH models have been employed. The author concludes that EGARCH provides a better fit for the SENSEX data and GJR-GARCH provides better estimates for NIFTY data.

Prashant Joshi and Kiran Pandya (2007) study the nature of volatility in the Indian stock market, namely, the BSE for the period from July1990 to Oct 2006. The study reveals that BSE Sensex exhibits volatility clustering. It also shows that the GARCH (1,1) model satisfactorily explains the volatility and is the most appropriate model for the BSE Sensex data series.

Prashant Joshi and Kiran Pandya (2012) explore the volatility in the Indian and Canadian stock markets. The authors have used the daily closing price data from January 2002 to July 2009. The results of the study indicate certain conventional facts about volatility such as volatility clustering and mean reverting behaviour. This is further confirmed by running the ARCH-LM test. This test shows the presence of heteroscedasticity in both the markets and the GARCH (1,1) effectively capture the volatility in both the markets. However it is observed that the volatility in the Canadian market is slightly higher compared to that of the Indian market.

Lakshmi Kalyanaraman (2014) has made an attempt to estimate the conditional volatility in the Saudi stock market using daily stock market returns for the period from August 2004 to October 2013. The author has applied AR (1)-GARCH (1, 1) model to capture the volatility in this study. The results indicate that the Saudi stock returns are characterised by volatility clustering and follow a non-normal distribution. It also indicates persistence, predictable and time-varying volatility. The results also indicate that the past volatility of returns influence the volatility for the current period.

Michael Techie Quaicoe, Frank B K Twenefour, Emmanuel M Baah, and Ezekiel N. N. Nortey (2015) aim at modelling the fluctuations in the Cedi/Dollar exchange rate. Through this study they test the applicability of range of (ARCH/GARCH) specification for modelling the volatility of the exchange rate series. The various models considered are ARMA, GARCH, IGARCH, EGARCH and MGARCH. The results of the study indicate that the exchange rate series is non-stationary and it also shows the presence of ARCH effect in the series. The ARMA (1, 1) plus GARCH (1, 1) model are found to be most appropriate for modelling the variations in the Cedi/Dollar exchange rate in Ghana.

Filiz Eryilmaz (2015) has made an attempt to model the volatility for BIST-100 returns in the Turkish Market by conducting the ARCH, GARCH, EGARCH and TGARCH models. The stationarity of the series was tested by analysing correlogram i.e. ACF and PACF coefficients. The results were further confirmed with ADF, PP, KPSS and NG-Perron test. The results revealed that the series became stationary at first difference. Further the ARCH-LM test was conducted to check for ARCH effect. Thus it was concluded that the BIST-100 series could be modelled using ARCH family models. Accordingly ARCH, GARCH, EGARCH AND TGARCH models were run. The author observed that the EGARCH (1,1) model was the most suitable to predict the BIST-100 return series.

2.1.3 Objective III: To predict the volatility in the Indian Equity market through symmetric and asymmetric GARCH models:

Robert E. Whaley (1993) proposes the use of volatility derivatives as simple, cost effective methods for hedging the market volatility risk of investment portfolios that consist of instruments like options or securities having option-like features. These he reveals will behave as effective risk management tools and will provide improved estimates of future realised volatility in a crisis market.

Pierre Giot (2002) attempts to ascertain if very high levels of VIX or VXN Indices imply over sold markets and could thus be viewed as a short-term or medium-term opportunity to buy stocks. The results of the study demonstrate that an increase in these indices leads to average negative returns on S&P100 and NASDAQ100 Stocks. The author further expects attractive positive returns in the immediate short-term. The study finally concludes that investors interested in entering oversold markets should wait until very high levels of these indices are witnessed. But they should restrict their strategy strictly to the short term.

Charles J. Corrado and Thomas W. Miller Jr (2003) examine the forecast quality of CBOE implied volatility indices based on the S&P100 i.e. VIX and Nasdaq100 i.e. VXN. The analysis is carried out by employing the OLS volatility forecast regression and Instrumental variable regression. The results indicate that the forecast quality of VIX and VXN has significantly improved in recent times. It is seen that VXN provides higher quality forecast of future realized volatility. VIX and VXN appear to contain significant forecast errors in the period from 1988-94. But no indication of forecast errors in the period from 1995-2002

Ercan Balaban, Asli Bayar, and Robert Faff (2003) have analysed the volatility prediction approaches across fourteen countries namely Belgium, Canada, Denmark, Finland, Germany, Hong Kong, Italy, Japan, Netherlands, Philippines, Singapore, Thailand, UK and US. The various volatility forecasting techniques evaluated include Random Walk Model, a Historical Mean Model, Moving Average, Weighted Moving Average, Exponential Weighted Moving Average, Exponential Smoothing, Regression Model, ARCH, GARCH, GJR-GARCH and E-GARCH models. The various techniques are compared based on symmetric, as well as, asymmetric error statistics. The results of the research reveal that based on symmetric error statistics the volatility forecasts provided by Exponential Smoothing Methods (ESM) are the most superior and those by ARCH type models are the worst. When under predictions are penalised, the performance of the ARCH type models are found to be superior compared to all the others, whereas when the over-predictions are penalized the ESM performs the best.

Ralf Becker, Adam Clemets, and Scott J. White (2007) study the information content of implied volatility index. They make an attempt to demonstrate if implied volatility includes any incremental information that could not be obtained from the information indicated in the model based forecasts. The authors compare VIX forecasts with the model based forecasts of GARCH, Stochastic Volatility, Realised Volatility class models, as well as, models following the MIDAS approach. They conclude that VIX index does not provide any additional information necessary for forecasting volatility.

Costas Siriopoulos and Anthanasios Fassas (2008) have proposed a volatility index for the Greek stock market based on FTSE/ATHEX-20 index prices. They follow a model-free methodology for its calculations. Their analysis indicates that the volatility index proposed gives superior forecasts of future realized volatility. It has an asymmetric contemporaneous and statistically significant relationship with the returns of the underlying index. The volatility transmission across international markets is also tested by studying the effect of the US and the German market on the Greek Index. It is seen that the US VIX has a profound impact on the Greek market.

Stavros A. Degiannakis (2008) employs a fractionally integrated ARMA model with VIX index as dependent variable, and volatility measures based on interday and intraday forecasts, as explanatory variables, to investigate whether they provide incremental information in forecasting of VIX. The results reveal that all the forecasting information is provided by the VIX index. The realized volatility, as well as, conditional volatility does not provide significant predictability information. Therefore, they do not provide any added value in the predictions of VIX index.

Robert E. Whaley (2009) describes the VIX and its history and purpose. He also explains as to how it fits within the array of the indexes that help where the economy stands relative to other points in recent decades.

Jui-Cheng Hung (2009) analysed the S&P 500 VIX index information content and range based volatilities by comparing their benefits to forecasting performance of GJR based volatility. The author adopted symmetric loss function to assess the efficiency and bias problem. To manage risk over and under estimation issues, value at risk and asymmetric loss functions are used. The Hansen’s SPA test is also employed to examine the forecast quality of GJR and

GJR-X models for S&P 500 index. The results show that VIX combined with range based estimators for GARCH type models enhances the forecast quality of the model. GJR-VIX model is the most preferred model as it demonstrates that VIX index has better information content for improving volatility performance.

Gonzalez-Perez & Novales (2011) developed a new daily volatility index for the Spanish markets using the model-free methodology. They further examine the relationship between this new index i.e. VIBEX-NEW and the Spanish stock market index i.e. IBEX and find that there exists a negative contemporaneous relationship between the two.

Debashish Bagchi (2012) has examined direct and cross-sectional relationship of India VIX in relation to three important parameters i.e. stock beta, market to book value of equity and market capitalization using multi regression analysis. The study shows that India VIX has a positive and significant relationship with the returns of the value weighted portfolios sorted on the basis of beta, market to book value of equity and market capitalization. The author further states that when market to book value of equity and market capitalization are considered as controlled variables, India VIX yields a positive and significant relationship with portfolio returns.

M. Thenmozhi and Abhijeet Chandra (2013) analyse the asymmetric relationship between the India VIX and stock returns. They also investigate the performance of India VIX as a refined measure of market volatility compared to traditional approaches. They explore the use of IVIX as an appropriate tool for timely trading and risk management in the market. Their results demonstrate that the Nifty returns are negatively correlated to changes in IVIX levels. It is also seen that IVIX provides better estimates of market volatility compared to conditional volatility models like GARCH/EGARCH. Analysis on timing strategy indicates that when the IVIX increases in markets the large cap equities help to maintain positive returns on investment portfolios, and when it decreases, the mid cap equities perform the same function.

Marcelo Fernandes, Marcelo C. Medeiros, and Marcelo Scharth (2013) examine the statistical properties of the CBOE daily market volatility index. The author employs parametric and semiparametric heterogeneous autoregressive process for modelling and forecasting the VIX Index. The findings reveal that the VIX index has a negative relationship with the S&P 500 index returns and it displays a positive relationship with the volume of S&P 500 index. The credit and term spread has a negative long term implication on the VIX index.

Clemens Kownatzki (2015) investigates the VIX index which is derived from S & P500 option prices as a representative of implied volatility and risk. The results show that the VIX does not accurately capture volatility prevalent in the market. In a normal market, it over estimates actual volatility and in times of crises the volatility is underestimated. The author further concludes that the VIX levels do not give any meaningful insight on issues as to how risk affects stock returns in the future. He suggests that a positive trend in VIX significantly improves future stock return forecasts. No-arbitrage conditions are explored by him by inverting the Black Scholes- Merton model and an alternative measure for volatility as well as implied risk free rate is developed. The author specifies that the model proposed by him produces implied risk free rates up to 130 pts higher than the average risk free rates. The proposed model also improves estimates of future realized volatility in a crises market.

S. S. S. Kumar (2010) investigates the behaviour of India VIX Index. The tools employed are Linear Regression and Autoregressive models. He aims to undertstand if the IVIX displays stylized facts of volatility. The study indicates that the IVIX reflects all the stylized facts of volatility. The author thus makes a proposition for introduction for exchange traded volatility derivatives in India as it mirrors most of the empirical regularities.

Utkarsh Majumdar and Arnab Banerjee (2004) compare the performance of a number of forecasting models namely GARCH, EGARCH, GJR-GARCH, APARCH & IGARCH in predicting the VIX volatility. The authors reveal that the asymmetric EGARCH model performs the best among the different models that are tested.

2.1.4 Objective IV: To study the dynamic linkages between Internationals equity markets through volatility Indices.

Sofiane Aboura (2003) finds that VX1, VIX and VDAX are good tools for predicting future realized volatility. The author also shows that past implied volatility informs more about future implied volatility than past realized volatility. Moreover the author has also studied the volatility transmissions between VX1, VIX and VDAX, and it is found that French volatility index is more sensitive to a shock of the US volatility index. It is also found that US volatility index is the most influential volatility index.

Ihsan Ullah Badshah (2009) investigated the asymmetric returns-volatility relationship with newly adopted robust volatility indices – VIX, VXN, VDAX, VSTOXX and the implied volatility transmission. He observed that VIX presents the highest asymmetric return-volatility relationship followed by the VSTOXX, VDAX, and VXN respectively. Secondly there were significant spill over effect across the volatility indexes and the VIX influenced the other three volatility indexes considerable. However, in the European context, the VDAX was found to be the dominant source of information.

Siriopoulos, Costas, Fassas, & Athanasios (2009) studied the information content of all publicly available implied volatility indices across the world. They further show that there is a statistically significant negative and asymmetric contemporaneous relationship between implied volatility changes and underlying equity index returns. They also contribute to the international equity market integration studies by investigating the linkages among major implied volatility of each market.

Elizaveta Krylova, Jussi Nikkinen, Sami Vahama (2009) analyse the cross-dynamics of volatility term structure slopes of implied foreign exchange options. They compile a wide ranging data set of OTC options of countries like Japan, Europe, Britain, Switzerland, Canada, and US. A principle component analysis with VDA and impulse response function is employed to examine the transmission of volatility structures across markets. The Linear and Non-linear Granger Causality Test is also employed to understand the causal dynamics. The study reveals that the Euro is the most dominant currency as its implied volatility term structure affects that of all others. But implied volatility term structure of Euro is unaffected by other currencies. The granger causality test gives evidence of significant non-linearities in the relationship between Euro and Swiss Franc.

Karam Pal Narwal, Ved Pal Sheera, and Ruhee Mittal (2011) examined implied volatility spill over and transmission between emerging (India) and mature stock markets (US, France, Germany and Switzerland), measured by their respective implied volatility indices i.e. IVIX, VIX, VCAC, VDAX and VSMI. The period of study was from Nov 2007 to Oct 2011. They employed multivariate GARCH models like BEKK-GARCH and DCC-GARCH. The results show that there is a moderate level of correlation between selected markets. It was also observed that information transmission and spillovers are running unidirectional from India to US markets and German to Indian market, and bidirectional from Indian to French market.

Puja Padhi (2011) examined the Implied Volatility linkages among the Asian, European and US stock markets from April 2009 to Feb 2011. Her results indicate that the US implied volatility index has substantial impact over the other international implied volatility indices but none of the examined volatility indices bears a notable impact over their Indian equivalent. The linkages were studied by employing the VAR model followed by impulse response function and variance decomposition analysis.

Ming-Lei-Liu and Oiang Ji (2013) explore the cross market volatility linkages among the stock, forex, gold and crude oil markets in terms of implied volatility indices. The Johansen Juselius Co-integration test followed by VDA and impulse response function is used as the core methodology. The analysis reveals that volatility is transmitted from stock markets to the other three markets. The forex market volatility is transmitted to crude oil and gold markets. The crude oil market is observed to be the most susceptible to volatility shocks. The volatility spillovers between oil, gold, stock and exchange market is also confirmed by VDA and Impulse response function.

Gupta and Kamilla (2015) examined linkages between implied volatility indices of developed financial markets (US, UK, Japan) and emerging financial markets (BRIC countries) using VAR modelling and variance decomposition method. The study suggests that US VIX has substantial impact on all the other Volatility Indices.

Thakolsri, Sethapamote, and Jiranyakul (2015) investigated the impact of changes in the VIX on the changes in the implied volatilities of Euro and the Thai stock markets through VAR model-Granger Causality test, Impulse Response Analysis, and Variance Decomposition Function. It is observed that the US index is the leading source of volatility transmission to all the other markets.

Rejeb and Boughrara (2015), examined the relationship between emerging and developed markets in normal times and in times of financial crises with respect to Volatility. The VAR methodology together with Bai and Perron's technique was used. It is reported that volatility spillovers are effective across financial markets. It may also be observed that geographical proximity plays a major role in amplifying the volatility transmission. Finally, it has been shown that financial liberalization is a significant and contributing factor in international transmission of volatility and the risk of contagion.

Pramod Kumar Naik and Puja Padhi (2015) analyse the relationship betweem trading volumes and equity market volatility by using market indices of four emerging economies namely brazil, Russia, India, and China. The relationship is inspected through EGARCH model. It indicates major volatility asymmetry across the four countries. Significant association between trading volume and stock market volatility is found. But it is also noticed that trading volume fails to decline the degree of volatility persistence in the market.

2.2 MAJOR FINDINGS DERIVED FROM REVIEW OF LITERATURE:

1. The literature suggests that, since the timing of the scheduled announcements is known in advance, implied volatility index rises before the release of scheduled macroeconomic announcements and drops sharply post announcement.

2. Indian investors regard announcements relating to MCIR, GDP, and Inflation in the valuation of financial assets.

3. The studies reveal the presence of time-varying volatility, volatility clustering, and high persistence and predictability of volatility for Indian stock market.

4. The GARCH (1,1) model provides a good forecast of volatility and provides most satisfactory results for the Indian stock market.

5. Nifty returns are negatively correlated to changes in IVIX levels. It is also seen that IVIX provides better estimates of market volatility compared to conditional volatility models like GARCH/EGARCH.

6. The literature also demonstrates the predominant role played by USA in the global market as the US VIX has substantial impact on all the other Volatility Indices.

2.3. RESEARCH GAP:

Even though considerable evidence is available on the implied volatility indices in developed countries, the literature is very scarce in the context of an emerging economy like India. India is considered as one of the world's fastest growing economies. With its reformist government and young population delivering a demographic dividend, the IMF predicts India will rise to become the third largest economy by 2020. The performance of the Indian stock market also has been extremely satisfactory hitting a new all-time high, but this has given way to confusion among investors. While some believe that the bull market has finally started and will take the market to much higher levels, others fear of a crash. In such a situation monitoring, modelling and forecasting short-term volatility will be of great importance to investors to safeguard their portfolios. This study differs from the previous works on the following grounds:

The linkage between macroeconomic factors and implied volatility indices is well documented. In our study we adopt a more extensive approach by focusing on all the scheduled news releases available for the study period. We try to validate the findings of the previous study for an emerging market like India and extend the work by employing Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model to model the asymmetries in India VIX and examine the impact of bad and good innovations on conditional variance.

Though there have been numerous studies on the information content, efficiency and predictive ability of IVIX, developing an appropriate model for predicting short term volatility is an unexplored area in the Indian context. This is the first study that aims at evaluating the forecasting performance of symmetric/asymmetric GARCH model for India VIX and understanding the shift in volatility pre and post introduction of the India VIX.

The study also makes an attempt to address the issue of implied volatility spillover in the context of three fastest growing emerging Asian economies namely India, China and South Korea with reference to developed economies like US and Germany. The study employs a longer volatility sample period compared to the previous works.

2.4 OBJECTIVE OF THE STUDY:

2.4.1 To study the impact of scheduled macroeconomic announcements on India VIX.

2.4.2 To investigate the changes in volatility in the Indian equity market before and after implementation of India VIX.

2.4.3 To examine the predictive ability of symmetric and asymmetric GARCH models in forecasting India VIX.

2.4.4 To study the dynamic linkages between international equity markets through volatility Indices

2.5 RESEARCH METHODOLOGY:

A primary description of the relevant data variables, sources, period of study and tools and techniques with respect to the objectives is given below:

2.5.1 Data Structure, Frequency, and Period:

The following table describes the objective-wise data variables employed in the study:

Table 2.1: Data Structure, Frequency, and Period

Objective	Series	Frequency	Period
I	India VIX Announcements: CPI/WPI IIP GDP Manpower survey RBI monetary information (Repo rate/ Reverse repo/Repurchase rate/CCR) Fiscal Deficit BoP current a/c Balance	Daily Monthly Monthly Quarterly Quarterly Quarterly, Mid-quarterly, Bi-monthly Monthly Quarterly	March 2009 to August 2016
II	Nifty 50 index	Daily	Jan 2000 to August 2016
III	India VIX	Daily	March 2009 to August 2016
IV	India VIX US VIX VXFXI VDAX VKOSPI	Daily	March 2009 to August 2016

2.5.2 Sources of Data:

Data on the relevant variables have been extracted from National Stock Exchange, Chicago Board of Options Exchange and Yahoo finance websites. Scheduled news releases follow a pre-decided schedule of which, the market participants are aware beforehand. The schedule concerning the announcements is extracted from Bloomberg database for the sample period. These announcements are available at around 11.00 am after the stock market opens on their scheduled report day. Other magazines and journals have also been referred to for the purpose of the study.

2.5.3 Period of study:

The period of study covered is from March 2009 to August 2016. Though the National Stock Exchange introduced VIX Index in April 2008, the data for the same is available on the NSE website only from March 2009. To analyse the changes in the Volatility in Indian Equity market before and after implementation of the India VIX, the period of study has been split into two phases. The period from 1-1-2000 to 31-3-2008 is considered as pre-IVIX phase whereas 1-4-2008 to 31-8-2016 is considered as post-IVIX period.

The period of study chosen seems relevant as this was a period when the world witnessed the worst financial crisis of all times. It was a phase when the volatility in international, as well as, domestic market was at an all-time high. The highest figure for the US VIX index was observed during this period. Thus selecting this period of study will help us monitor reaction of the Indian equity market through this phase and also the recovery processes post the global financial crisis.

2.5.4 Tools and Techniques:

The various statistical concepts used in the study for the purpose of carrying out analysis are as follows:

Arithmetic Mean:

The most popular measure of central tendency is the Arithmetic Mean. The Arithmetic Mean is also referred to as the average or simply as the Mean. It is arrived at by computing the sum of all the observations in the series and dividing it by the total number of observations. The Arithmetic Mean is given by the formula:

$$\bar{X} = \frac{\sum X}{N}$$

Where $\bar{X}$ (referred to as X-bar) is the symbol for Arithmetic Mean

$\sum X$ is the sum of all observations

N is the total number of observations

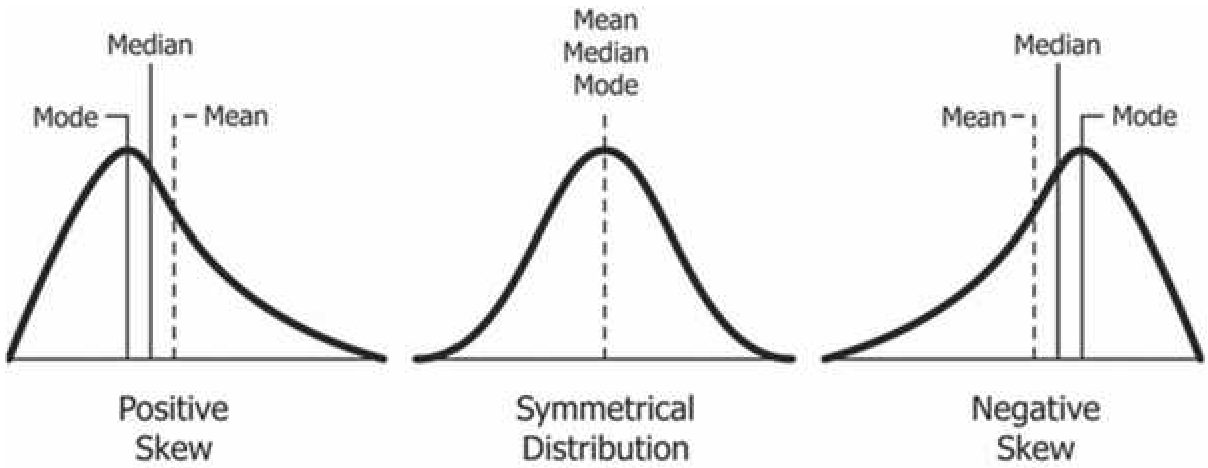
Variance and Standard deviation:

These are popular measures of dispersion. They indicate the average degree to which each point differs from the mean. The Standard Deviation and Variance are derived from the mean. The Standard Deviation is referred to as the positive square root of the Arithmetic Mean of the squares of the deviations of the given observations from their Arithmetic Mean. The Greek alphabet σ (sigma) is the symbol for standard deviation. The square of standard deviation is the Variance σ^2. The Standard Deviation is considered the basic measure for risk.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Skewness:

Skewness is a measure of symmetry of the asset returns around the Mean. In a normal distribution, the graph appears as a classical, symmetrical "bell shaped curve". The skewness for a normal distribution is zero, and any symmetric data should have a skewness near zero. Negative values for the skewness indicate data that are skewed left which is also termed as negatively skewed distribution, and positive values for the skewness indicate data that are skewed right or positively skewed distribution. Skewness basically shows how outlier events influence the shape of the distribution.

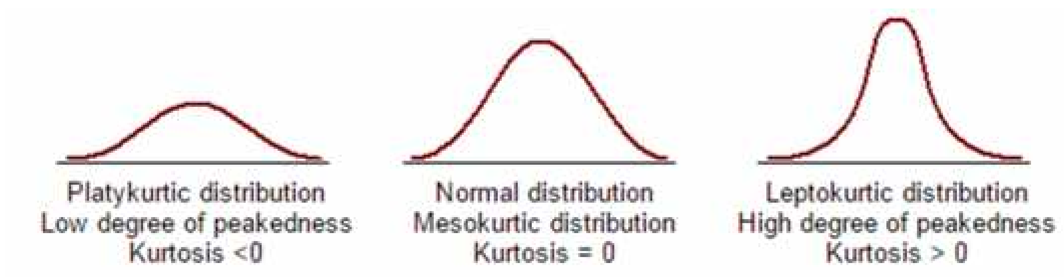


Kurtosis:

The thickness or heaviness of the tails of a distribution is measured by Kurtosis. It describes the shape of a probability distribution. Kurtosis helps understand the risk of the distribution using outlier events. A data set can display three categories of kurtosis:

- Mesokurtic
- Leptokurtic
- Platykurtic

Mesokurtic distribution has fatter tails than a standard normal distribution and has a slightly lower peak. This type of kurtosis resembles a bell shaped curve and is the most similar to a standard normal distribution. **Leptokurtic** distribution displays greater kurtosis than a Mesokurtic distribution. It has extremely thick tails and a very thin and tall peak. A **Platykurtic** distribution has slender tails and a peak that is smaller than a Mesokurtic distribution.



Jarque-Bera test:

The Jarque-Bera test helps in testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$\text{Jarque-Bera} = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

Where S stands for Skewness, and K for Kurtosis

Correlation Analysis:

It measures the strengths of association between two variables and the direction of the relationship. The correlation coefficient varies between +1 and -1. When the value of the correlation coefficient lies around ± 1, it is said to be a perfect degree of association between the two variables. As the correlation coefficient value goes towards 0, the relationship between the two variables will be weaker. A positive correlation coefficient indicates a positive relationship between the variables and a negative coefficient indicates a negative relationship between the variables. The correlation coefficient is denoted by "r".

Stationarity Tests:

The most important step before developing an econometric model is to test for non-stationarity of data series. Empirical work constructed on time series data assumes the data series to be stationary. Using non stationary data for building econometric models will give rise to spurious regression. A data series is said to be *Stationary* if it has Time Invariant Mean, Variance, and Auto-covariance. A time series having time varying mean or variance or both is referred to as a *Non-stationary series* or presence of *Unit Root* in data series. The problem with non-stationary data is that in standard procedures of a regression analysis, it can provide misleading results. But these results will often be totally spurious and therefore of little practical value. Popular tests for checking the presence of unit root is the **Augmented Dickey–Fuller (ADF) Test** and **the Phillip Perron Test.**

Regression analysis:

Regression analysis is a statistical method used to study the relationship/dependence of one variable, the dependent variable, on one or more other variables, the explanatory variables or independent variables. The simplest form of a regression model is

$$y = \alpha + \beta_1 x + \varepsilon$$

Where, y represents the dependent variable and x is the independent or explanatory variable, α and β_1 are the coefficients that determine the coordinates of the straight line at any point. α is the constant or intercept term which indicates the value of y when x equals to zero, and β is the slope coefficient which indicates the amount that *y* will change when *x* increases by one unit. The independent and dependent variables will be specified by the underlying theory. The term ε is referred to as the stochastic error or disturbance term. The disturbance term captures the effect of the factors omitted from the model i.e. it is added to a regression equation to introduce all of the variation in dependent variable that cannot be explained by the included independent variables. The simple regression model may be extended to include more than one independent or explanatory variable, and is referred to as **Multivariate Linear Regression Model**.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 \ldots\ldots\ldots.. \beta_i x_i + \varepsilon$$

The Coefficients of a regression model are estimated using the Ordinary Least Squares (OLS) technique. It is the most commonly used regression estimation procedure. The OLS entails taking each vertical distance from the point to the line, squaring it and then minimising the total sum of the areas of squares (hence 'least squares'). The model has to satisfy Assumptions in order for OLS estimators to be the best available. The assumptions for a classical regression model are:

- The regression model is linear in the coefficients, correctly specified and includes the error or disturbance term.
- The Error Term has a population mean equal to zero.
- All explanatory variables are uncorrelated with the Error Term.
- No Serial or Auto correlation in error term - Observations of the Error Term are uncorrelated with each other.
- No Heteroscedasticity – the Error Term has a constant variance.
- No perfect multicollinearity – No explanatory variable is a perfect linear function of any other explanatory variable(s).
- The Error Term is normally distributed.

Ljung-Box Q statistics:

The Ljung-Box Q statistic test is performed to identify whether a series of observations over time are random and independent. The test is applied to the residuals of a time series after fitting an appropriate model to the data. It is performed to test for autocorrelation in the residuals. If the autocorrelations are very small, we conclude that the model does not exhibit significant lack of fit. The Ljung-Box Q (LBQ) statistic tests the null hypothesis that autocorrelations up to lag k equal zero, that is, the data values are random and independent up to a certain number of lags. If the LBQ is greater than a specified critical value, autocorrelations for one or more lags might be significantly different from zero, indicating the values are not random and independent over time.

Autoregressive Conditional Heteroscedasticity (ARCH) Model:

An important assumption of a classical regression model as discussed above is that the variance of the error term is homoscedastic i.e. constant over a period of time. But in case of financial time series data the variance of the error term is unlikely to remain constant. It is heteroscedastic in nature. In such a scenario it makes sense to consider a model that does not assume constant variance. One such model that is widely used in finance is Engle's ARCH model. ARCH stands for autoregressive conditional heteroscedasticity. Another motivation to use ARCH class models is because financial time series displays a characteristic known as *volatility clustering*. It is the tendency of large changes in asset prices to follow large changes, and small changes to follow small changes. i.e. volatility occurs in bursts. An ideal model to capture this phenomenon in a time series is the ARCH family of models.

The ARCH models help to model the conditional mean, as well as, the conditional variance. There are two equations that are specified in an ARCH model. The **mean equation** describes the behaviour of the dependent variable y_t over time. This can be expressed in any form the researcher wishes. The **variance equation** models the volatility by allowing conditional variance of the error term σ_t^2, to depend on the squared error.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$$

This model is termed as the ARCH (1) model as the conditional variance depends on one lagged squared error. This model can be easily extended for cases when the conditional variance depends on q lags of squared error. The extended version is known as the ARCH (q) model.

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots \dots \dots \dots \dots \dots .. + \alpha_q u_{t-q}^2$$

But though the ARCH model provides a framework for analysis of volatility in time series data, it has certain constraints like deciding on the appropriate value of lags of squared residuals, as very large values of q would result in the model not providing parsimonious estimates. Thus, to overcome these inherent issues of an ARCH (q) model, Tim Bollerlev in 1986 developed the **GARCH model**. In this model the Conditional variance is allowed to depend on its own past lags. The GARCH model is expressed as

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-t}^2$$

Using the GARCH models it is possible to express h_t as a function of long term average value (α_0), volatility during the previous period ($\alpha_1 u_{t-1}^2$) and the variance from the previous period ($\beta_1 h_{t-1}^2$) . The GARCH (1,1) model can be extended to GARCH (p,q) where the current conditional variance is modelled as a function of q lags of the squared error term and p lags of the conditional variance. But normally a GARCH (1,1) model is considered sufficient to capture the volatility clustering in the data.

Asymmetric GARCH Models:

The GARCH models enforce a symmetric response of volatility to positive and negative shocks. But in financial time series, it is argued that a negative shock is likely to have higher impact on volatility than a positive shock. This phenomenon of asymmetries in equity returns is termed as ‘leverage effect’ i.e. a fall in the share prices of the firm leads to a rise in the debt to equity ratio of the firm. Threshold GARCH (TGARCH) or the GJR GARCH and the Exponential GARCH (EGARCH) models are the popular asymmetric GARCH models.

TGARCH/GJR GARCH Model:

The TGARCH model was developed in 1994 and the GJR GARCH model named after its developers Glosten, Jagannathan and Runkle in 1993 is an extension of the vanilla GARCH model with an additional term to capture the asymmetries in the data. The conditional variance in this case is modelled as

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

Where $I_{t-1} = 1, If\ u_{t-1} < 0$

$= 0, otherwise$

For leverage effect $\gamma > 0$ and for non-negativity condition $\alpha_0 > 0, \alpha_1 > 0$, $\beta \geq 0$ and $\alpha_1 + \gamma \geq 0$. The model is admissible even if $\gamma < 0$, but $\alpha_1 + \gamma \geq 0$.

EGARCH Model:

Nelson proposed the EGARCH model in 1991. The variance equation specification is given as:

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right]$$

The advantages of the above model over an original GARCH specification are: Firstly, there is no need to artificially impose non-negativity constraints on the parameters as $\log(\sigma_t^2)$ is modelled, and secondly, it allows capturing the asymmetries in the series.

γ term provides for asymmetries in the EGARCH specification. A Negative γ implies negative relationship between volatility and returns in the series.

Vector Autoregressive Model (VAR):

To study the linkages between the international implied volatility indices the study employs the VAR methodology. The VAR specification is a well-recognised methodology to analyse dynamic linkages between variables. Sims in 1980 developed and popularised the Vector Auto regression Model as a natural generalisation of univariate auto regressive models. It is considered as a hybrid between a univariate time series model and simultaneous equation model. It provides a multivariate system where changes in a particular variable are related to changes in its own lags and to changes in other variables and the lags of these variables. They help in identifying the key variables which influence the other variables in the framework. VARs are flexible models which offer rich structure to enable capturing more properties of the data. These are A-theoretical models, as they use limited information about the relationship between variables to specify the models.

A VAR model in its standard form can be expressed as:

$$y_t = \alpha + \sum_{K=0}^{P} \varphi_K y_{t-K} + \varepsilon_t$$

Where y_t is the m x 1 vector of dependent variables containing m x n observations at time t, α is the m x 1 vector of intercepts, φ_K is the m x m matrix of autoregressive coefficients $\{\varphi_{K}, K = 1,2, \dots \dots P\}$, ε_t is m x 1 vector of error terms assumed to satisfy the basic OLS regression assumptions of errors. *P* indicates the lag order for the VAR system. Appropriate lag order determination, *P*, for the VAR system is an important issue. The Standard information criteria are used to determine the order of the VAR system. Four different selection criteria, namely the Likelihood Ratio (LR) tests, Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQIC) are used to select the appropriate lag length for the model. The optimal lag length in a VAR system is determined by minimizing the suitable information criterion. In addition, given that the residuals of the VAR should exhibit no serial correlation if there are enough lags in the model, the residual serial correlation is tested to confirm the adequacy of the lag order.

Impulse Response and Variance Decomposition:

The dynamics of a VAR system, such as, which variable has the most statistically significant impact on the future values of other variables in the system, may be understood by examining the **impulse response function** and **variance decomposition** of a VAR model.

In the Impulse Response Function a one unit shock is applied to the innovation (error term) of each variable and its impact on the current and future values of other variables in the VAR system is observed, such that a shock to the i^{th} variable in the system directly affects that variable and also gets transmitted to other variables in the system. The shock then gradually dies away, provided the VAR system is stable. IRF hints at the responsiveness of the dependent variable in the VAR system to shocks to each of the variables. In the VAR framework if there are total of g variables, then g^2 impulse responses will be generated. In the VAR system the effect of unit shock of one endogenous variable on the other variable is captured through the Impulse response function, whereas, the variance decomposition analysis enables us in understanding the importance of one endogenous variable in affecting the other variable.

Variance Decomposition analysis offers a different method to examine the VAR dynamics. It explains the proportion of the movements in the dependent variables that are due to their 'own' shocks, versus shocks to the other variables in the system. So, a shock to the i^{th} variable in the system will directly affect that variable of course, but it will also be transmitted to all of the other variables in the system through the dynamic structure of the VAR. Variance decomposition determines how much of the *s-step-ahead* forecast error variance of a given variable is explained by innovations to each explanatory variable for s = 1, 2, …. The VDA enables one to understand how significant the innovations of all variables in the VAR system are to forecast error variance of each variable for specified number of days ahead. Ordering of the variables is a crucial aspect in calculating impulse responses and variance decompositions. Ideally, ordering should be suggested by financial theory.

2.5.5 Objective wise Methodologies:

1. **To study the impact of Scheduled macroeconomic announcements on India VIX:**

For the purpose of achieving the first objective OLS dummy regression model and advanced econometric models such as the GARCH (1, 1) model and the asymmetric EGARCH (1, 1) model has been employed.

2. To investigate the changes in Volatility in Indian Equity market before and after implementation of India VIX:

The changes in volatility before and after introduction of India VIX has been analysed by fitting the basic GARCH (1,1) model. The results are further validated by employing GARCH (1,1) model with an event dummy.

3. To predict the volatility in the Indian Equity market through symmetric and asymmetric GARCH models:

The above objective is achieved by employing symmetric and asymmetric GARCH family models such as the GARCH (1,1), TGARCH (1,1) and EGARCH (1,1) models respectively.

4. To study the dynamic linkages between International equity markets through volatility Indices:

The linkages between the global equity markets are studied by fitting the dynamic VAR model followed by the impulse response function and variance decomposition analysis.

2.6 LIMITATIONS OF THE STUDY:

1. The study does not consider all the macroeconomic announcements released by the authorities due to non-availability of data for the same during the said period.
2. The volatility index is a fairly recent introduction in the Indian equity market and so limited literature and data is available on the same.
3. Only the Indian, US, German, South Korean and Chinese index have been considered in studying the dynamic linkages between implied volatility indices.

2.7 CHAPTERIZATION SCHEME:

The study is divided into Seven chapters:

Chapter I: Introduction

This chapter provides the introductory framework and focuses on the background with which the study is conducted. The basic concept, causes, types and models of volatility, implied volatility indices and India VIX is discussed here. The significance of the thesis is highlighted in this chapter.

Chapter II: Review of literature and research methodology:

Extensive literature related to the concerned to the area of study is discussed in Chapter II. The research gap and research methodology which includes data description, period of study and detailed methodology is given here. The limitations of the study and the chapterization scheme are highlighted in this chapter.

Chapter III: To study the impact of scheduled macroeconomic announcements on INDIA VIX.

Chapter II examines the impact of scheduled macroeconomic announcements namely: Inflation; IIP; GDP; RBI Monetary Information; Employment Report; Fiscal Deficit; and BOP'S Current Account Balance on India VIX. The results are achieved by employing GARCH (1,1) and asymmetric EGARCH (1,1) model.

Chapter IV: To investigate the changes in volatility in the Indian equity market before and after implementation of INDIA VIX.

In this chapter, the changes in volatility before and after the introduction of the VIX Index in the Indian equity market are analysed. GARCH (1,1) model with a dummy is used for this purpose.

Chapter V: To examine the predictive ability of symmetric and asymmetric GARCH models in forecasting INDIA VIX.

This chapter aims at examining the predictive ability of symmetric and asymmetric GARCH models for forecasting the VIX index. Different models are estimated, compared and an appropriate model for the Indian market has been chosen.

Chapter VI: To study the dynamic linkages between international equity markets through volatility indices

The dynamic linkages between international volatility indices using VAR framework are studied in this chapter.

Chapter VII: Findings and Conclusion

This chapter summarises the objective wise findings of the study. The conclusion, implications and scope for further research are also discussed in this chapter.

IMPACT OF SCHEDULED MACROECONOMIC ANNOUNCEMENTS ON INDIA VIX

3.1 INTRODUCTION:

The link between macroeconomic risk and security returns is well documented in financial economics. Macroeconomic data is an important source of information not only about the actual state of real economies but also about their future prospects. These macroeconomic factors are also essential for valuation of financial assets. Information such as the Gross Domestic Product, Index of Industrial Production, Inflation and other central bank communication are vital indicators of the health of the economy and are closely monitored by market participants. The rational investors over-react on the Fed's (RBI) forthcoming monetary policy statements and these kinds of announcements are keenly monitored by the financial analysts and press (Shaikh and Padhi, 2013). While a lot of information about the economy arrives in the market, over time certain important macroeconomic news is released in the form of pre-scheduled announcements. The investors are not aware about the news content of the announcements but they know that there will be arrival of news. Thus if the security prices respond to this news, then the volatility in the market will be higher around these announcements. Under the Efficient Market Hypothesis Theory, an efficient market immediately impounds all macroeconomic news. In an efficient securities market we expect stock prices to adjust to new information very quickly (Donders and Vorst, 1996). Understanding the impact of scheduled macroeconomic announcements on financial markets is indeed of great interest to test the market efficiency hypothesis and anticipate the reaction of domestic, as well as, foreign investors and policymakers to news arrival. Through this study we explore the impact of scheduled news release on market uncertainty. The proxy for Market uncertainty is taken to be NSE's Volatility Index i.e. India VIX. A volatility Index incorporates all the available information that is relevant for forming the expectation about the future volatility. Thus, a volatility index may be considered as the best estimate of market uncertainty (Padhi, 2011). Indian Volatility Index (IVIX) is constructed based on the methodology of the US Volatility Index and has gained a lot of popularity in recent times as it is considered a barometer of market uncertainty.

3.1.1 Macroeconomic announcements and Volatility Index:

The Black-Scholes-Merton (1973) option pricing model is the most popular and widely used model for the valuation of options. The model explains that the option value depends on underlying stock price, time to expiration, exercise price, riskless interest rate and underlying asset price volatility. The same model can be inverted to calculate implied volatility by using all determinants of an option value except volatility. Implied volatility as shown by Black-Scholes-Merton is therefore inferred as the markets expectation of average stock return volatility over the remaining life of the option contract. Considerable Existing literature shows that implied volatility is greatly influenced by macroeconomic news announcements. Edrington and Lee (1996) studied the impact of information releases on market uncertainty by considering the implied standard deviation from T-Bonds, Eurodollar and Deutschemark Option Markets. The scheduled macroeconomic announcements considered were employment report and producer price index. The authors observed that since the timing of the scheduled announcements are known in advance, the pre-release Implied Standard Deviations (ISDs) rise as it impounds the anticipated impact of important releases on volatility and post-release the uncertainty gets resolved and the ISDs decline. Jussi Nikkinen and Petri Sahlström (2001) extend this study to a multinational setup. They studied the impact of US Macroeconomic news release on the Implied Volatility Index of its own domestic market and also on a foreign stock market i.e. the Finnish market. The results of their research reveal that Implied Volatilities increase before the macroeconomic news release and falls after the announcement in the US and the Finnish markets. Nikkinen and Sahlström (2004) investigated the impact of scheduled domestic and US macroeconomic announcements on the implied volatilities in the German and Finnish markets. Scheduled announcements regarding the US employment report and FOMC (Federal Open Market Committee) meeting days were found to be the most influential. Nikkinen, Omran, Sahlström and Ajio (2006) investigated the impact of schedule US macroeconomic news announcements on global stock markets. The results reveal that G7 countries, European countries other than G7, developed Asian countries and emerging Asian countries react to US Macroeconomic news and therefore are closely integrated whereas Latin American and transition economies do not react to US news.

From the above studies we can conclude that Macroeconomic news has significant influence on the asset prices in terms of prices, trading volume, bid-ask spreads, daily return and more specifically on the market microstructure. Edrington and Lee (1996) categorise announcements mainly into two: scheduled and unscheduled. A scheduled announcement is one where the market participants know beforehand it is forthcoming. These are releases which follow a pre-decided schedule in their announcement. But an unscheduled announcement is an unanticipated news release. In this study, the focus is on the Scheduled news releases that affect the market. Market uncertainty is observed to be higher around these announcements. The explanation for this behaviour is that the announcement contains relevant information about the value of financial assets. As a result of price adjustment process, volatility is expected to be higher than normal on scheduled announcement days. Further the empirical works of Ederington and Lee (1996) and Nikkinen and Sahlström (2001 and 2004), provide evidence that market uncertainty is higher on non- announcement days and it reverts back to normal level following the release on the day of the announcement. The uncertainty in the market rises prior to the announcement because of the surprise element in the news. Bulk of these studies focus on implications of macroeconomic variables on mature markets and not many studies are done on emerging economies like India. In the Indian context, Shaikh and Padhi (2013) have made an attempt to link NSE's India VIX to scheduled macroeconomic announcements. They employ the Ordinary Least Square, GARCH models and conclude that India VIX rises significantly prior to the release of macroeconomic news and falls back to its normal levels post news release. The researcher through this study explores the impact of scheduled macroeconomic announcements on India VIX further by considering all the scheduled macroeconomic releases available during the period of study and extend the work by employing Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model to model the asymmetries in India VIX and examine the impact of bad and good innovations on conditional variance. An attempt has also been made to validate the findings of the previous study for an emerging market like India.

3.2 DATA AND METHODOLOGY:

3.2.1 Data sources and Description

The present study employs daily closing values of India VIX for the period from 1-04-2009 to 31-08-2016. Based on earlier literature it is evident that there is a significant impact of macroeconomic announcements on implied volatilities. Hence to understand the impact following scheduled macroeconomic announcements, variables available for the above period are considered: Inflation (CPI/WPI); Index of Industrial Production (IIP); Gross Domestic Products (GDP); RBI's Monetary Information (Repo/Reverse Repo/Repurchase rate/CRR); Employment Survey Report; Fiscal Deficit; and Current Account Balance. The timing and the dates of announcements are extracted from Bloomberg for the sample period. Detailed explanation of each variable is provided below:

3.2.1.1 Consumer Price Index: Consumer Price Index (CPI) measures the changes over time in general level of prices of goods and services that consumers purchase for the purpose of consumption. CPI figures are widely used as a macroeconomic parameter of inflation. It is further used as a tool by governments for inflation targeting and for monitoring price stability. The dataset is published by the Central Statistical Office and released on the 12th of every month.

3.2.1.2 Index of Industrial Production: A composite indicator that measures the short-term changes in the volume of production of a basket of industrial products during a given period is called the Index of Industrial Production. It indicates the growth rates in different industry groups of the economy. The Central Statistical

Organization (CSO), Ministry of Statistics and Programme Implementation compiles and publishes the data six weeks after the reference month ends.

3.2.1.3 Gross Domestic Product: GDP growth rate is an important indicator of the economic performance of a country. The final value of the goods and services produced within the geographical boundaries of a country during a specified period of time – normally a year – is referred to as Gross Domestic Product. GDP data is released on quarterly basis by The Central Statistical Organization (CSO), Ministry of Statistics and Programme Implementation.

3.2.1.4 RBI's Monetary Information Disclosure: Reserve Bank of India announces Monetary Policy in the month of April every year. This is followed by three quarterly reviews in July, October, and January which is known as the Monetary Credit Information Review. In addition, the RBI had four mid-quarter monetary policy (MCIR) reviews after each quarterly review. But, from 2014 April the Reserve Bank of India has shifted to a system of reviewing its policy statement bi-monthly. Vital areas such as financial stability, financial markets, interest rates, credit delivery, regulatory norms, financial inclusion and institutional developments are addressed in the monetary policy of the RBI.

3.2.1.5 Employment Survey: The employment survey measures the levels of employment in various sectors of the economy, employment potential, incidence of unemployment, etc. The survey is essential as it helps in formulating programmes for generation employment and for easing the poverty situation by providing self-employment and wage employment. The Labour Bureau and the Director General of Employment and Training (DGE&T) in the Union Ministry of Labour have been the Central agencies collecting and disseminating employment data. The National Sample Survey Organisation (NSSO), Registrar General and Census Commissioner of India and the Central Statistical Organisation (CSO) wings of the Ministry for statistics and programme implementation are the other major agencies collecting data on employment through the Economic Census. The data is released on a quarterly basis.

3.2.1.6 Fiscal Deficit: Fiscal Deficit is the difference between a country's total revenue and total expenditure of the government. Generally fiscal deficit takes place due to capital expenditure incurred to create long-term assets such as factories, buildings, and other infrastructural development or due to deficit in collection of revenue. The budget document of the government is the principal source of fiscal data. It is also the responsibility of the Reserve Bank of India to compile and publish the Consolidated General Government Fiscal Data for the purpose of the Special Data Dissemination Standards (SDDS) of the International Monetary Fund. The data is made available through the RBI website and published monthly in the RBI bulletin.

3.2.1.7 BOP Current a/c balance: The current account component of Balance of Payment of a country shows its profile in goods and services trade. Technically, the current account explains the monetary value of goods and service (services is contained under invisibles) exported and imported by the country during an accounting period. The Balance of Payment statistics are compiled in accordance with the methodology set out in the IMF Balance of Payments Manual, 5th edition (BPM5) and is published by the Reserve Bank of India for every quarter with a lag of three months as per IMF's Special Data Dissemination Standards (SDDS) requirements.

The table below gives details on the frequency and timing of each variable under consideration:

Table 3.1: The Announcement Details for CPI, IIP, GDP, MI, Employment Survey, Fiscal Deficit, BOP Current a/c balance:

Variable	Frequency of Announcement	Releasing Authority	Total announcements for the period from 1-4-09 to 31-08-2016.
Inflation(CPI)	Monthly	Ministry for statistics and programme implementation	81
IIP	Monthly	Ministry for statistics and programme implementation	90
GDP	Quarterly	Ministry for statistics and programme implementation,	28
MI	Quarterly , mid-quarterly, bi-monthly	RBI	54
Employment Survey	Quarterly	Ministry for statistics and programme implementation, Ministry of Labour & Employment	30
Fiscal Deficit	Monthly	RBI	45
BOP current a/c balance	Quarterly	RBI	30

3.2.1.8 Descriptive Statistics:

Before moving on to analysing the behaviour of the IVIX through an appropriate econometric model, the properties of the series are discussed:

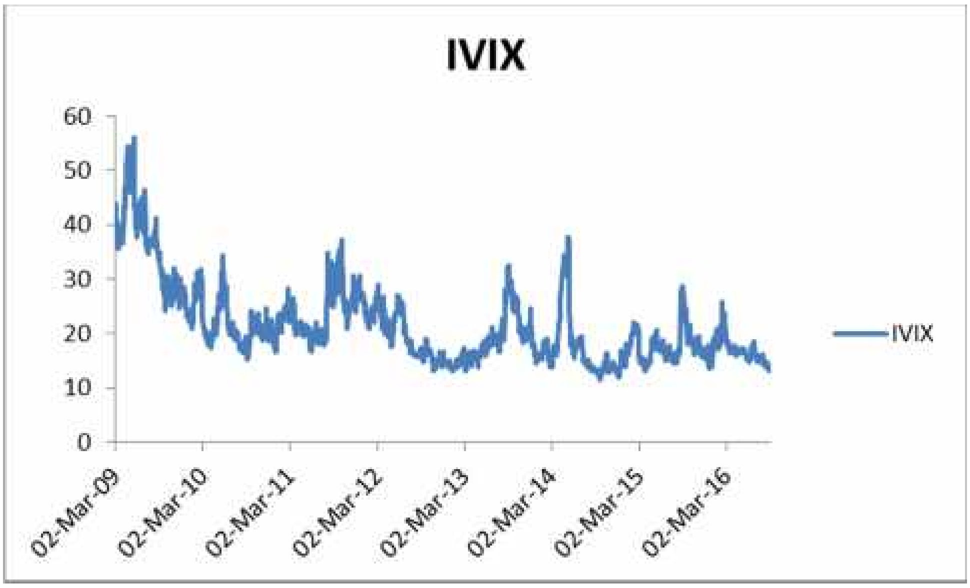
Table 3.2: Descriptive Statistics of India VIX for the Period from March 2009 To August 2016

Statistics	IVIX (level)	Log-Returns of IVIX
Mean	21.36237	-0.000633
Median	19.25000	-0.002300
Maximum	56.07000	0.496900
Minimum	11.56500	-0.414400
Std. Dev.	7.315994	0.051867
Skewness	1.690442	0.428660
Kurtosis	6.357673	10.84308
Jarque-Bera Statistics	1759.587* (0.0000)	4824.285* (0.0000)
ADF test Statistics	-1.8929	-44.4553*
Observations	1860	1860

Notes: Figures in the parenthesis ( ) indicates p-value.
*- denote the significance at one percent level.

Table 3.2 reports the descriptive statistic for the sample period March 2009 to August 2016. The average India VIX was observed to be 21.36 points with an average negative -0.06 % log-return. The maximum India VIX figure observed for the period is 56.07 points and minimum is 11.56 points. It is evident from the above table that India VIX log-returns series has a non-zero skewness and the value of the kurtosis is greater than 3, indicative that the returns series have a heavier tail or leptokurtic with regards to the standard normal distribution. The normality of the data series is tested using the Jarque-Bera statistics. It examines the null hypothesis that the return series follows a Normal distribution. The high value of Jarque-Bera test statistics confirm that the series is non-normally distributed and rejects the hypothesis of a normal distribution at one percent level of significance for the log-returns of IVIX. The ADF test statistics is significant at one percent level, indicating that the log-returns series is stationary. Besides, the figure 3.1 shows the time-series plot of IVIX index, implying that there is no problem of trend in the time series of IVIX.

Figure 3.1: Time Series Plot of India VIX index for the period from March 2009 to August 2016



3.2.2 Methodology:

From the existing literature it is known that financial assets become more volatile around the scheduled macroeconomic news release. Therefore, this study aims to examine the behaviour of IVIX before and after news release report days. Normally, the Capital Asset Pricing Model is employed in studying the asset price volatility on the news release days by classifying returns as normal and abnormal. But, employing such models may not be possible when dealing with the implied volatilities. Hence, for the present study, the mean-reverting mechanism is analysed by calculating the log-return of the IVIX time series. The scholarly works of Ederington and Lee (1996), and Nikkinen and Sahlström (2004) are the inspiration and basis for the present research work, the relevance of their findings is investigated in the Indian Equity Market, and the reaction of IVIX around scheduled macroeconomic announcements is observed. To analyse the impact of such announcements Dummy variable technique is employed. The following OLS Regression is developed to analyse the behaviour of IVIX with dummy variables.

OLS Model 1:

$$\ln(VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_t + \beta_2 DIIP_t + \beta_3 DINFT_t + \beta_4 DMI_t + \beta_5 DEMPY_t + \beta_6 DFISDEF_t + \beta_7 CURBAL_t + \varepsilon t \quad (1)$$

.

OLS Model 2: The uncertainty one day before the scheduled macroeconomic announcements is analysed through model 2

$$\ln(VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_{t-1} + \beta_2 DIIP_{t-1} + \beta_3 DINFT_{t-1} + \beta_4 DMI_{t-1} + \beta_5 DEMPY_{t-1} + \beta_6 DFISDEF_{t-1} + \beta_7 CURBAL_{t-1} + \varepsilon t \quad (2)$$

OLS Model 3: This model is developed to study the impact of India VIX one day after the announcements.

$$\ln(VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_{t+1} + \beta_2 DIIP_{t+1} + \beta_3 DINFT_{t+1} + \beta_4 DMI_{t+1} + \beta_5 DEMPY_{t+1} + \beta_6 DFISDEF_{t+1} + \beta_7 CURBAL_{t+1} + \varepsilon_t \quad (3)$$

In Models1, 2, and 3

$\ln(VIX^{India}/VIX^{India}_{t-1})$ = Daily change calculated for India VIX.

α = captures the impact on India VIX during the non-announcement days.

β = captures the impact of scheduled monetary and macroeconomic announcement, it assumes the value 1 - on the day, a day before, and a day after the scheduled announcements of GDP, IIP, Inflation, MI, Employment, Fiscal Deficit, BOP Current A/C Balance and 0 otherwise.

t, t-1, t+1 = time period i.e. report day, one day before, one day after.

ε_t= Residual term capturing innovations/shocks.

The Following statements are tested in the context of Indian Volatility Index:

- During the non-announcements days, the IVIX rises hence intercept should be non-zero and positive, and also should be statistically significant.
- On the scheduled macroeconomic news release day, the IVIX should go down, and goes to its normal level, as it impounds the information disclosure. Hence, all the slope coefficients of Inflation, IIP, GDP, RBI's monetary information, Employment Survey, Fiscal Deficit and BOP's Current A/c balance should be negative, and should be statistically significant.
- Before the scheduled news announcements IVIX rises significantly. Hence, all the slope coefficients of Inflation, IIP, GDP, RBI's monetary information, Employment Survey, Fiscal Deficit and BOP's Current A/c balance should be positive and statically significant.
- After the announcements of scheduled news, IVIX goes to its normal level, i.e. it declines up to certain days. Hence, all the slope coefficients of INFLATION, IIP, GDP, RBI's monetary information, Employment Survey, Fiscal Deficit and BOP's Current A/c balance should be negative, and should be statistically significant.

3.3 EMPIRICAL RESULTS AND DISCUSSION:

The above model is estimated to understand the linkages between macroeconomic announcements and India VIX. The output of the OLS regression models is discussed in the table below.

Table 3.3: Results of OLS regression (Dependent Variable: Log-Returns of IVIX):

Model 1			Model 2			Model 3		
Independent Variables	**Coefficient**	**t-statistics**	**Independent Variables**	**Coefficient**	**t-statistics**	**Independent Variables**	**Coefficient**	**t-statistics**
Constant	-0.00016	-0.12647	Constant	-0.00135	-1.0402	Constant	-0.00037	-0.28328
GDP Report Day	-0.01081	-1.05583	GDP Report, One Day Before	-0.01513	-1.47659	GDP Report, One Day After	-0.00173	-0.16995
IIP Report Day	-0.00564	-0.93532	IIP Report, One Day Before	0.008706	1.442166	IIP Report, One Day After	-0.00349	-0.5766
INF Report Day	0.006147	0.969976	INF Report, One Day Before	-0.00473	-0.74541	INF Report, One Day After	-0.00107	-0.16784
MI Report Day	-0.02059*	-2.8766	MI Report, One Day Before	0.020212*	2.796834	MI Report, One Day After	0.003118	0.434117
EMPL Report Day	0.021044**	2.202982	EMPL Report, One Day Before	0.008545	0.89414	EMPL Report One Day After	-0.00909	-0.94829
FISCAL DEF Report Day	-0.00392	-0.4715	FISCAL DEF Report, One Day Before	-0.00391	-0.4695	FISCAL DEF Report, One Day After	0.008775	1.048709
CURRENT A/C BAL Report Day	0.003481	0.362114	CURRENT A/C BAL Report, One Day Before	0.007047	0.744788	CURRENT A/C BAL Report, One Day After	-0.01087	-1.12669
ARCH-LM Statistics	11.78881 (0.0006)		ARCH-LM Statistics	11.81105 (0.0006)		ARCH-LM Statistics	11.87677 (0.0006)	

Notes: * & **- denote the significance at one and five percent level, respectively.

Table 3.3 reports the results of OLS regression of the before, after, and report day impact of macroeconomic announcements namely GDP, IIP, Inflation, RBI Monetary Information, Employment Survey Report, Fiscal Deficit, BOP's Current A/C Balance on the Indian implied volatility index i.e. IVIX. Model 1 studies the behaviour of IVIX during the report day of these announcements. On the report day we assume the intercept to be positive, non-zero and statistically significant. And the slope coefficients are expected to be negative, non-zero and statistically significant. It is noticed that the intercept appears non-zero and negative in the case of report day, but statistically insignificant. The slope of RBI's Monetary Information and Employment Survey report are found to be statistically significant at 1% and 5% levels respectively. This demonstrates that the release of RBI's Monetary Information and Employment survey reports influence the behaviour of IVIX on report day. Further the Monetary Information news leads to a 2.059% decline in IVIX, whereas the Employment Survey Release increases the IVIX by 2.1044% on report day. All other slopes are found to be statistically insignificant. Model 2 studies the behaviours of IVIX during a day before the macroeconomic announcements. The Intercept is expected to be positive, non-zero and statistically significant and the slope coefficients to be positive, non-zero and statistically significant in Model 2. The results show that the intercept is found to be negative, and not statistically significant a day before the scheduled announcements. In addition, no slope coefficients are found to be significant except, the slope of RBI Monetary Information. This indicates that investors closely monitor the release of monetary news. This leads to higher IVIX values and a rise in uncertainty and speculation in the market. As per our assumption, the intercept should be Positive, Non-Zero, and Statistically

Significant, and the Slope Coefficients are expected to be Negative, Non-Zero and Statistically Significant a day after the announcements. Model 3 captures the behaviour of IVIX during a day after the macroeconomic announcements. The intercept is found to be negative and not statistically significant during one day after the scheduled announcements. In addition, none of the slope coefficients appear statistically significant and bear the expected sign. This is indicative of the fact that the behaviour of IVIX is not influenced by macroeconomic announcements one day after their release.

To take the analysis further we analysed the residuals of the above model through Lagrange's Multiplier (LM) test for ARCH-effect. The test shows significant presence of conditional heteroscedasticity in the residuals. Thus we proceed to fitting GARCH (1, 1) model for the entire regression.

GARCH (1,1) Model 4:

Mean equation:

$$\ln (VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_t + \beta_2 DIIP_t + \beta_3 DINFT_t + \beta_4 DMI_t + \beta_5 DEMPY_t + \beta_6 DFISDEF_t + \beta_7 CURBAL_t + \varepsilon t \qquad (4)$$

Variance equation:

$$h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} \qquad (5)$$

GARCH (1,1) Model 5:

Mean equation:

$$\ln (VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_{t-1} + \beta_2 DIIP_{t-1} + \beta_3 DINFT_{t-1} + \beta_4 DMI_{t-1} + \beta_5 DEMPY_{t-1} + \beta_6 DFISDEF_{t-1} + \beta_7 CURBAL_{t-1} + \varepsilon t \qquad (6)$$

Variance equation:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (7)$$

GARCH (1, 1) Model 6:

Mean Equation:

$$\ln (VIX^{India}/VIX^{India}_{t-1}) = \alpha + \beta_1 DGDP_{t+1} + \beta_2 DIIP_{t+1} + \beta_3 DINFT_{t+1} + \beta_4 DMI_{t+1} + \beta_5 DEMPY_{t+1} + \beta_6 DFISDEF_{t+1} + \beta_7 CURBAL_{t+1} + \varepsilon t \qquad (8)$$

Variance equation:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (9)$$

In the above models a GARCH framework is employed to examine the reaction of India VIX to scheduled macroeconomic news. In the mean equation of the models,

α = captures the impact on India VIX during the non-announcement days and

β = captures the impact of scheduled monetary and macroeconomic announcement, it assumes the value 1 - on the day, a day before, and a day after the scheduled announcements of GDP, IIP, Inflation, MI, Employment, Fiscal Deficit, BOP Current A/C Balance, and 0 otherwise. The variance equation aids us in understanding the short-term volatility dynamics in the India VIX series. h_t is the conditional variance, which is described as a function of squared residuals ε^2_{t-1} from the mean equation and past variance h_{t-1}. The sum of parameters of the model i.e. $\alpha + \beta < 1$ and non- negative.

Table 3.4: Results of GARCH (1, 1) Model (Dependent Variable: Log-Returns of IVIX)

Model 4			Model 5			Model 6		
Mean Equation			**Mean Equation**			**Mean Equation**		
Independent Variables	**Coefficient**	**Z-statistics**	**Independent Variables**	**Coefficient**	**Z-statistics**	**Independent Variables**	**Coefficient**	**Z-statistics**
Constant	-4.99E-05	-0.03887	Constant	-0.001601	-1.262541	Constant	-0.00082	-0.650215
GDP Report Day	-0.009102	-1.149223	GDP Report, One Day Before	-0.004365	-0.429577	GDP Report, One Day After	-0.004107	-0.384571
IIP Report Day	-0.008661	-1.385617	IIP Report, One Day Before	0.00749	1.104078	IIP Report, One Day After	-0.001292	-0.197526
INF Report Day	0.005609	0.83895	INF Report, One Day Before	-0.00708	-1.187381	INF Report, One Day After	0.005016	0.720002
MI Report Day	-0.019931*	-2.848849	M I Report, One Day Before	0.025066*	3.874959	M I Report, One Day After	0.003993	0.43676
EMPL ReportDay	0.019187**	2.061987	EMPL Report, One Day Before	0.010484	0.905963	EMPL Report, One Day After	-0.009049	-0.70902
Fiscal Deficit Report Day	-0.004474	-0.612958	FiscalDeficitReport, One Day Before	-0.006659	-0.686273	FiscalDeficitReport, One Day After	0.007112	0.868545
Currenta/cBal Report Day	0.001727	0.180034	Currenta/cBalReport, One Day Before	0.007642	0.577071	CurrentA/cBalReport, One Day After	-0.011792	-1.292842
Variance Equation			**Variance Equation**			**Variance Equation**		
Constant	0.000336*	5.158923	Constant	0.000314*	5.49426	Constant	0.000308*	5.230815
ARCH effect	0.075615*	8.7539	ARCH effect	0.078358*	9.045994	ARCH effect	0.073529*	8.396171
GARCH effect	0.799535*	25.74087	GARCH effect	0.805557*	28.69132	GARCH effect	0.812844*	28.45409
ARCH-LM Statistics	0.035309 (0.851)		ARCH-LM Statistics	0.027256 (0.8689)		ARCH-LM Statistics	0.034339 (0.853)	
Notes: * , **- denote the significance at one percent level and five percent level respectively								

Table 3.4 reports the results of the GARCH (1,1) Model. The behaviour of IVIX on the report day is specified in Model 4. The results reveal that the intercept is negative and statistically insignificant. This could mean that the markets do not experience high degree of volatility because of the forthcoming announcements. Besides, the slope of the GDP, IIP, Fiscal Deficit are found to be negative and that of Inflation and BOP's Current A/C Balance appear to be positive. But the coefficients of all these variables are not statistically significant. The potential reason for this behaviour is that Indian investors do not react seriously to the above variables. As shown in the OLS results, only the slope of RBI Monetary Information and Employment Survey are found to be statistically significant at 1% and 5% level of significance respectively. Thus confirming that monetary policy of the RBI news and employment report news is observed by the market participants in their financial planning. RBI's disclosure of Monetary Information leads to a decrease in IVIX by 1.993%. This could be indicative of the fact that the monetary policy of RBI was in favour of the markets which resolved much of the uncertainty prevalent present. Whereas we can say that unfavourable employment figures lead to an increase of 1.918% in IVIX on employment report day. We study the behaviour of IVIX during a day before the macroeconomic announcements in Model 5. The results indicate that, the intercept is found to be negative and not statistically significant one day before the scheduled announcements, thus implying that the volatility in the Indian market does not rise prior to the announcements and is maintained at normal levels. In addition, we see that slope coefficient of GDP, IIP, Inflation, Employment Survey, Fiscal Deficit, Current A/C Balance are statistically insignificant. The slope coefficient of RBI Monetary Information appears to be positive and statistically significant at 1% level of significance. This confirms that investors over react to forthcoming RBI monetary information release thus leading to a rise in IVIX levels. Model 6 studies the behaviour of IVIX during a day after the macroeconomic announcements. The estimates of the model reveal that none of the slope coefficients analysed are statistically significant, indicating that the market movement is more mechanical one day after the macroeconomic announcements and does not follow any particular pattern as observed in other studies done in international markets.

A variant of the GARCH family of models is used to estimate leverage effect and account for information asymmetry on the India VIX. The basic (vanilla) GARCH (1,1) model does not account for impact of positive and negative innovations or information shocks. To account for asymmetry in variance, Nelson's (1991) Exponential GARCH model is used. In the EGARCH model the variance h_t is taken to be an asymmetric function of lagged disturbance ε_t. The presence of leverage effect and the impact of asymmetry are tested by the hypothesis $\gamma = 0$, $\gamma \neq 0$, when the impact of asymmetry is present. In the EGARCH model the persistence of volatility is described by α.

EGARCH Model 7:

Mean equation:

$$\ln\left(VIX^{India}/VIX^{India}_{t-1}\right) = \alpha + \beta_{43} DGDP_t + \beta_{44} DIIP_t + \beta_{45} DINFT_t + \beta_{46} DMI_t + \beta_{47} DEMPY_t + \beta_{48} DFISDEF_t + \beta_{49} CURBAL_t + \varepsilon t \qquad (10)$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

EGARCH Model 8:

Mean equation:

$$\ln\left(VIX^{India}/VIX^{India}_{t-1}\right) = \alpha + \beta_{50}DGDP_{t-1} + \beta_{51}DIIP_{t-1} + \beta_{52}DINFT_{t-1} + \beta_{53}DMI_{t-1} + \beta_{54}DEMPY_{t-1} + \beta_{55}DFISDEF_{t-1} + \beta_{56}CURBAL_{t-1} + \varepsilon t \quad (11)$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

EGARCH Model 9:

Mean Equation:

$$\ln\left(VIX^{India}/VIX^{India}_{t-1}\right) = \alpha + \beta_{57}DGDP_{t+1} + \beta_{58}DIIP_{t+1} + \beta_{59}DINFT_{t+1} + \beta_{60}DMI_{t+1} + \beta_{61}DEMPY_{t+1} + \beta_{62}DFISDEF_{t+1} + \beta_{63}CURBAL_{t+1} + \varepsilon t \quad (12)$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

Table 3.5: Results of EGARCH Model (Dependent Variable: Log-Returns of IVIX)

Model 7			**Model 8**			**Model 9**		
Mean Equation			**Mean Equation**			**Mean Equation**		
Independent Variables	**Coefficient**	**Z-statistics**	**Independent Variables**	**Coefficient**	**Z-statistics**	**Independent Variables**	**Coefficient**	**Z-statistics**
Constant	0.000983	0.752116	Constant	-0.00033	-0.24995	Constant	-0.00082	-0.65022
GDP Report Day	-0.00945	-1.05267	GDP Report, One Day Before	0.002149	0.236096	GDP Report, One Day After	-0.00411	-0.38457
IIP Report Day	-0.00661	-1.09006	IIP Report, One Day Before	0.005582	0.833567	IIP Report, One Day After	-0.00129	-0.19753
INF Report Day	0.005783	0.854826	INF Report, One Day Before	-0.00396	-0.72758	INF Report, One Day After	0.005016	0.720002
MI Report Day	-0.0168*	-2.67288	MI Report, One Day Before	0.023944*	3.565246	MI Report, One Day After	0.003993	0.43676
EMPL Report Day	0.021576*	2.581241	EMPL Report, One Day Before	0.012444	1.39193	EMPL Report, One Day After	-0.00905	-0.70902
FISCAL DEF Report Day	0.001302	0.173263	FISCAL DEF Report, One Day Before	-0.0031	-0.3605	FISCAL DEF Report, One Day After	0.007112	0.868545
Current A/C Bal Report Day	0.005413	0.710783	Current A/C Bal Report, One Day Before	0.006193	0.64469	Current A/C Bal Report, One Day After	-0.01179	-1.29284
Variance Equation			**Variance Equation**			**Variance Equation**		
Constant	-0.22923*	-6.33752	Constant	-0.23807*	-6.00752	Constant	0.000308*	5.230815
GARCH effect	0.965515*	184.4639	GARCH effect	0.965307*	172.3409	GARCH effect	0.812844*	28.45409
Leverage effect	0.115872*	13.18709	Leverage effect	0.115732*	12.93794	Leverage effect	0.073529*	8.396171
ARCH-LM Statistics	0.773515 (0.3792)		ARCH-LM Statistics	0.692905 (0.4053)		ARCH-LM Statistics	0.714663 (0.398)	

Notes: *- denote the significance at one percent level. Figures in the parentheses ( ) indicates p-value.

Table 3.5 represents the output of EGARCH models. Model 7 captures the reaction of India VIX on the report day. The results show that the intercept appears non-zero, positive on the report day but statistically insignificant. This implies that the forthcoming news leads to ambiguity in the market but it fails to impact India VIX. The slope coefficients of the GDP, IIP, Inflation, Fiscal Deficit, and BOP Current A/C Balance are found to be statistically insignificant. This reveals that these macroeconomic announcements do not influence the IVIX and the reaction of investors is indifferent to them, whereas only the slopes of RBI's Monetary Information and Employment are found to be positive and negative respectively, and statistically significant at 1% level of significance. Model 8 studies the behaviour of IVIX during the day before the macroeconomic announcements. As per the statements, the intercept is found to be positive, but it is not statistically significant during one day before the scheduled announcements. In addition, no slope coefficients are found to be statistically significant except for RBI's Monetary Information. Model 9 studies the behaviour of IVIX during a day after the macroeconomic announcements. The intercept is found to be negative and statistically insignificant. In addition, it is seen that none of the slope coefficients appear to be statistically significant. Moreover, the table results reveal that the IVIX exhibits positive and statistically significant leverage effects at one percent level. This indicates that positive shocks (good news) have greater impact on this market than the negative shocks (bad news).

3.5 CONCLUSION:

The present study examines the linkages between scheduled macroeconomic announcement and India VIX for the period from March 2009 to August 2016. The behaviour of India VIX around Scheduled releases of Inflation, IIP, GDP, RBI

Monetary Information, Employment, Fiscal Deficit, and BOP Current A/C Balance is observed.

It is anticipated that the India VIX should rise the day before the scheduled news announcement and decline on the day of the scheduled announcements and fall back to its normal levels the day after. We validate these results using OLS, GARCH and EGARCH models. Our empirical results show no significant influence of macroeconomic news on report day and day before on India VIX, except RBI Monetary Information disclosure and Employment Survey Report. Besides, the findings demonstrate the indifferent response of India VIX one day after the scheduled news announcements. Thus the findings of the studies done by Edrington and Lee (1996) , and Nikkinen and Sahlström (2001 and 2004) which claim that before the announcement of macroeconomic news, the implied volatility index increases significantly and on the day of macroeconomic announcements, uncertainty about the news gets resolved and VIX goes to its customary level, does not hold true for an emerging market like India. Our results are also contradictory to the findings of Shaikh and Padhi (2013) in the Indian context. Moreover, Under the Efficient market hypothesis theory, an efficient market immediately impounds all macroeconomic news and expects stock prices to adjust to new information very quickly. We also expect the investors to observe these news releases in their portfolio selection and management. However, the findings of the study reveal that investors need not consider the scheduled macroeconomic except the RBI Monetary information disclosure and employment report in their financial planning as they have no significant influence on market volatility . The results are also indicative of the inefficiency of the Indian options market.

TO STUDY THE EXTENT OF VOLATILITY IN THE INDIAN EQUITY MARKET BEFORE AND AFTER INTRODUCTION OF INDIA VIX

4.1 INTRODUCTION

The study of stock market volatility has always gained a lot of focus from the economic research community. Volatility represents the fluctuations in the returns of financial products. It is an important measure of the rate of risk of an asset. Volatility assumes great importance in foretelling the returns of a financial asset and is a vital input in pricing options and derivative products as it indicates risk in a product. Thus, understanding and predicting volatility can be of significance to market participants.

The arrival of new information in the market and the consequent dispersion in beliefs among market players will give rise to volatility. High volatility compared to the equilibrium values of the stocks, can have significant impact on the returns of financial products. Substantial changes in the volatility of asset prices can have negative impact on risk averse investors. Its implications can be also noted on consumption patterns, corporate capital, business strategies and macroeconomic indicators. Thus extreme volatility could affect the health of an economy by leading to major structural and regulatory changes.

Many economic models have been discussed by experts to describe and predict volatility. But most of these models assume the variance of returns of the asset to be constant over a period of time. However, this assumption is rejected through empirical evidence as financial time series such as stock returns, exhibit a phenomenon known as volatility clustering. This means that large changes in these series tend to be followed by large changes, and small significant changes by small changes.

This behaviour exhibited by stock returns or any other time series data is technically termed as ARCH process or Autoregressive Conditional Heteroscedasticity. Accurate modelling and forecasting of the variance has assumed importance as variance is regarded as the primary measure of risk in any risk management system. It was in 1982, that Engle for the very first time proposed the ARCH process with time-varying conditional variance. The ARCH process uses past disturbances to model the variances of the series and allows the variances of the error term to vary overtime (Karmakar, 2005). In 1986, Bollerslev further extended the ARCH process by allowing the conditional variance, to be a function of past period's squared errors, as well as, its past conditional variance and termed it the GARCH process (Generalized Autoregressive Conditional Heteroscedasticity). Following the introduction of the ARCH and GARCH models, several refinements to these models have been introduced such EGARCH, TGARCH, GJR-GARCH and so on.

There are a multitude of scholarly studies done in the area of modelling of stock returns: Kalyanarama (2014) has applied AR (1)-GARCH (1,1) model to capture the volatility in the Saudi stock market. The results indicate that the Saudi stock returns are characterised by volatility clustering and follow a non-normal distribution. It also indicates persistence, predictable and time-varying volatility. Wagar (July 2014) has estimated the volatility in the Pakistan stock market i.e. KSE by employing various univariate GARCH family models, i.e. the GARCH (1,1), EGARCH (1,1), and TGARCH(1,1). In the Indian context, Karmakar made an attempt to capture the stock market volatility by using the GARCH (1,1) model. The results of the study revealed the presence of time-varying volatility with volatility clustering, and high persistence and predictability of volatility. Sinha (2009) makes an attempt to model volatility on two major national indices in India. It is observed that the EGARCH model adequately captures volatility on BSE, whereas GJR-GARCH model appropriately models the conditional variance in the returns of NSE. In our study we make an attempt to estimate the volatility in the Indian stock market by employing the GARCH family of models. We further explore the changes in volatility of returns on NSE before and after implementation of the NSE Volatility Index (IVIX). Thus the time series for capturing the volatility has been split into two periods i.e. the Pre- IVIX introduction period (1-1-2000 to 31-3-2008) and the Post-IVIX introduction period (1-4-2008 to 31-8-2016).

4.2 DATA AND METHODOLOGY

The sample comprises of daily data of CNX Nifty for the period from 1st January 2000 to 31st August 2016 compiled and published by NSE India. The period of study has been split into two phases to estimate the volatility in the Indian Stock Market before and after the implementation of IVIX. Since IVIX was introduced by NSE in April 2008, the period from 1-1-2000 to 31-3-2008 is considered as the pre-IVIX phase, whereas 1-4-2007 to 31-8-2016 is considered as post-IVIX period.

The volatility is estimated on the returns of CNX Nifty which is defined as follows:

$$R_{t = \text{Log}} \ (P_{t} / P_{t-1}) \ldots\ldots\ldots\ldots (1)$$

Where R_t is the logarithmic daily returns at time t and P_t and P_{t-1} are daily values of CXN Nifty at two successive days i.e. t and t-1 respectively.

We further aim at fitting an appropriate GARCH model for our sample to calculate the conditional volatility. In recent times modelling and predicting volatility with the ARCH family of models has assumed excessive importance. The ARCH model given by Robert Engle in 1982 suggested that conditional variance h_t can be modelled as a function of lagged ε. i.e. predictable volatility is dependent on the past news (Karmakar, 2005). Engle gave the q^{th} order ARCH model, which is defined as follows:

$$h_t = \omega + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \ldots\ldots\ldots\ldots + \alpha_q\varepsilon^2_{t-q} \qquad (2)$$

where, $\omega > 0$, $\alpha_1, \alpha_2 \ldots\ldots \alpha_q \geq 0$ and $\varepsilon_{t}/\Psi_{t-1} \sim N(0, h_t)$. The ARCH (q) model suggests that an old news which reached the market q periods ago has less impact on current market volatility. The effect of a shock on current volatility I periods ago ($I \leq q$) is thus explained by α_1. The extension to the ARCH model is the GARCH model proposed by Bollerslev (1986). In this model the Conditional Variance is represented as the function of its own lags and previous realized variance (Waqar, July 2014).

It is defined as:

$$h_t = \omega + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \ldots\ldots\ldots\ldots + \alpha_q\varepsilon^2_{t-q} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \ldots\ldots\ldots\ldots \beta_p h_{t-p} \quad (3)$$

Where, $\omega > 0$, $\alpha_1, \alpha_2 \ldots\ldots \alpha_q \geq 0$, $\beta_1, \beta_2 \ldots\ldots\ldots\ldots \beta_p \geq 0$. The α_1 and β_1 parameters of a GARCH model indicate the short-term volatility dynamics of the resulting time series. A large β_1 coefficient indicates that the volatility is persistent i.e. is takes long time to die out. Whereas, a large α_1 indicates the reaction of volatility to market movements is quite intense. If $\alpha_1 + \beta_1$ is close to unity, then a shock at time t will persist for many future periods. A high value $\alpha_1 + \beta_1$ implies long memory (Karmakar, 2005). The most commonly used GARCH model is the GARCH (1,1) model which is also referred to as the Vanilla GARCH or Generic GARCH model.

4.3 EMPIRICAL RESULTS AND DISCUSSION

Before developing an appropriate GARCH model for our return series, to estimate volatility we discuss the properties of the series by calculating descriptive statistics, check for stationarity using ADF and PP test, and also investigate Volatility Clustering.

Figure 4.1 shows the daily returns of NIFTY Index during the sample periods, viz. Pre-IVIX introduction period and Post-IVIX introduction period. It can be seen that the daily closing prices of NIFTY has an upward trend during both the periods.

Figure 4.1: Daily Closing Prices of NIFTY Index during the Sample Periods

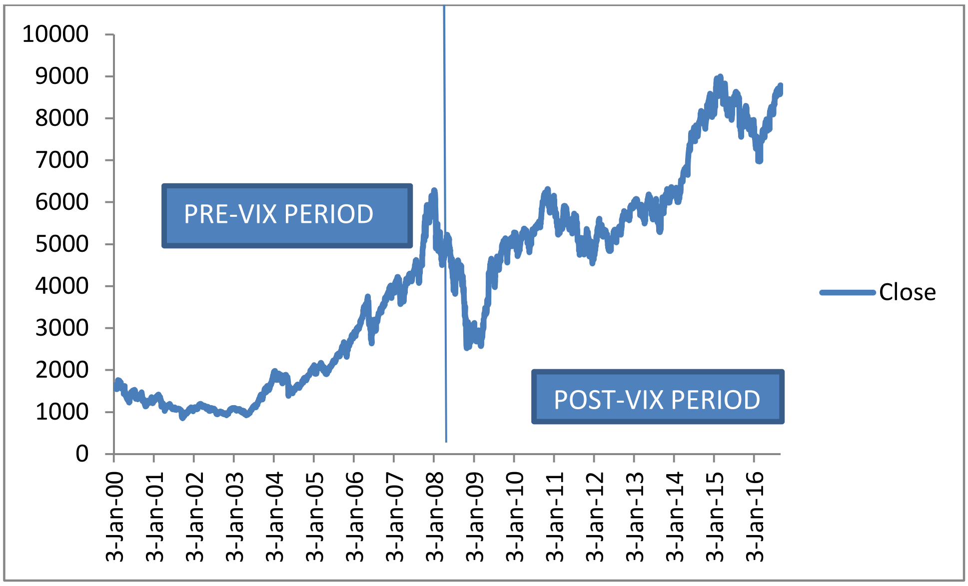
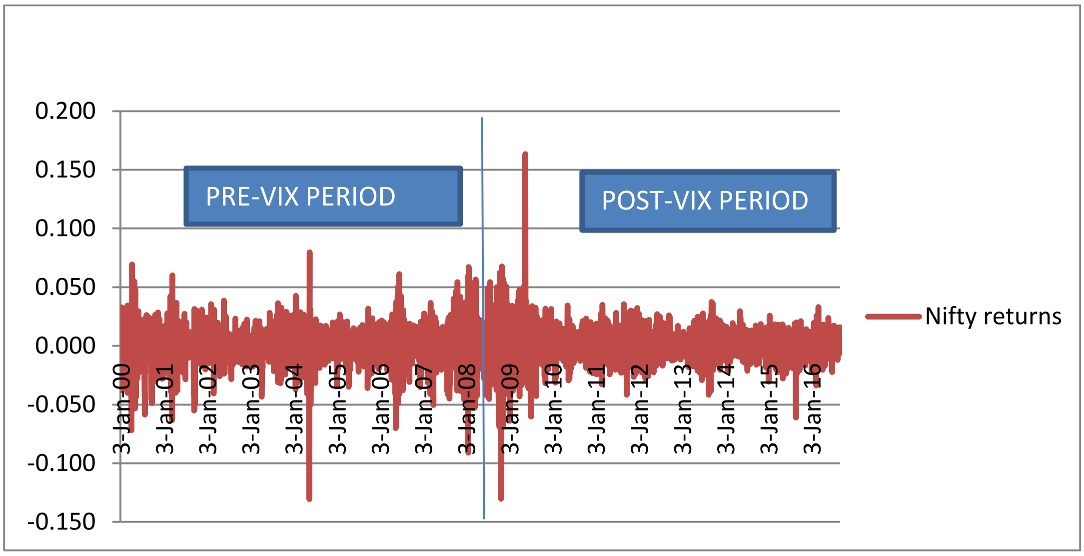


Figure 4. 2: Daily Returns of NIFTY Index during the Sample Periods



Besides, Figure 4.2 shows the daily returns of NIFTY index during the Pre-IVIX introduction period and the Post-IVIX introduction period. The visual representation shows that the volatility in the returns series during the following years of Post-IVIX introduction period is relatively lesser than the Pre-IVIX introduction period.

In order to test the distribution of the return series, the descriptive statistics of the daily market returns of NIFTY for the two sample periods, i.e. the Pre-IVIX introduction and the Post-IVIX introduction periods are computed and reported in Table 1. It is clearly seen that the average returns of NIFTY is positive during the Pre-IVIX introduction and the Post-IVIX introduction periods. The average returns of NIFTY are found to be high (0.067 percent) during the Pre-IVIX introduction period compared to the Post-IVIX introduction (0.0185 percent). However, the standard deviation is seen to be high (0.015277) during the Pre-IVIX introduction period. The higher value of standard deviation explains that the NSE is considered to be the more volatile market during the Pre-IVIX introduction period.

Table 4.1: Descriptive Statistics of NIFTY Return

Statistics	**Pre-IVIX Introduction Period**	**Post-IVIX Introduction Period**
Mean	0.000667	0.000185
Std. Deviation	0.015277	0.015156
Skewness	-0.71256	0.083182
Kurtosis	8.158365	14.31363
Jarque-Bera Statistics	2344.874* (0.000)	11650.35* (0.000)
Notes: Figures in the parenthesis ( ) indicates p-value. *- denote the significance at one percent level.		

Statistically, the value of Skewness zero and Kurtosis value three represents that the observed distribution is perfectly normally distributed. The table results show that returns series have non-zero skewness and the value of the Kurtosis is greater than 3 in both the sample periods, meaning that the returns series have a heavier tail or leptokurtic than the standard normal distribution. The daily stock returns during the

Pre-IVIX introduction and the Post-IVIX introduction periods are, thus, not normally distributed – which is further verified by the values of the Jarque-Bera statistics and its associated probability values. The Jarque-Bera statistics is used to test the normality of the data series. It examines the null hypothesis that the return series is normal against the alternative hypothesis that the return series is non-normal. From the table results, it is confirmed that the high value of the Jarque-Bera test statistics rejects the hypothesis of a normal distribution at one percent level of significance for the daily market returns of NIFTY during both the sample periods. Hence, the non-zero skewness and leptokurtic frequency distribution of return series during the Pre-IVIX introduction and the Post-IVIX introduction periods indicate that the distribution is not normal.

Given the time series nature of the data, an initial step in the analysis is to test whether return series is stationary or not. The study employed the Augmented Dickey Fuller test and the Philip-Perron unit root tests for the NIFTY series during the Pre-IVIX introduction and the Post-IVIX introduction periods and the results are reported in Table 2. Under the ADF and PP tests, the null hypothesis of a unit root (non-stationary) is tested against the alternative of no unit root (stationary). The ADF and PP test statistics rejects the null hypothesis of a unit root at one percent level of significance for both sample periods. This indicates that the returns series examined are stationary.

Table 4.2: Unit Root Test Results

Results of the Pre-IVIX Introduction Period		
Variables	**ADF test statistics**	**PP test statistics**
NSE-NIFTY Returns	-32.5153*	-40.5482*
Results of the Post-IVIX Introduction Period		
NSE-NIFTY Returns	-43.7077*	-43.6126*
Notes: * – indicates significance at one per cent level. Optimal lag length is determined by the Akaike Information Criterion (AIC).		

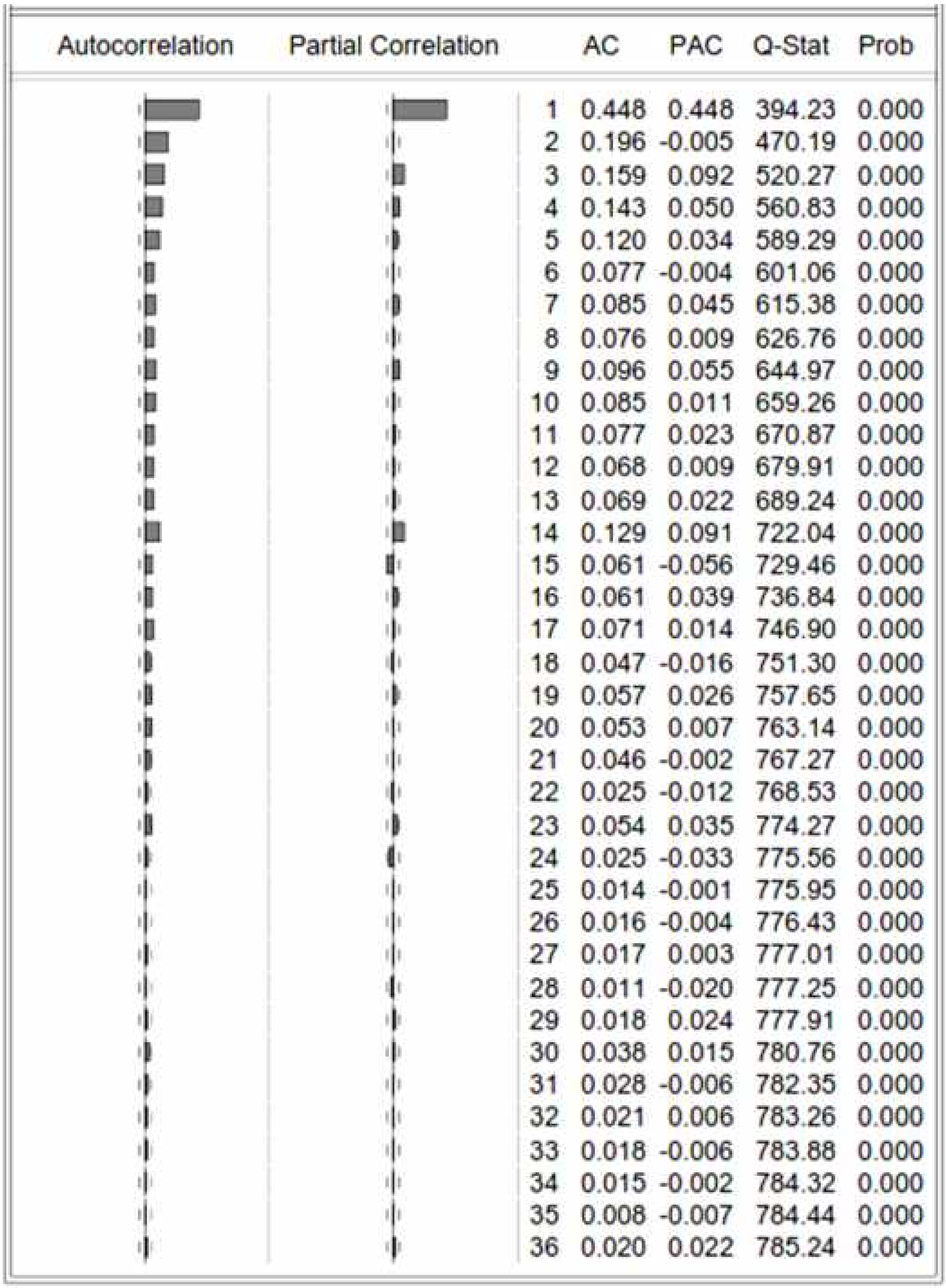
To test whether there is ARCH effect in the NIFTY return during the Pre-IVIX introduction and Post-IVIX introduction periods, the Engle (1982) ARCH-LM test statistics was conducted in order to test the null hypothesis of no ARCH effects on the NIFTY return series during the Pre-IVIX introduction and the Post-IVIX introduction periods and its result are shown in Table 4.3. The ARCH-LM test statistics are highly significant at one per cent level, confirming the existence of significant ARCH effects on the return data series during the Pre-IVIX introduction and Post-IVIX introduction periods. Figures 4.3 and 4.4 also exhibit the autocorrelation values and Q^2-statistics of NIFTY returns for two sample periods, respectively. These results are also consistent with the findings of Table 4.3, suggesting the presence of ARCH effects in the residuals of the returns and hence the results warrant for the estimation of the GARCH family models.

Table 4.3: ARCH-LM Test Results of NIFTY Return for the Pre-IVIX Introduction and Post-IVIX Introduction Periods

ARCH-LM [1] Test Statistic	
Pre-IVIX Introduction Period	442.319* (0.0000)
Post-IVIX Introduction Period	32.45951* (0.0000)
Note: * indicates significance at one percent level. ARCH-LM [1] is a Lagrange multiplier test for ARCH effect of order 1 in the residuals (Engle, 1982).	

Moreover, Figures 4.5 and 4.6 exhibits the residual series of the NIFTY during the Pre-IVIX introduction and the Post-IVIX introduction periods, respectively. From the Figures 4.5 and 4.6, it appears that there are stretches of time where the volatility is relatively high and relatively less which suggests an apparent volatility clustering or ARCH effects during the Pre-IVIX introduction period and the Post-IVIX introduction period. However, the volatility clustering in the returns series during the years following the Post-IVIX introduction period is relatively lesser than the Pre-IVIX introduction period.

Figure 4.3: Autocorrelation for the NIFTY Returns during the Pre-IVIX Introduction Period



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.448	0.448	394.23	0.000
		2	0.196	-0.005	470.19	0.000
		3	0.159	0.092	520.27	0.000
		4	0.143	0.050	560.83	0.000
		5	0.120	0.034	589.29	0.000
		6	0.077	-0.004	601.06	0.000
		7	0.085	0.045	615.38	0.000
		8	0.076	0.009	626.76	0.000
		9	0.096	0.055	644.97	0.000
		10	0.085	0.011	659.26	0.000
		11	0.077	0.023	670.87	0.000
		12	0.068	0.009	679.91	0.000
		13	0.069	0.022	689.24	0.000
		14	0.129	0.091	722.04	0.000
		15	0.061	-0.056	729.46	0.000
		16	0.061	0.039	736.84	0.000
		17	0.071	0.014	746.90	0.000
		18	0.047	-0.016	751.30	0.000
		19	0.057	0.026	757.65	0.000
		20	0.053	0.007	763.14	0.000
		21	0.046	-0.002	767.27	0.000
		22	0.025	-0.012	768.53	0.000
		23	0.054	0.035	774.27	0.000
		24	0.025	-0.033	775.56	0.000
		25	0.014	-0.001	775.95	0.000
		26	0.016	-0.004	776.43	0.000
		27	0.017	0.003	777.01	0.000
		28	0.011	-0.020	777.25	0.000
		29	0.018	0.024	777.91	0.000
		30	0.038	0.015	780.76	0.000
		31	0.028	-0.006	782.35	0.000
		32	0.021	0.006	783.26	0.000
		33	0.018	-0.006	783.88	0.000
		34	0.015	-0.002	784.32	0.000
		35	0.008	-0.007	784.44	0.000
		36	0.020	0.022	785.24	0.000

Figure 4.4: Autocorrelation for the NIFTY Returns during the Post-IVIX Introduction Period

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.117	0.117	30.010	0.000
		2	0.181	0.170	101.66	0.000
		3	0.116	0.082	130.92	0.000
		4	0.188	0.147	208.47	0.000
		5	0.144	0.091	253.85	0.000
		6	0.114	0.041	282.19	0.000
		7	0.172	0.110	347.05	0.000
		8	0.092	0.014	365.77	0.000
		9	0.150	0.070	414.93	0.000
		10	0.174	0.110	481.59	0.000
		11	0.156	0.065	534.74	0.000
		12	0.091	-0.004	553.00	0.000
		13	0.114	0.024	581.53	0.000
		14	0.094	-0.004	601.14	0.000
		15	0.122	0.036	634.08	0.000
		16	0.093	0.011	653.12	0.000
		17	0.082	-0.010	667.84	0.000
		18	0.116	0.042	697.75	0.000
		19	0.063	-0.019	706.47	0.000
		20	0.100	0.010	728.33	0.000
		21	0.091	0.024	746.75	0.000
		22	0.075	-0.007	759.23	0.000
		23	0.087	0.023	775.93	0.000
		24	0.068	0.002	786.29	0.000
		25	0.063	-0.017	795.07	0.000
		26	0.097	0.043	816.01	0.000
		27	0.078	0.015	829.50	0.000
		28	0.069	-0.002	840.11	0.000
		29	0.117	0.068	870.34	0.000
		30	0.055	-0.017	877.03	0.000
		31	0.060	-0.016	885.10	0.000
		32	0.046	-0.007	889.87	0.000
		33	0.044	-0.033	894.18	0.000
		34	0.099	0.055	915.87	0.000
		35	0.130	0.095	953.49	0.000
		36	0.061	-0.020	961.65	0.000

Figure 4.5: Volatility Clustering of NIFTY returns during the Pre-IVIX Introduction Period

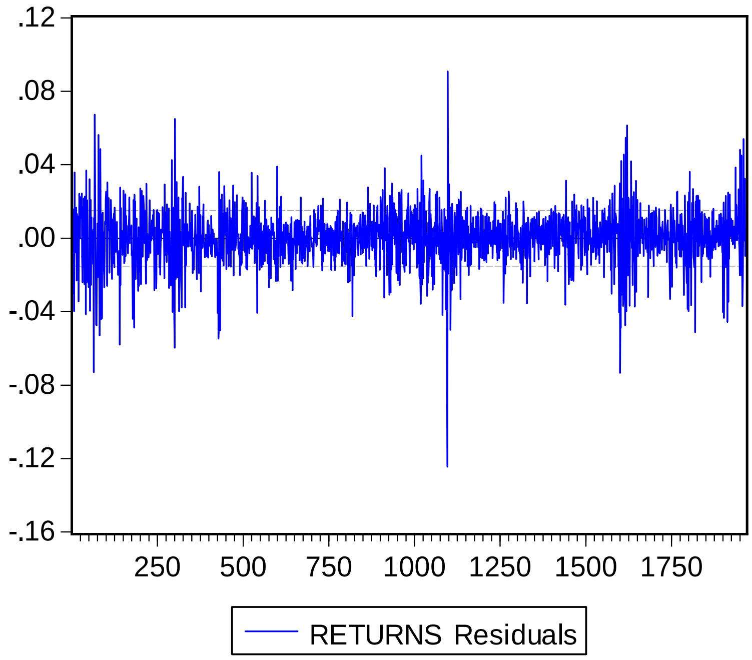
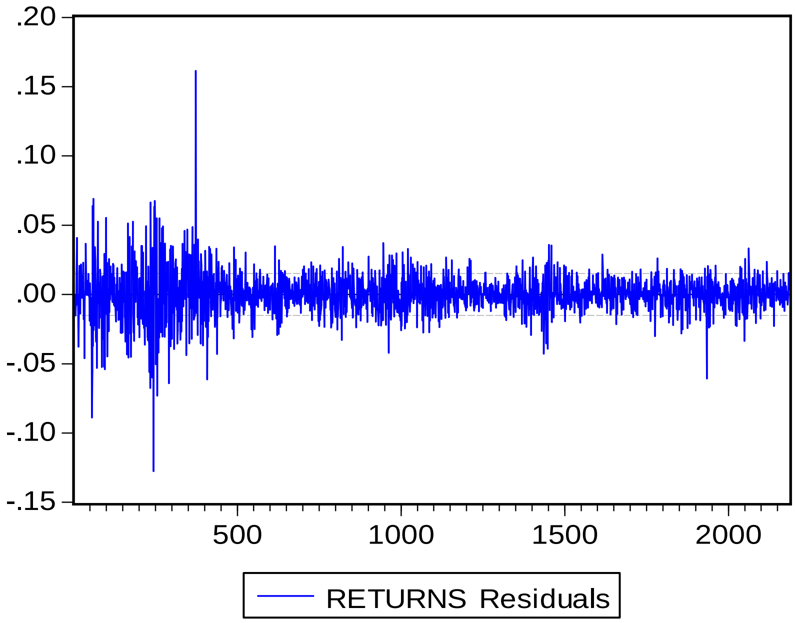


Figure 4.6: Volatility Clustering of NIFTY returns during the Post-IVIX Introduction Period



After volatility clustering is confirmed with return series and stationarity using ADF test, heteroscedasticity effect using ARCH-LM test, we suggest that the GARCH-type models are capable and deemed fit for modelling the return volatility of the Indian market, as it sufficiently captures the volatility clustering and heteroscedastic effects.

Therefore, GARCH-type family models are used for modelling the volatility of return series in the Indian stock market during the Pre-IVIX introduction period and the Post-IVIX introduction period.

Table 4.4: Estimates of GARCH (1,1) model

$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t$ $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$						
Period	$\mathbf{a_0}$	$\mathbf{a_1}$	α_0	α_1	β_1	**ARCH-LM [1] Test Statistics**
Pre-IVIX Introduction	0.001258* (4.684064)	0.101062* (4.050009)	1.18E-05* (7.857966)	0.059193* (11.13534)	0.790486* (52.74535)	0.558328 {0.455024}
Post-IVIX Introduction	0.000549** (2.368797)	0.076394* (3.202458)	1.81E-06* (4.566437)	0.078040* (9.349827)	0.714453* (101.6525)	0.830603 {0.362199}
Note: Figures in ( ) & { } parentheses are Z-statistics and probability value respectively. * & ** denote the significance at one and five percent level respectively. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects of order 1 in the residuals (Engle, 1982).						

Table 4.4 depicts the estimates of the GARCH (1,1) model to compare the volatility persistency of the Indian stock market before and after the introduction of IVIX. Comparing parameters across the two sub-periods, it can be seen that estimated coefficient α_1 increases from 0.0591 to 0.0780 in the post-IVIX introduction period, which confirms that the impact of recent news has a greater impact on price changes. This implies that the information is being impounded more quickly following the onset of IVIX. Besides, the persistence coefficient β_1 has decreased from 0.7905 to 0.7144 in the post-IVIX introduction period which indicates that an increase in the rate of information flows reduce the uncertainty about previous news. In other words, following the onset of Indian VIX, the 'old news' have lesser impact in determining the volatility of the Indian spot market. This is also confirmed by the sum of coefficients α_1 and $\beta_{1,}$ ($\alpha_1 + \beta_1$), that changes from 0.9231 (pre-IVIX) to 0.7924 (post-IVIX) suggesting persistence of shocks from the Pre-IVIX introduction period to the Post-IVIX introduction period is reduced.

Besides, the GARCH (1,1) model with a dummy was employed to examine whether the introduction of IVIX stabilizes the spot market volatility in India.

Table 4.5: Estimates of GARCH (1, 1) model for the Impact of IVIX on Spot Market Volatility (Whole Period)

$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t$ $h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} + DIVIX$						
a_0	a_1	α_0	α_1	β_1	**DIVIX**	**ARCH-LM [1] test Statistics**
0.000878* (4.573143)	0.0883* (5.25573)	5.64E-06* (8.718056	0.111964* (15.91072)	0.867828* (112.47)	-1.61E-06* (-2.97183)	0.029583 {0.8634}

Notes: Figures in ( ) & { } parentheses are Z-statistics and probability value, respectively. * & ** denote the significance at one and five percent level, respectively. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects of order 1 in the residuals (Engle, 1982).

Table 4.5 depicts the estimates of GARCH(1,1) model, the empirical results reveal that introduction of IVIX Dummy coefficient (DIVIX**)**, which takes the value of 0 for the Pre-IVIX introduction period (1-1-2000 to 31-3-2008) and takes the value 1 for the Post-IVIX introduction period (1-4-2008 to 31-8-2016). The IVIX Dummy coefficient (DIVIX) is found to be negative and statistically significant at one percent level, implying that the volatility of the spot market has declined after the introduction of IVIX in India.

4.4 CONCLUSION:

On the whole, the empirical results of the GARCH (1,1) model with a dummy indicates that the volatility of the spot market has declined after the introduction of IVIX in India. In addition, the results of the standard GARCH (1,1) model provides the evidence that recent news has a greater impact on the spot market changes in the post-IVIX introduction period. At the same time, the persistence of volatility shocks has declined in the post-IVIX scenario indicating increased efficiency of the Indian stock market. Hence, the study suggests that the introduction of IVIX have improved the speed and quality of information flowing in the Indian stock market and has helped to curb spot market volatility in India.

TO EXAMINE THE PREDICTIVE ABILITY OF SYMMETRIC AND ASYMMETRIC GARCH MODELS

5.1 INTRODUCTION:

Uncertainty faced by investors is the starting point for every financial model and the basic element of every financial model involves investigating the impact of uncertainty on the behaviour of investors and, ultimately, on market prices. The very existence of financial economics as a discipline is based on uncertainty. Volatility is the purest measure of risk in financial economics. The tradeoff between return and risk is critical for all investment decisions as inaccurate volatility forecasts can leave financial institutions deprived of capital for operations and investment. High volatility levels are perceived as an indicator of market inefficiency and a potential threat to the very integrity of market mechanism. The volatility in the stock market affects investment spending and investor confidence. Thus risk averse investors may shift their investments to less risky avenues. A volatile stock market may also lose on important foreign investment. This in turn hampers the economic progress.

Professional option traders such as hedge funds and banks' proprietary traders are interested primarily in the volatility implied by an option's market price when making buy and sell decisions. Higher levels of implied volatility (IV) indicate the option to be overpriced, and vice versa. Earnings from volatility positions in options, such as straddles, are largely dependent on the movements in implied volatility.

Implied volatility (discussed in Chapter 1) is derived by solving an option pricing model such as the Black-Scholes option pricing model for the volatility when the prevailing market price for an option is known. The Black-Scholes (BS) option pricing model indicates that the price of an option at time t is a function of S (the price of underlying security), X (the strike price), r (the risk free interest rate), T (time to option maturity) and σ (volatility of the underlying asset over time period from t to T). Given that S_t; X; r and T are observable, once the market has produced a price based on a transaction for the option, we could inverse the BS formula to derive σ that market uses as an input. Such a volatility estimate is called option implied volatility.

To gauge the market anxiety and to serve as a proxy for overall market uncertainty, CBOE introduced the implied volatility based Volatility Index (VIX) in 1993. Whaley in his work *Understanding VIX* (2009) describes that the VIX has two important uses: firstly, it serves as a reference point of short-term volatility; and secondly, VIX allows trading of pure volatility. The US VIX was the first volatility Index to be introduced and soon became popular as the benchmark for measuring volatility. The US VIX now has many imitators internationally. India's premier exchange the NSE introduced its volatility Index i.e. the India VIX in 2008. It adopted the CBOE methodology with some alterations to suit the Indian market. (S.S.S.Kumar, 2010) demonstrates that the India VIX reflects certain characteristics known as stylised facts of volatility:

Some important stylised facts are: It is said to display Volatility clustering and persistence and mean reverting behaviour. Further volatility is said to be negatively related to stock returns and positively related to trading volume. In addition to these (Mujumdar & Banarjee, 2004) expects implied volatility to have asymmetric structure and non-normal distribution with heavier tails.

Off late Volatility forecasting has occupied the attention of academicians and practitioners as it plays a vital role in an array of areas like investment, security valuation, risk management and monetary policy making. Accurate volatility predictions offer the following advantages. Firstly, volatility as measured by the standard deviation or variance of returns is regarded as a basic measure of the total risk of financial assets. Secondly, volatility is a vital variable directly used in the Black-Scholes formula for option pricing. In the past, historical volatility methods were employed to estimate the future volatility. But in recent times, there is a growing body of literature that advocates the use of more sophisticated time-series models in volatility predictions for accurate options valuation. Finally, with the introduction of VIX futures it is possible to trade volatility like any other commodity, so accurate predictions of future volatility will give the investor the potential to make a greater profit.

Therefore thorough this chapter an attempt has been made to model and forecast NSE's implied volatility Index i.e. the India VIX. The predictive efficiency of the India VIX index has been explored before. But this is the first attempt made in the Indian context to build a model that would reliably forecast the future direction of India VIX, thus providing valuable signals to option traders. Numerous models to forecast market volatility have been developed in the literature and applied in practice. These range from the extremely simple random walk model to the relatively complex conditional heteroskedastic models of the GARCH family. The GARCH models have been regarded to provide superior forecasts on volatility and have amassed huge following in financial literature. The objective of the current study is to examine the forecasting ability of symmetric and asymmetric GARCH models. The performance of the basic GARCH, EGARCH, and TGARCH models is evaluated in forecasting the India VIX.

5.2 DATA AND METHODOLOGY:

5.2.1 Data:

The daily closing levels of India VIX are considered from 2nd March 2009 to 31st August 2016. The India VIX data is extracted from the NSE India website. For the purpose Of the study the data has been split into two parts i. e the in-sample and the out-sample data.

In-sample Data: The period from March 2nd, 2009 to June 1st, 2016 is considered as in-sample period. It consists of 1797 data points. The in sample data is used to build a model that has high degree of predictability.

Out-sample Data: The period from June 1st, 2016 to August 31st, 2016 is considered out-sample period. It consists of 64 data points. The model developed through in-sample data will be tested for forecasting performance on out-sample data. The forecasts provided by the models will be compared with the actual values of India VIX.

5.2.2: Methodology:

5.2.2.1 Methods of volatility forecasting:

The most commonly applied class of time-varying models are the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Ever since their introduction by Engle in 1982, and subsequent generalization by Bollerslev in 1986, these models have been extended in numerous ways which usually involve alternative formulations for the volatility process. ARCH class models help in capturing the *volatility clustering* phenomenon in financial time series. They are usually defined by their first two moments, the Mean and the Variance Equation. The Mean equation describes the behaviour of the dependent variable over time. This can be expressed in any form the researcher wishes. The functional forms of different models have been expressed below:

The ARCH (q) model is expressed as:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots \ldots\ldots\ldots\ldots\ldots.. + \alpha_q u_{t-q}^2$$

Tim Bollerlev in 1986 developed the GARCH model. In this model the Conditional variance is allowed to depend on its own past lags. The GARCH model is expressed as

$$h_t = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \ldots\ldots\ldots\ldots + \alpha_q u^2_{t-q} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + \ldots.\beta_p h_{t-p}$$

The GARCH (1,1) model can be extended to GARCH (p,q) where the current conditional variance is modelled as a function of q lags of the squared error term and p lags of the conditional variance. The GARCH models enforce a symmetric response of volatility to positive and negative shocks. But in financial time series, it is argued that a negative shock is likely to have higher impact on volatility than a positive shock. The Threshold GARCH (TGARCH) or the GJR GARCH and the Exponential GARCH (EGARCH) models are the popular extensions of the GARCH models that capture the asymmetries in financial data.

The TGARCH model was developed by Zakoin in 1994 and the GJR GARCH model named after its developers Glosten, Jagannathan and Runkle (1993) is an extension of the vanilla GARCH model with an additional term to capture the asymmetries in the data. The conditional variance in this case is modelled as

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1}$$

Where $I_{t-1} = 1, If\ u_{t-1} < 0$

$= 0, otherwise$

For leverage effect $\gamma > 0$ and for non-negativity condition $\alpha_0 > 0, \alpha_1 > 0, \beta \geq 0$ and $\alpha_1 + \gamma \geq 0$. The model is admissible even if $\gamma < 0$, but $\alpha_1 + \gamma \geq 0$.

Nelson proposed the EGARCH model in 1991. The variance equation specification is given as:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

γ term provides for asymmetries in the EGARCH specification. A Negative γ I mplies negative relationship between volatility and returns in the series.

5.2.2.2 Measuring Forecast performance:

Comparing forecast performance of competing models is one of the most important aspects of any forecasting exercise. We evaluate the predictive ability of the competing models using popular evaluation measures used in previous studies. They are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Theils Inequality Coefficient. These are termed as symmetric forecast error statistics as they treat over-predictions and under-predictions equally. These are defined as follows:

RMSE = $\sqrt{\frac{1}{n} \sum_{i=n}^{n} \left|\hat{\sigma_i} - \sigma_i\right|^2}$

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

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

Theils inequality coefficient = $\frac{\sum_{i=n}^{n} (\hat{\sigma_i} - \sigma_i)^2}{\sum_{i=n}^{n} (\hat{\sigma_{i-1}} - \sigma_i)^2}$

The evaluation techniques discussed above are employed in this study. The model having the least forecast errors is ranked as the best model. Further the out-sample forecasts given by these three models is compared with the actual India VIX and the one giving the least deviations is selected.

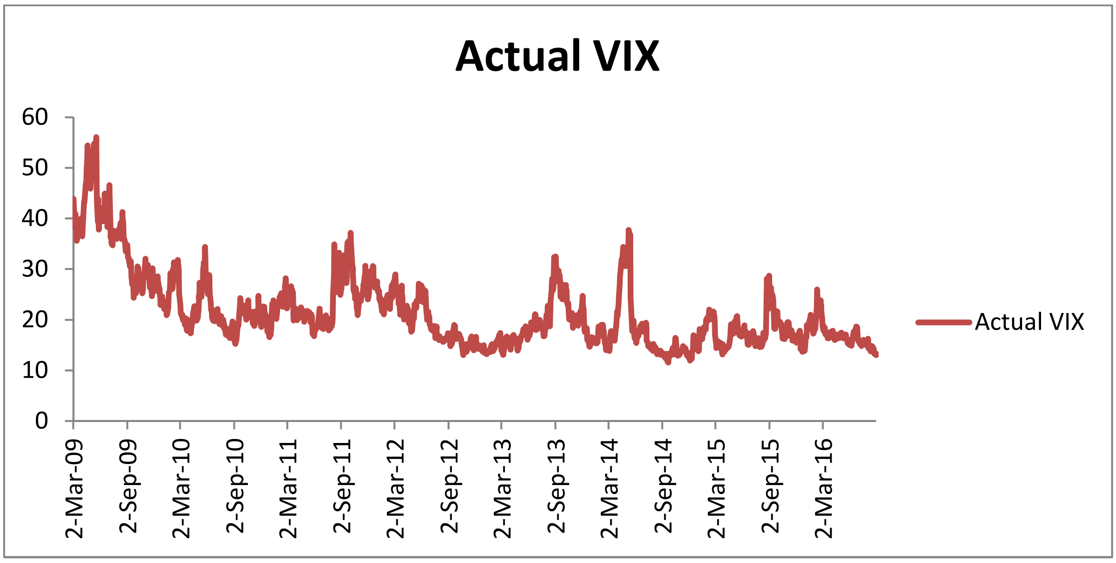
5.3 EMPIRICAL RESULTS AND DISCUSSION:

Before developing an appropriate GARCH model it is pertinent to discuss the properties of the India VIX. The descriptive statistics of the daily closing price of India VIX index for the sample period is reported in the Table 5.1. The mean value of daily India VIX index is found to be 21.37, and the maximum and minimum values during the study period seems to be 56.07 and 11.56, respectively. Figure 1 shows the daily India VIX index closing price during the sample period and it seems to have an upward and downward trend. The standard deviation is found to be higher (7.33) as it largely deviated from the mean value of 21.37. The India VIX index closing price series is positively skewed (1.68) and that of Kurtosis value is more than 3 (6.33), i.e. excess kurtosis, thus they are leptokurtic. Likewise, a highly significant large JB statistic confirms that the return series are not normally distributed. The Jarque-Bera statistics is found to be statistically significant at one percent level, rejecting the null hypothesis of India VIX index closing price series is normally distributed, confirming that the series is non-normal.

Table 5.1: Descriptive Statistics of Daily Closing Price of IndiaVIX Index

Statistics	**India VIX**
Mean	21.37409
Maximum	56.07000
Minimum	11.56500
Std. Deviation	7.331476
Skewness	1.688209
Kurtosis	6.332048
Jarque-Bera	1744.901* (0.0000)
Notes: Figures in the parenthesis ( ) indicates p-value. *- denote the significance at one percent level.	

Figure 5.1: Daily Closing Price of India VIX Index for the period from March 2009 to August 2016



Given the time-series nature of the data, an initial step in the analysis is to test whether price-series is stationary or not. The study employed ADF unit root test for the daily closing price of India VIX Index series and the results are reported in Table 5.2. The ADF statistics result indicates that the price series is stationary. The ADF test statistics reject the hypothesis of a unit root at 1% level of significance in price series, implying the fact that the VIX series is stationary.

Table 5.2: Augmented Dickey-Fuller Test Results

Variables	Intercept	Intercept & Trend
VIX	-4.251616*	-5.095607*
Notes: * – indicates significance at one per cent level. Optimal lag length is determined by the Akaike Information Criterion (AIC).		

To test whether there is ARCH effect in the Indian VIX price series, the Ljung-Box Q^2 statistics is used on squared residual series of the mean model and the results are presented in the Table 5.3. $Q^2[1]$, $Q^2[4]$, $Q^2[12]$ and $Q^2[24]$ represents the Ljung-Box

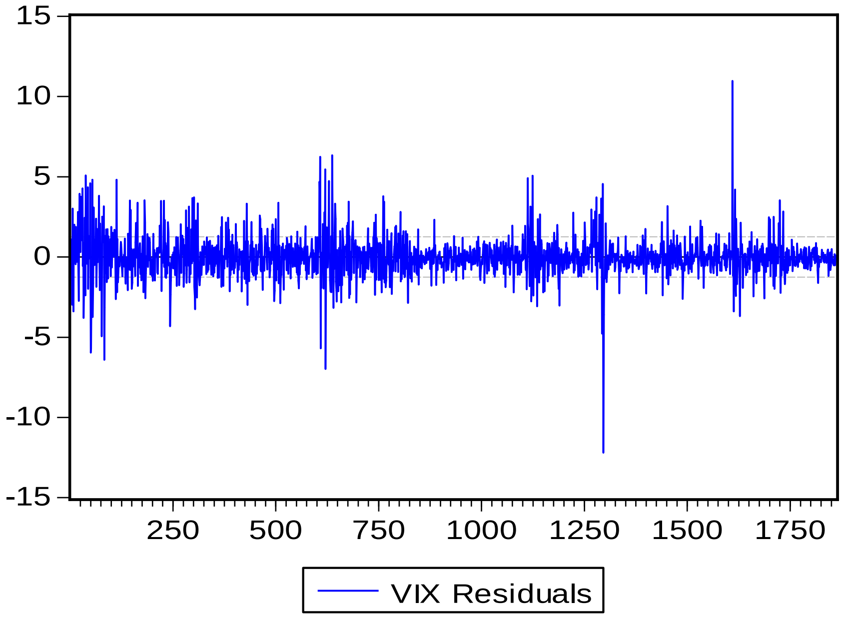
Q^2-statistics for the squared standardized residuals using 1, 4, 12, and 24 lags, respectively. The Ljung-Box Q^2-statistics test the null hypothesis of no ARCH effect against the alternative hypothesis of ARCH effect. From the Ljung-Box Q^2 test statistics of all lags, it is observed that the null hypothesis is rejected at one per cent level of significance, indicating the existence of ARCH effect in the India VIX Index during the sample period. Furthermore, the Engle (1982) ARCH-LM test statistics was conducted in order to test the null hypothesis of no ARCH effect on the India VIX Index price series and its results are shown in Table 5.3. The ARCH-LM test statistics are highly significant at one per cent level, confirming the existence of significant ARCH effects on the price data series during the study period. Hence, the results of both the tests confirm the presence of ARCH effects in the residuals of time series models in the VIX series and hence the results warrant for the estimation of GARCH family models.

Table 5.3: Ljung-Box (1978) Q^2 statistics and ARCH-LM Test Results for Indian VIX Closing Price

ARCH-LM [1] test statistics	**Q^2[1]-test statistics**	**Q^2[4]-test statistics**	**Q^2[12]-test statistics**	**Q^2[24]-test statistics**
67.89339 * (0.0000)	**65.708*** (0.0000)	114.88* (0.0000)	178.02* (0.0000)	229.32* (0.0000)

Notes: * – indicates significance at one percent level. Q^2[1], Q^2[4], Q^2[12], and Q^2[24] represents the Ljung-Box Q-statistics for the model squared standardized residuals using 1, 4, 12, and 24 lags, respectively. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects in the residuals (Engle, 1982).

Figure 5.2: Volatility Clustering of India VIX during March 2009 to August 2016



Moreover, Figure 5.2 exhibits the residual series of the India VIX Index. From the figure, it appears that there are stretches of time where the volatility is relatively high and relatively less which suggests an apparent volatility clustering or ARCH effects in some periods. Statistically, volatility clustering implies a strong autocorrelation in squared returns.

After volatility clustering is confirmed with daily closing price of India VIX Index series and stationarity using ADF test, heteroscedasticity effect using Ljung-Box (1978) Q^2 statistics and ARCH-LM test, the study suggests that the GARCH-type models are capable and deemed fit for modelling the VIX Index of the Indian market, as it sufficiently captures the volatility clustering and heteroscedastic effects. Therefore, the GARCH-type family models are used to examine the predictive ability of Indian VIX series during the sample period.

Table 5.4: Results of Estimated GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) Models

Estimates of GARCH (1,1) model						
a_0	a_1	α_0	α_i	β_j		**ARCH-LM [1] test Statistics**
0.354561 (4.252187)*	0.980092 (260.8508)*	0.085268 (8.904390)*	0.124594 (10.51266)*	0.824013 (52.25459)*	–	0.069674 {0.791842}
Akaike Information Criteria (AIC): 2.951293 Schwarz Information Criteria (SIC): 2.996586						
Estimates of EGARCH (1,1) model						
β_0	β_1	α_0	α_1	δ_1	¥ 1	**ARCH-LM [1] test Statistics**
0.412268 (10.72547)*	0.979953 (415.5723)*	-0.007226 (-0.994745)*	0.962766 (196.5465)*	0.009475 (0.924005)*	0.202547 (21.99726)*	0.021369 {0.883796}
Akaike Information Criteria (AIC): 2.987545 Schwarz Information Criteria (SIC): 3.005897						
Estimates of TGARCH (1,1) model						
A	***B***	α_0	β_i	λ_j	δ	**ARCH-LM [1] test Statistics**
0.518161 (6.556297)*	0.973833 (249.7634)*	0.064465 (8.792096)*	0.185517 (9.951399)*	0.869968 (73.90744)*	-0.214376 (10.52049)*	0.034382 {0.852918}
Akaike Information Criteria (AIC): 3.023511 Schwarz Information Criteria (SIC): 3.041863						
Notes: Figures in ( ) & { } parentheses are Z-statistics and probability value, respectively. * - denotes the significance at one percent level. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects in the residuals (Engle, 1982).						

Table 5.4 shows the estimates of parsimonious GARCH (1,1), EGARCH(1,1), and TGARCH(1,1) models for daily closing price of Indian VIX Index. The table result reveals that the ARCH and GARCH terms in conditional variance equations are positive and significant at one per cent level in all estimations, implying a strong support for the ARCH and GARCH effects. Besides, the table result shows that conditional variance equations of GARCH (1,1), EGARCH(1,1), and TGARCH(1,1) models were all close to unity, implying that innovation to the conditional variance is

highly persistent and takes longer time to dissipate. It was an indication of a covariance stationary model with a high degree of persistence and long memory in the conditional variance. In the EGARCH (1,1) model, the dependence of volatility on its past behaviour is confirmed, as α_1 and δ_1 coefficients appear to be statistically significant. Besides, the asymmetric coefficient γ_1 (0.202547) shows that the VIX index exhibits statistically significant asymmetric effects at one percent level. This indicates that positive shocks (good news) have greater impact on this VIX Index than the negative shocks (bad news). Consequently, this suggests that there is a larger impact on volatility due to the noise traders in the Indian VIX during market upward movement than market downward movement under the same magnitude of innovation, i.e. the volatility of positive innovations is larger than that of negative innovations. In contrast, the result of the TGARCH (1,1) model reveals that asymmetric effect captured by the parameter estimate δ (-0.214376) which is less than zero suggesting that positive news has greater influence than negative news.

To check the robustness of the estimated mean equations of the GARCH-type models, the Lagrange Multiplier (ARCH-LM) test was used to test the presence of remaining ARCH effects in the standardized residuals. With mean and variance equations of the GARCH models being appropriately defined, there should be no ARCH effect left in the standardized residuals. The ARCH-LM [1] test for all the GARCH models indicate that there are no ARCH effects in the standardized residuals of the variance equations.

Overall, using the minimum Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) values as model selection criteria for the GARCH models, the preferred model is the GARCH (1,1) model based on the minimum Akaike

Information Criteria and Schwarz Information Criteria. Despite the presence of an asymmetric response to news, as suggested by minimum AIC and SIC, the GARCH (1 1) is the unbiased estimate leading to consistent and precise inferences pertaining to the modelling and forecasting of Indian VIX price series.

Table 5.5: Forecast Performance of Estimated Models for the Out-of-Sample Period

Forecast Error Statistics	**GARCH Model**	**EGARCH Model**	**TGARCH Model**
Root Mean Squared Error	2.063653^{1}	3.275960^{3}	3.198215^{2}
Mean Absolute Error	1.779888^{1}	2.754733^{3}	2.699817^{2}
Mean Absolute Percent Error	12.01555^{1}	18.77567^{3}	18.39514^{2}
Theil Inequality Coefficient	0.063757^{1}	0.097448^{3}	0.095257^{2}
Overall Rank			

Notes: Out-of-Sample forecasts for last 64 observations (1st June 2016 to 31st August 2016). Superscripts (1), (2) & (3) denote rank of the model. The best performing model has a rank 1.

The models were also evaluated in terms of their forecasting ability of future VIX index. The chapter uses the standard (symmetric) loss functions to evaluate the forecasting performance of the competing models: the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient. In table 5.5, the results of out-sample forecast performance of the estimated models are shown for the last 64 observations, i.e. from 1st June 2016 to 31st August 2016. The model that exhibits the lowest values of the error measurements is considered to be the best one. The results show that the GARCH (1,1) model outperformed all the other models in forecasting India VIX price series. This is followed by the TGARCH (1,1) model that performed better in forecasting the India VIX price series. To summarize, the empirical results indicate that the symmetric GARCH model does perform better in forecasting India VIX price series rather than the asymmetric GARCH model, despite leverage effect.

Table 5.6: Actual Vs Forecasted India VIX for the Out-Sample Period

Date	Actual VIX	VIXF-GARCH	VIXF-EGARCH	VIXF-TGARCH
1-Jun-16	15.835	16.080	16.136	16.143
2-Jun-16	15.0875	16.115	16.224	16.239
3-Jun-16	14.995	16.148	16.311	16.332
6-Jun-16	15.355	16.181	16.397	16.423
7-Jun-16	14.87	16.214	16.480	16.512
8-Jun-16	15.1425	16.246	16.562	16.598
9-Jun-16	15.6725	16.277	16.642	16.681
10-Jun-16	15.97	16.307	16.721	16.763
13-Jun-16	16.5825	16.337	16.798	16.843
14-Jun-16	17.19	16.366	16.874	16.920
15-Jun-16	17.055	16.395	16.948	16.996
16-Jun-16	17.6975	16.423	17.020	17.069
17-Jun-16	17.35	16.451	17.091	17.141
20-Jun-16	17.5175	16.478	17.161	17.210
21-Jun-16	17.26	16.504	17.229	17.278
22-Jun-16	18.185	16.530	17.296	17.344
23-Jun-16	18.02	16.556	17.361	17.408
24-Jun-16	18.6275	16.581	17.426	17.471
27-Jun-16	18.53	16.605	17.489	17.532
28-Jun-16	17.725	16.629	17.550	17.591
29-Jun-16	16.155	16.653	17.611	17.649
30-Jun-16	16.29	16.676	17.670	17.706
1-Jul-16	15.7375	16.698	17.728	17.760
4-Jul-16	15.5775	16.721	17.785	17.814
5-Jul-16	15.3625	16.742	17.840	17.866
7-Jul-16	15.3075	16.763	17.895	17.917
8-Jul-16	15.0825	16.784	17.949	17.966
11-Jul-16	14.8475	16.805	18.001	18.014
12-Jul-16	14.7825	16.825	18.052	18.061
13-Jul-16	15.325	16.844	18.103	18.106
14-Jul-16	15.61	16.864	18.152	18.151
15-Jul-16	15.6375	16.882	18.201	18.194
18-Jul-16	15.9875	16.901	18.248	18.236
19-Jul-16	15.795	16.919	18.294	18.277
20-Jul-16	15.99	16.937	18.340	18.317
21-Jul-16	15.7125	16.954	18.384	18.356
22-Jul-16	15.4975	16.971	18.428	18.394
25-Jul-16	15.7175	16.988	18.471	18.431

26-Jul-16	15.62	17.004	18.513	18.466
27-Jul-16	15.4275	17.020	18.554	18.501
28-Jul-16	15.1475	17.036	18.594	18.535
29-Jul-16	14.9175	17.051	18.634	18.569
1-Aug-16	15.18	17.066	18.673	18.601
2-Aug-16	15.6925	17.081	18.711	18.632
3-Aug-16	16.2375	17.096	18.748	18.663
4-Aug-16	15.14	17.110	18.784	18.693
5-Aug-16	14.3525	17.124	18.820	18.722
8-Aug-16	14.5875	17.137	18.855	18.750
9-Aug-16	14.5375	17.151	18.889	18.778
10-Aug-16	14.9225	17.164	18.923	18.804
11-Aug-16	14.2125	17.177	18.956	18.830
12-Aug-16	13.77	17.189	18.988	18.856
16-Aug-16	14.1825	17.202	19.019	18.881
17-Aug-16	14.78	17.214	19.050	18.905
18-Aug-16	14.55	17.226	19.081	18.928
19-Aug-16	14.5375	17.237	19.111	18.951
22-Aug-16	14.235	17.249	19.140	18.973
23-Aug-16	13.8975	17.260	19.168	18.995
24-Aug-16	13.4875	17.271	19.196	19.016
25-Aug-16	13.285	17.282	19.224	19.037
26-Aug-16	13.57	17.292	19.251	19.057
29-Aug-16	13.165	17.302	19.277	19.076
30-Aug-16	13.02	17.312	19.303	19.095
31-Aug-16	13.2425	17.322	19.328	19.114

Finally, the Table 5.6 shows the comparison of actual VIX along with the forecasted values of Indian VIX which is predicted through GARCH (1,1), EGARCH(1,1), and TGARCH models for the last 64 observations i.e. from 1st June 2016 to 31st August 2016. The table reveals that forecasted series of VIX from the GARCH (1,1) model has the lesser deviation from the realized VIX.

5.4 CONCLUSION

Volatility Forecasting plays an important role in investment decision, security valuation, risk management, and monetary policy formulation. Forecasting implied volatility is a key parameter in pricing of options. There is extensive literature available on volatility forecasting for implied volatility indices of developed markets. But very limited work is done in terms of emerging economies. Moreover S. S. Kumar (2010) and Shaikh and Padhi (2015) examine the behaviour and forecasting efficiency of the India VIX respectively. But this is the first study that makes an attempt to test the predictive ability of symmetric GARCH (1,1) and asymmetric TGARCH (1, 1) and EGARCH (1, 1) models in forecasting the India VIX index. The estimated results from the models confirm the dependency of volatility on its past behaviour and reveal that innovation to the conditional variance is highly persistent and takes longer time to dissipate.

The estimates of the EGARCH (1,1) model, shows that the VIX index exhibits statistically significant asymmetric effects at one percent level. This indicates that positive shocks (good news) have greater impact on this VIX Index than the negative shocks (bad news), suggestive of the fact that there is a larger impact on volatility due to the noise traders in the Indian VIX during market upward movement than market downward movement under the same magnitude of innovation,. The result of the TGARCH (1,1) model also suggests the presence of asymmetry in data, confirming that positive shocks have greater impact than negative news. The models were then evaluated in terms of their forecasting ability of future VIX index by employing standard (symmetric) loss functions. The results show that the GARCH (1,1) model outperformed all the other models in forecasting Indian VIX price series.

TO STUDY THE DYNAMIC LINKAGES BETWEEN INTERNATIONAL EQUITY MARKETS THROUGH IMPLIED VOLATILITY INDICES

6.1 INTRODUCTION:

The study of volatility spillovers and transmission between international stock markets has assumed greater importance as it is essential to understand the mechanism of market integration, economic cycles, and financial crises. Market integration, in terms of implied volatility spillovers, has been an issue of growing interest in recent times especially in the aftermath of events like the Asian and Russian Crises at the end of the 1990s, the Subprime crises in 2008, the Eurozone crises, and the Chinese crises in 2015.

Implied Volatility, a futuristic measure of expected volatility, helps market participants in the assessment of risk over a given period of time. And as revealed in all the previous literature, the information content of implied volatility is far superior over ex-post i.e. historical measures of volatility. A negative contemporaneous relationship is observed between the underlying Index and the Volatility Index in different financial markets. The volatility Index can thus be considered as the world's premier barometer of investor sentiments and market volatility (Narwal, Sheera, and Mittal, 2011).'

In an integrated market, Volatility spillovers in terms of implied volatility can have far reaching implications for risk managers, market regulators, traders and international portfolio managers. They need to understand which market leads the other and which market is the prime source of implied information. For constructing volatility forecasts and taking accurate investment decisions it becomes essential to be well informed about dependencies in implied volatilities. By investigating the degree of interactions between implied volatilities one can examine the level of integration between equity markets (Padhi, 2011).

Therefore the objective of this chapter is to study the linkages between selected developed equity markets and emerging markets i.e. to investigate whether there is market integration in terms of implied volatility spillovers. An effort has also been made to know the degree of volatility transmissions between markets, how does a shock to one market affect the other market, what is the scale, sign of the effect, and for how long does the effect persist.

Volatility spillover or global equity market integration has been a popular area of research in financial literature, but in recent times there has been a gradual shift towards examining international integration in terms of implied Volatilities. The following studies have analysed the international volatility indices: Aboura (2003) found that VX1, VIX, and VDAX are good tools for predicting future realized volatility. She also shows that past implied volatility informs more about future implied volatility than past realized volatility. Moreover she has also studied the volatility transmissions between VX1, VIX, and VDAX, and it is found that the French volatility index is more sensitive to a shock of the US volatility index. Badshah (2009) investigated the asymmetric returns-volatility relationship with newly adopted robust volatility indices – VIX, VXN, VDAX, VSTOXX and the implied volatility transmission. He observed that VIX presents the highest asymmetric return-volatility relationship followed by the VSTOXX, VDAX, and VXN respectively. Secondly, there were significant spill over effect across the volatility indexes and the VIX influenced the other three volatility indexes considerably. However in the European context, the VDAX was found to be the dominant source of information. Siriopoulos, Costas, Fassas and Athanasios (2009) studied the information content of all publicly available implied volatility indices across the world. They further show that there is a statistically significant negative and asymmetric contemporaneous relationship between implied volatility changes and underlying equity index returns. They also contribute to the international equity market integration studies by investigating the linkages among major implied volatility of each market. Thakolsri, Sethapamote, and Jiranyakul (2015) investigated the impact of changes in the VIX on the changes in the implied volatilities of Euro and the Thai stock markets through VAR model-Granger Causality test, Impulse Response Analysis, and Variance Decomposition Function. It is observed that the US index is the leading source of volatility transmission to all the other markets. Rejeb and Boughara (2015) examined the relationship between emerging and developed markets in normal times and in times of financial crises with respect to Volatility. The VAR methodology together with Bai and Perron's technique was used. It is reported that volatility spillovers are effective across financial markets. It may also be observed that Geographical proximity plays a major role in amplifying the volatility transmission. Finally, it has been shown that financial liberalization is a significant and contributing factor in international transmission of volatility and the risk of contagion.

Some studies done in the Indian context are Narwal, Sheera, and Mittal (2011) examined implied volatility spillover and transmission between emerging (India) and mature stock markets (US, France, Germany, and Switzerland), measured by their respective implied volatility indices i.e. IVIX, VIX, VCAC, VDAX, and VSMI. Their results show that there is moderate level of correlation between selected markets and information transmission, and spill overs are running unidirectional from India to US markets and German to Indian market and bidirectional from Indian to French market.

Padhi (2011) examined the Implied Volatility linkages among the Asian, European and US stock markets. Her results indicate that the US Implied Volatility index has substantial impact over the other international Implied Volatility indices but none of the examined volatility indices bears a notable impact over their Indian Equivalent. Gupta and Kamilla (2015) examined linkages between implied volatility indices of developed financial markets (US, UK, Japan) and emerging financial markets (BRIC countries) using VAR modelling and variance decomposition method. The study suggests that US VIX has substantial impact on all the other Volatility Indices.

From the literature review it may be noted that though numerous studies discussing implied volatility spill overs are available for developed economies. This question still remains to be addressed in context of emerging Asian economies. The Indian, Chinese, and South Korean equity markets are one of the fasts growing, and moreover implied volatility indices (Volatility indices) is a novel concept in these economies. It would be very interesting to note the responses of these markets to volatility transmissions from larger markets like US and Germany. This study differs from the previous studies in two distinctive ways: firstly, a longer volatility sample period is used, covering the global crises, as well as, the post crises phase. Secondly, this study has been undertaken in the context of emerging markets like India, China, and South Korea, with reference to developed markets of the US and Germany to find linkages among the implied volatility indices which has not been discussed before to the best of the knowledge of the researcher.

6.2 DATA AND METHODOLOGY

6.2.1 Data and Description

The sample consists of daily changes in the values of Implied Volatility Indices from March 2009 to August 2016. In this study we have made an attempt to study the dynamic linkages between implied volatilities of selected countries i.e. US (VIX), Germany (VDAX), India (IVIX), China (VXFXI), and Korea (VKOSPI).

The motto of selecting the sample for this study is to examine the linkages between developed and emerging economies. A detailed description of each selected volatility index is given below:

US VIX Index: It was is 1993 that the Chicago Board Options Exchange introduced the CBOE Volatility Index, it was designed to measure the market's expectation of 30-day volatility implied by at-the-money S&P 100 Index option prices. It soon became the premier benchmark for the U.S. stock market volatility and became popular as the "fear index". In 2003, CBOE updated the VIX to reflect a new way to measure expected volatility. The new VIX is based on the S&P 500 Index which is the core index for U.S. equities. In addition to the VIX the CBOE calculates several other volatility indexes including the CBOE Short-Term Volatility Index, the CBOE Nasdaq-100® Volatility Index, CBOE Russell 2000 Volatility Index, and so on. It was also the first exchange to introduce the use of the VIX methodology to estimate expected volatility of certain commodities and foreign currencies.

VDAX: In 1994 the Deutsche Borse introduced the VDAX index to measure the 45 day implied volatility in the German equity market. Later in 2005 it modified the VDAX and launched the VDAX-NEW index based on DAX options, traded at the derivatives Eurex exchange. The DAX deutsche Borse together with Goldman Sachs developed the methodology of VDAX-NEW. The VDAX-NEW volatility index for the German DAX 30 stock index uses model-free implied volatility measures like the new VIX that incorporates more robust information on options. Its measure aligns with the consensus view of option traders (who are usually professionals) about the future direction of the volatility of the stock market over the next 30 days.

India VIX: India VIX is a volatility index computed by the National Stock Exchange from the order book of NIFTY Options. It is a measure of the market's expectation or investor's perception of volatility over the near term. The best bid-ask quotes of near and next-month NIFTY options contracts which are traded on the F&O segment of NSE are used. It indicates the expected market volatility over the next 30 calendar days. Higher the India VIX values, higher the expected volatility, and vice versa.

VXFXI: The Chicago Board of Options Exchange now applies its proprietary VIX methodology to create indexes that reflect expected volatility for options on select exchange-traded funds. One such volatility index is the VXFXI i.e. the China ETF Volatility Index (ticker VXFXI), which reflects the implied volatility of the FTSE China 25 Index Fund. In case of VXFXI i.e. the Chinese ETF Index calculated by CBOE (Chicago Board of Options Exchange) the data is available from March 2011. Therefore some data points will be missing. The data for VIX, VDAX and VXFXI is collected from the CBOE website whereas the IVIX and VKOSPI data is collected from NSE and yahoo finance respectively

VKOSPI: KRX has developed a volatility index that suits the Korean market situation. This volatility index is called VKOSPI (Volatility index of KOSPI200). The volatility index of KRX indicates the implied volatility of KOSPI200 for the period of thirty days as currently expected by investors based on the KOSPI200 option price.

The data for the same is published from April 2009. The KRX being the official provider of the Kospi 200 index and Kospi 200 option prices, the VKOSPI can be used as a more objective measure of Korean stock market volatility.

6.2.2 Methodology

The study employs the VAR (p) system to ascertain the lead-lag effects in examining the transmission of shocks of the implied volatility series of one index over the other indices in the system. VAR models help in identifying the important variables which influence the other variables in the framework. A VAR model in its standard form can be expressed as:

$$y_t = \alpha + \sum_{K=0}^{P} \varphi_K y_{t-K} + \varepsilon_t$$

In this study, $y_t = (\sigma_{VIX}, \sigma_{VKOSPI}, \sigma_{VXFXI}, \sigma_{IVIX}, \sigma_{VDAX})$ 5 x 1 vector of dependent variables, containing 5 x 1272 observations at time t, α is the 5 x 1 vector of intercepts, φ_K = 5 x 5 matrix of autoregressive coefficients $\{\varphi_K, K = 1,2, \dots \dots P\}, \varepsilon_t$ is 5 x 1 vector of error terms assumed to satisfy the basic OLS regression assumptions of errors. *P* indicates the lag order for the VAR system.

6.3 EMPIRICAL RESULTS AND DISCUSSION

Before analysing the international market integration in terms of implied volatility indices, the descriptive statistics of the daily change of the five Implied Volatility Indices is discussed in the table below:

Table 6.1: Descriptive Statistics of Volatility Indices from 02-03-2009 to 31-08-2016

	IVIX	VDAX	VIX	VKOSPI	VXFXI
Mean	-0.0005	-0.0002	-0.0006	-0.0005	-0.0004
Median	-0.0023	0.000	-0.0050	-0.0012	-0.0049
Maximum	0.4969	0.2550	0.4055	0.4344	0.3658
Minimum	-0.4144	-0.2508	-0.3252	-0.2640	-0.1851
Std. Dev.	0.0538	0.0558	0.0783	0.0553	0.0533
Skewness	0.6748	0.4291	0.7106	0.9888	1.0610
Kurtosis	14.1458	4.8444	6.3167	10.3578	7.6675
Jarque-Bera	6680.641 (0.0000)	219.3262 (0.0000)	690.0961 (0.0000)	3076.536 (0.0000)	1393.294 (0.0000)
Observations	1272	1272	1272	1272	1272
Notes: Figures in the parenthesis ( ) indicates p-value. *- denotes the significance at one percent level.					

From Table 6.1 it is evident that the mean values of all the five volatility indices are negative. Standard Deviation is low for all the 5 implied volatility index series. The test for skewness indicates that all other volatility indices are positively skewed. Further, all five series are highly leptokurtic with respect to the normal distribution. Likewise, a highly significant large JB statistic confirms that the five series are not normally distributed. The Jarque-Bera statistics is found to be statistically significant at one percent level, rejecting the null hypothesis of five series being normally distributed, confirming that they are all non-normally distributed. The Figures 6.1, 6.2, 6.3, 6.4, and 6.5 below show the time-series plots of the five implied volatility indices discussed in this study. The graphs below indicate that the US market was the most volatile during the period from 2009 to 2012. The highest figures for VIX index (up to 50%) are recorded during this period. This is mainly because of the sub-prime crises and recessionary trend observed in the US market during this period. The VKOSPI seems most volatile during the period from 2011 to 2012. The Chinese index experienced high volatility in the years 2011 to 2012 and 2015 to 2016. This was the period when the Chinese economy was hit by crisis and the volatility in the Chinese stock market soared up to more than 60%. The IVIX seems most volatile during the 2009 to 2010 period with IVIX going up to 55%. The volatility in the German market is the highest during the 2011 to 2012 period with the VDAX recording the highest figures during this period. On an average, the implied volatility figures are in the range of 15-25% for all the markets. From the Asian markets the Chinese market seems the most volatile while the volatility in the South Korean market is the least for the sample period.

Figure 6.1: Time Series Plot of VIX index for the period from March 2009 to August 2016

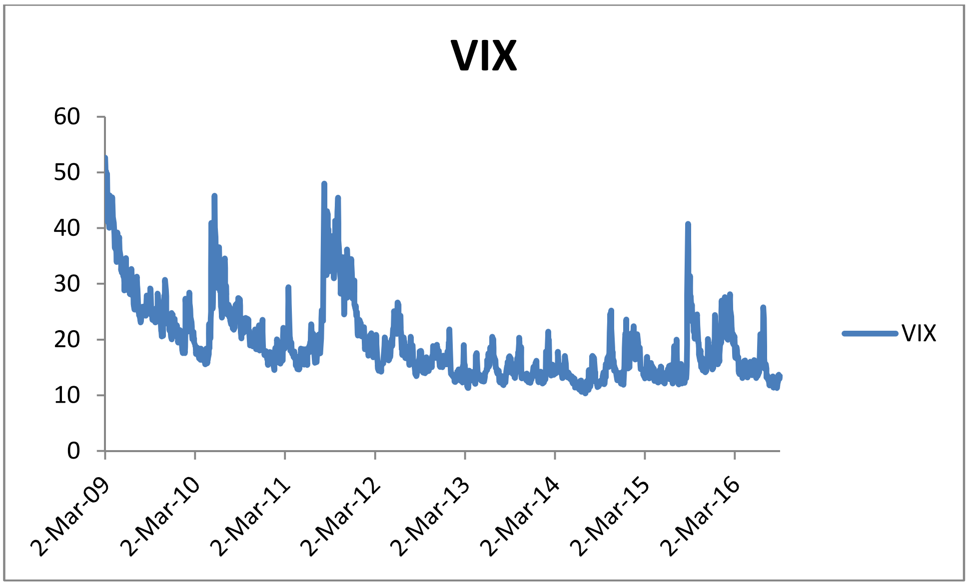


Figure 6.2: Time Series Plot of VKOSPI index for the period from March 2009 to August 2016

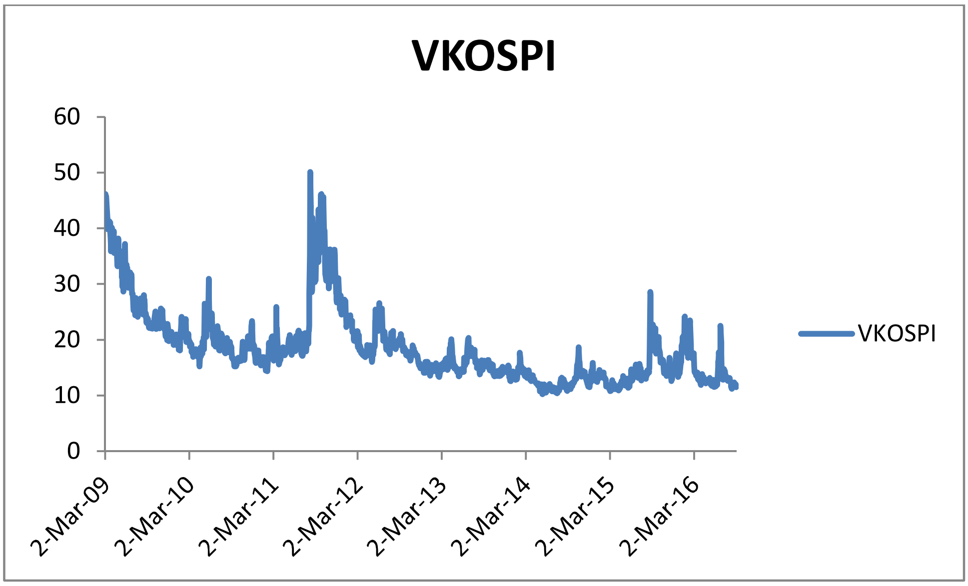


Figure 6.3: Time Series Plot of VXFXI index for the period from March 2009 to August 2016

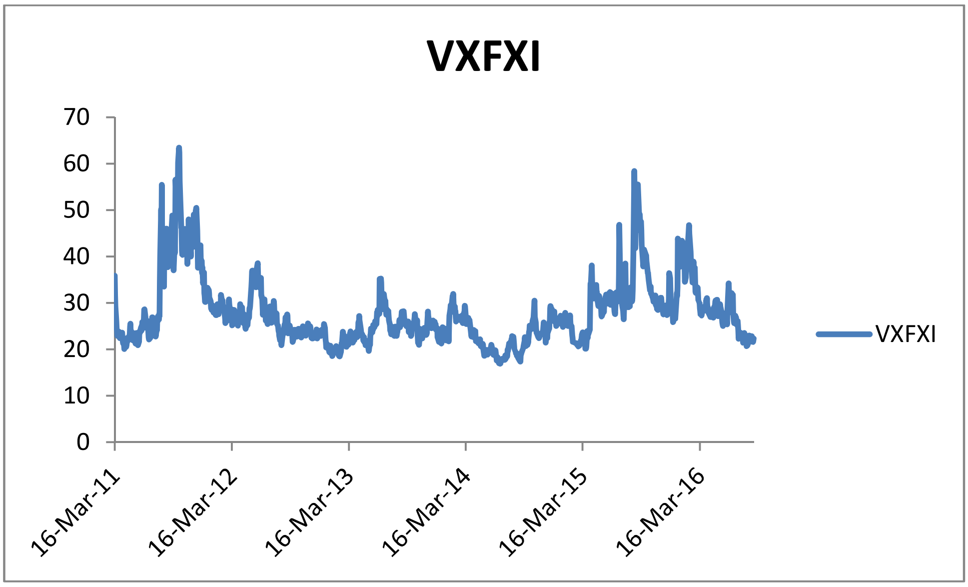


Figure 6.4: Time Series Plot of India VIX index for the period from March 2009 to August 2016

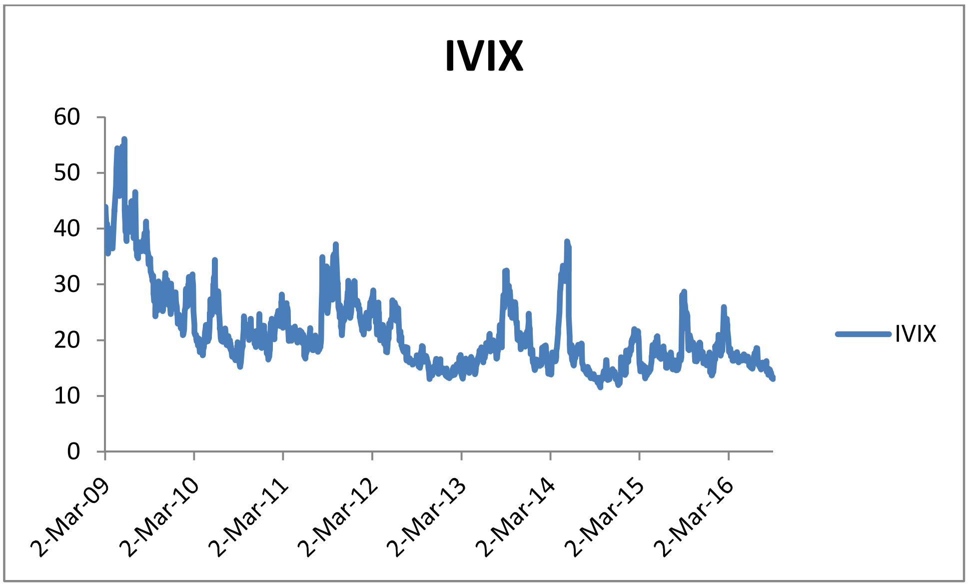


Figure 6.5: Time Series Plot of VDAX index for the period from March 2009 to August 2016

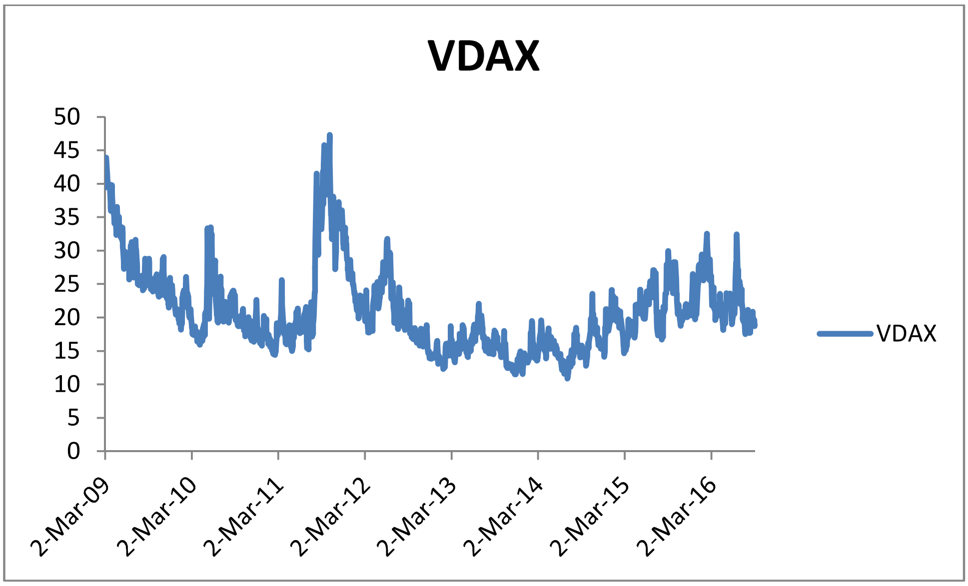


Table 6.2: Pearson's Correlation Coefficients of Volatility Indices from March 2009 to August 2016

	VIX	VKOSPI	VXFXI	IVIX	VDAX
VIX	1				
VKOSPI	0.2032	1			
VXFXI	0.6604	0.3489	1		
IVIX	0.2548	0.4120	0.3527	1	
VDAX	0.4852	0.2800	0.4669	0.3115	1

As a preliminary step to understanding the linkages between these five markets. The Pearson's Correlation analysis is conducted. Table 6.2 displays the Pearson's Correlation Coefficient analysis results on the implied volatility series. Moderate level of correlation can be observed amongst the five volatility indices. The lowest degree of correlation is observed between the US and the Korean Index (0. 2032) However, the highest degree of correlation is observed between US and China (0.6604).

The stationarity of the sample is investigated by using the Augmented Dickey Fuller (ADF) test and Phillips-Perron unit root test. From Table 6.3 it can be observed that the unit root statistics of the ADF and PP tests reject the null hypothesis of stationarity of the series in their level form at the 1% level of significance.

Table 6.3: Unit Root Test Results

Variable	ADF	PP
VIX	-46.12047*	-52.44682*
VKOSPI	-23.87663*	-48.20267*
VXFXI	-35.7711*	-37.27036*
IVIX	-43.0068*	-43.42798*
VDAX	-42.29042*	-46.51576*
Notes: * indicates significance at one per cent level. Optimal lag length is determined by the Akaike Information Criterion (AIC).		

Appropriate lag order determination, p, for the VAR system is an important issue. The order of the VAR is determined based on the standard lag length criteria. In addition, given that the residuals of the VAR should exhibit no serial correlation if there are enough lags in the model, the residual serial correlation is tested to confirm the adequacy of the lag order. Four different selection criteria, namely the Likelihood Ratio (LR) tests, Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC) and Hannan-Quinn Information Criterion (HQIC) are used to select the appropriate lag length for the model.

Table 6.4 : VAR order selection tests

Lag	LR	AIC	SC	HQ
0	NA	-15.7855	-15.761	-15.7762
1	363.0877	-16.1011	-15.95377*	-16.0451
2	115.3885	-16.16786*	-15.8977	-16.06518*
3	40.68921	-16.1592	-15.7663	-16.0099
4	46.53134	-16.1567	-15.641	-15.9607
5	55.77779	-16.164	-15.5255	-15.9213
6	43.56732*	-16.159	-15.3977	-15.8696
7	37.65057	-16.148	-15.2639	-15.812
8	24.25183	-16.1233	-15.1164	-15.7406

* indicates lag order selected by the criterion

From table 6.4 it is observed that AIC suggests 2 lags, HQIC suggests 2 lags, LR suggests 6 lags, and SIC suggests 1 lag. Hence, the parsimonious AIC with lag 2 is chosen, and accordingly, analysis is conducted with lag 2 for the equation of the VAR system.

Table 6.5: Summary Statistics of the VAR (2) Model

Dependent Variable	Adjusted R^2	F-Statistic	P Value
VIX	0.024	4.059	0.000
VKOSPI	0.173	27.514	0.000
VXFXI	0.016	3.105	0.000
IVIX	0.071	10.755	0.000
VDAX	0.082	12.363	0.000

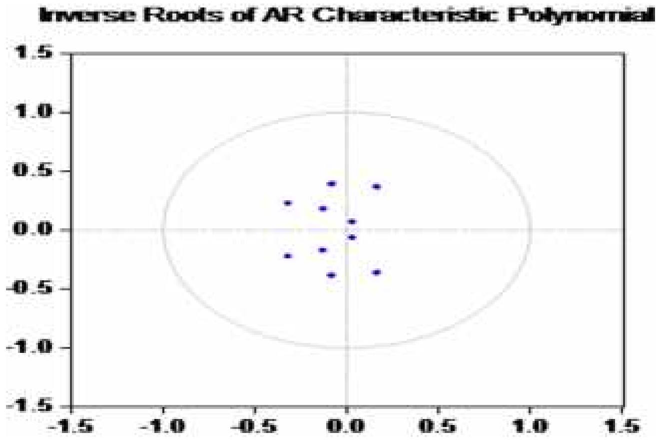
Table 6.5 indicates the summary statistics of the VAR (2) estimation results. The F-statistics indicate that the estimated VAR (2) model is statistically highly significant, and the Adjusted R^2 ranges from 0.016 for VXFXI to 0.173 for VKOSPI.

The stability of the estimated VAR model with 2 lags is tested by examining the inverse roots of the character AR polynomials. All the inverse roots should lie within the unit circle and should have modulus of less than one, for the VAR model to be stable. The results of the VAR model stability test are presented in Table 6.6. The results reveal that the estimated VAR model with 2 lags is stable as all roots lie within the unit circle.

Table 6.6: Inverse Roots of AR Characteristic Polynomial of the estimated VAR (2) model

ROOTS	MODULUS
0.166590 - 0.364208i	0.4005
0.166590 + 0.364208i	0.4005
-0.078056 - 0.389515i	0.397259
-0.078056 - 0.389515i	0.397259
-0.316085 - 0.227263i	0.389305
-0.316085 - 0.227263i	0.389305
-0.125102 - 0.175178i	0.215262
-0.125102 - 0.175178i	0.215262
0.031696 - 0.067439i	0.074516
0.031696 - 0.067439i	0.074516
No root lies outside the unit circle. VAR satisfies the stability condition.	

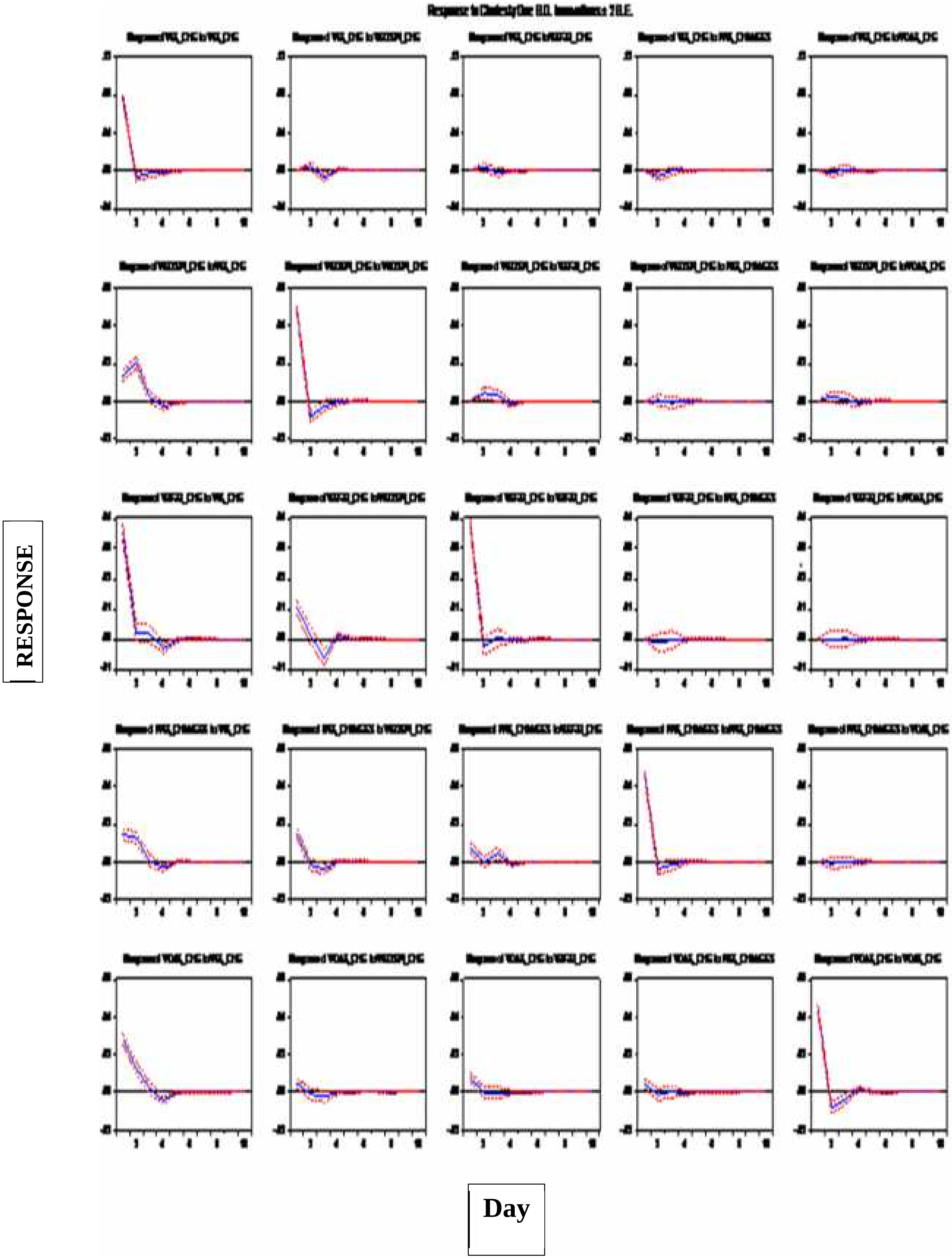
Fig: 6.6: Inverse Roots of AR Characteristic Polynomial of the Estimated VAR (2) Model.



6.3.1 Impulse Response Function

The study further employ the impulse response function to measure the responses of the variables—in our case IVIX, VIX, VDAX, VKOSPI, VXFXI—in the dynamic VAR system to a shock to each variable. In the impulse response function a one standard error shock is applied to the error of a variable, and the effect on the dynamic VAR system over a specified period of time is recorded (Padhi, 2011). The figure below reports the impulse responses of implied volatility in one market to a shock in the implied volatility in other markets. In figure 6.2, Day 1 indicates contemporaneous effects; Day 2 is a 1-day lagged effect, etc. A total of 25 impulse responses could be calculated since there are 5 variables in the system. A unit shock is applied to VIX, VKOSPI, VXFXI, IVIX , VDAX and the corresponding impulse responses of IVIX on Day 1 are observed. Similarly, the same unit shock is applied to each volatility index and responses of IVIX on Day 2 are noted and so on. As can be seen, the effects of the shock on IVIX are both positive and negative. The IVIX seems to be affected most by the US index. The impulse response function confirms the previous results of the present study. From Day 4 onward up to Day 6, the effect of the same shock each time gradually dies out and thus induces no more change in the IVIX index. Likewise a unit of shock is applied to each of the indices and its corresponding impulse responses are noted for each of the variables.

Figure 6.7: Impulse Response Function. The graphs report the impact of one standard deviation error in Volatility Index on itself and on the other Indices in the VAR system. Two Standard Error confidence bounds are presented around each impulse response function.



6.3.2 Variance Decomposition

The effect of unit shock of one endogenous variable on the other variable in the VAR system is captured through the Impulse response function, whereas to know the importance of one endogenous variable in affecting the other variable the Variance Decomposition analysis is applied. This analysis enables one to understand how significant the innovations of all variables in the VAR system are to forecast error variance of each variable for a specified number of days ahead.

The Tables below provide the Variance Decomposition Analysis results for VIX, VKOSPI, VXFXI, IVIX and VDAX. The first column of the tables below indicates the time duration (in terms of days), the second column shows standard error, and the remaining five columns report the forecast error variance of each variable in percentage due to specific innovations of the other variables in the system. The total of each row adds up to 100 percent.

Table 6.7: Variance Decomposition of VIX

Period	S.E.	VIX	VKOSPI	VXFXI	IVIX	VDAX
1	0.077363	100	0	0	0	0
2	0.07815	98.73166	0.370424	0.208714	0.613808	0.075394
3	0.078559	97.81553	1.193964	0.260966	0.60826	0.121279
4	0.078592	97.79111	1.216592	0.261983	0.608681	0.121634
5	0.078597	97.77823	1.222269	0.266313	0.608756	0.12443
6	0.078599	97.77659	1.222278	0.267475	0.608765	0.124897
7	0.078599	97.7765	1.222283	0.267502	0.60878	0.124929
8	0.078599	97.77644	1.222325	0.267508	0.60878	0.124945
9	0.078599	97.77644	1.222326	0.267508	0.60878	0.124945
10	0.078599	97.77644	1.222326	0.267508	0.60878	0.124945

Table 6.7 reports the variance decomposition results for VIX. It can be noted here that the 1 day ahead forecast error variance of VIX is explained by it alone and it explains

97.77644 % of its 10 day ahead forecast error variance. None of the Asian, as well as, the German markets hold strong explanatory powers. It is seen that the volatility in the US market is largely driven by domestic innovations.

Table 6.8: Variance Decomposition of VKOSPI

Period	S.E.	VIX	VKOSPI	VXFXI	IVIX	VDAX
1	0.050301	7.16259	92.83741	0	0	0
2	0.055206	19.98651	79.21572	0.598028	0.007597	0.192154
3	0.055406	19.94319	78.84721	0.940779	0.026616	0.242204
4	0.05551	20.09957	78.56655	1.025375	0.035409	0.273098
5	0.055514	20.10763	78.55571	1.027195	0.036051	0.273419
6	0.055516	20.10772	78.55523	1.027125	0.036058	0.273867
7	0.055516	20.10889	78.55402	1.027137	0.036085	0.273866
8	0.055516	20.10899	78.55388	1.027179	0.036085	0.273866
9	0.055516	20.109	78.55387	1.02718	0.036087	0.273866
10	0.055516	20.109	78.55387	1.02718	0.036087	0.273866

From table 6.8, it may be noted that VKOSPI explains 92.84% of its own 1 day ahead forecast and 78.55% of its 10 day ahead forecasts. It is noted that VIX contributes to explaining 7.16% of the 1 day ahead forecast of VKOSPI and 20.109% of the 10 day ahead forecast error variance of the South Korean Index. VXFXI explains around 1.027% of the 10 day ahead forecast error variance of VKOSPI. The South Korean market volatility seems to be influenced largely by domestic factors. Of the four markets examined, it seems highly influenced by shocks from the US market. But the above table also indicates delayed reaction of the South Korean market to innovations in the US market, as the percentage share of the US market innovations increases from 7.16259% on day 1 to 20.109% on day 10.

Table 6.9: Variance Decomposition of VXFXI

Period	S.E.	VIX	VKOSPI	VXFXI	IVIX	VDAX
1	0.052775	44.70601	3.932521	51.36146	0	0
2	0.052921	44.65051	3.989775	51.29483	0.064376	0.000512
3	0.053315	44.08118	5.299342	50.54857	0.069522	0.001384
4	0.053416	44.23342	5.326451	50.36513	0.071748	0.003248
5	0.05342	44.23001	5.325708	50.36818	0.072116	0.003995
6	0.053421	44.23001	5.326245	50.36708	0.072308	0.004361
7	0.053421	44.23005	5.326292	50.36698	0.072318	0.004362
8	0.053421	44.23005	5.326382	50.36689	0.072318	0.004364
9	0.053421	44.23006	5.326382	50.36688	0.072319	0.004364
10	0.053421	44.23006	5.326382	50.36688	0.072319	0.004364

From the Variance Decomposition analysis of VXFXI, it is seen that domestic factors explain 51.361% of 1 day ahead forecast error variance of VXFXI. It is significantly integrated with VIX as it explains 44.70601% of 1 day ahead forecast error variance of VXFXI. The Chinese volatility index is minimally integrated with the other Asian indices. The VKOSPI explains 3.932521% of 1 day ahead forecast error variance, whereas IVIX and VDAX show absolutely no influence on the volatility of the Chinese market. If we look at the 10 day ahead forecasts for VXFXI then it may be noted that VXFXI explains 50.36% of its own forecast error variance. VIX explains 44.23%, VKOSPI 5.32%, IVIX 0.072 % and VDAX 0.004 % of the 10 day ahead Forecast Error Variance for VXFXI.

Table 6.10: Variance Decomposition of IVIX

Period	S.E.	VIX	VKOSPI	VXFXI	IVIX	VDAX
1	0.05184	7.912169	8.512867	2.022799	81.55217	0
2	0.053538	13.02938	8.080481	1.899959	76.9659	0.024284
3	0.053887	12.86401	8.528394	2.532951	76.04972	0.024919
4	0.053998	13.1496	8.495706	2.591665	75.73814	0.024889
5	0.054	13.14906	8.495962	2.596035	75.73311	0.025837
6	0.054002	13.14853	8.499509	2.596326	75.72977	0.025864
7	0.054002	13.14889	8.499479	2.596322	75.72941	0.02589
8	0.054002	13.14895	8.499504	2.596347	75.72931	0.02589
9	0.054002	13.14896	8.499502	2.59635	75.72929	0.025892
10	0.054002	13.14896	8.499503	2.59635	75.72929	0.025892

The above table reports the variance decomposition results for IVIX. It can be noted here that the 81.5527% 1 day ahead forecast error variance of IVIX is explained by it alone, whereas 8.512867%, 7.912169%, and 2.022799% is explained by VKOSPI, VIX and VXFXI respectively. If we observe the 10 day ahead forecast error variance of IVIX, 75.72929% is explained by itself, 13.14896% by VIX, 8.499503% by VKOSPI and 2.59635% by VXFXI. Of the four markets examined it seems highly influenced by shocks from the US market. But a delayed reaction is noticed in the Indian market to innovations in the US market, as the percentage share of US market innovations increases from 7.912169 % on day 1 to 13.14896 % on day 10.

Table 6.11: Variance Decomposition of VDAX

Period	S.E.	VIX	VKOSPI	VXFXI	IVIX	VDAX
1	0.053371	27.89226	0.765533	1.974267	0.695632	68.67231
2	0.055522	31.1029	0.746285	1.82849	0.703597	65.61872
3	0.055735	30.98072	0.911428	1.817398	0.702994	65.58746
4	0.055924	31.34533	0.905339	1.806643	0.725869	65.21682
5	0.055927	31.34595	0.907212	1.808963	0.726519	65.21136
6	0.05593	31.34687	0.911803	1.808751	0.727285	65.20529
7	0.05593	31.34706	0.911815	1.8088	0.727306	65.20502
8	0.05593	31.34698	0.911948	1.808845	0.727311	65.20491
9	0.05593	31.34699	0.911948	1.80885	0.727311	65.20491
10	0.05593	31.34698	0.911948	1.808851	0.727311	65.2049

Table 6.11 reports the Variance Decomposition results of VDAX. VDAX explains 68.67231% of its 1 day ahead forecasts, followed by VIX explaining 27.89226%, and VXFXI explaining 1.974267% forecast error variance respectively. If we look at the 10 day ahead forecast then it may be noted that VDAX explain 65.2049 % of its forecast error variance whereas VIX and VXFXI explains 31.34698% and 1.808851% respectively. None of the other indices play a significant role.

Thus from the Variance Decomposition Analysis it can be concluded that the volatility in the five markets seems to be driven mainly by shocks in their respective domestic markets. Of the five indices examined, VIX emerges as an influential Volatility Index which explains 20.109%, 44.23006%, 13.14896%, 31.34698% of 1 day ahead forecast error variance for VKOSPI, VXFXI, IVIX, and VDAX respectively. The South Korean market exhibits properties of a leading market in the Asian region. Explaining 3.932521% forecast error variance on day 1 and 5.326382% on day 10 of China, whereas 8.512867% forecast error variance on day 1 and 8.499503% on day 10 of the India. The innovations in the German market fail to explain the forecast error variance in the other four markets. It is also interesting to note that the India VIX is not influenced much by other volatility indices (especially the US Index) compared to

China which though in the same stage of development as India is more integrated with international markets.

6.4 CONCLUSION

The literature on international integration among markets is falls into three categories according to Gagnon and Karolyi (2006). The first category mainly focuses on the potential diversification benefits of investing internationally, the second category studies possible structural patterns in the co-movements of international markets, while the third category deals with the lead–lag relationships between markets across the globe. This research is based on the third category of studies.

This study reveals that there exist linkages between all five international volatility indices. The ever expanding globalization in the finance and investment industry is the main reason behind these linkages. From the five implied volatility indices i.e. IVIX, VIX, VDAX, VKOSPI, and VXFXI examined in this study, the VIX appears to bear the highest explanatory power. Therefore, this index should be closely observed by overseas regulatory authorities as an early warning signal for future turbulence in their domestic markets.

Amongst the Asian indices examined, The South Korean Index is considered to be a leading index as it substantially influences other markets while does not itself get influenced by other markets substantially. Our results for the India VIX reveal that there is a moderate level of influence of the US index on it. The IVIX seems to be also integrated minimally with its Asian equivalents. But it is also observed that none of the sample market's Volatility Index has a substantial influence over the IVIX. A possible reason for this could be that the Indian equity markets bear a lesser degree of integration to the global financial system. But this is likely to change once India expands its financial systems and brings them on par with the global financial markets.

FINDINGS AND CONCLUSION

7.1 INTRODUCTION:

"No power on earth can stop an idea whose time has come," said the then finance minister Manmohan Singh quoting Victor Hugo while presenting the Union Budget on 24 July 1991. And thus began the much awaited process of economic liberalisation in India. The New Economic Policy paved the path for growth and development of the Indian economy. The liberalisation, privatisation, globalisation together with reforms in the financial sector resulted in greater integration of the Indian financial markets with the global markets. From then on several measures have been undertaken to enhance the role of the financial sector in the economic development and to make it more efficient. These reforms have completely revamped the Indian capital market and have made it more attractive to domestic, as well as, global investors. India has now emerged as an attractive investment destination. It stands third (after China and USA) as an attractive destination for investment. It is likely to become one of the largest economies of the world by the year 2025 as per projections made by internationally renowned consultants and IMF.

But for a sustained growth of any economy, stable and efficient stock markets are a prerequisite. Stock market volatility is a phenomenon that hampers and poses a threat to the smooth and efficient functioning of a market. Volatility indicates the vulnerability of the financial market and therefore plays a key role in assessing the risk/return trade off. Volatility has significant influence on market players since it leads to significant changes in financial market prices (returns). High levels of volatility can create negative influence on investors, who prefer to avoid risk. A volatile stock market may also lose on important foreign investment. This in turn hampers the economic growth of a country. Besides, changes in volatility also affect consumption patterns, corporate plans such as: corporate capital, leverage ratio, business measures and government policies.

As discussed before volatility is also an important input in asset pricing. The fundamental theories of modern finance, such as Arbitrage Pricing Model, Capital Asset Pricing Model, and Portfolio Theory, which aim at creating a balance between risk and prospective return, lay significant emphasis on volatility. It is also a vital input in option pricing. Thus to get a fair idea of expected volatility in the market, researchers developed the Volatility Index, which is considered a measure of the market's expectation of volatility over the near term. The researchers worldwide have made an attempt to study the behaviour and information content of volatility Index. But the literature is quite limited in the Indian context. The Indian volatility index (IVIX) is a fairly recent development. Thus through this study the author explores different dimensions of the India VIX Index. The findings of the study are discussed below.

7.2 MAJOR FINDINGS OF THE STUDY:

7.2.1 Objective 1: Impact of scheduled macroeconomic announcements on India VIX:

Through this objective the impact of scheduled news release on market uncertainty is explored. The proxy for market uncertainty is taken to be NSE's Volatility Index i.e. India VIX. The present study uses daily closing values of India VIX for the period from 1-04-2009 to 31-08-2016. The study focuses on the scheduled macroeconomic releases available during study period. Scheduled macroeconomic variables considered are Inflation (CPI/WPI), Index of Industrial Production (IIP), Gross Domestic Products (GDP), RBI's Monetary Information(Repo/Reverse Repo/Repurchase rate/CRR), Employment Survey report, Fiscal Deficit and BOP's Current Account Balance. The Following statements are tested in the context of Indian Volatility Index:

- During the non-announcements days, the IVIX rises hence intercept should be non-zero and positive, and also should be statistically significant.
- On the scheduled macroeconomic news release day, the IVIX should go down, and goes to its normal level, as it impounds the information disclosure. Hence, all the slope coefficients of Inflation, IIP, GDP, RBI's monetary information, Manpower Survey, Fiscal Deficit and BOP's Current A/c balance should be negative, and should be statistically significant.
- Before the scheduled news announcements IVIX rises significantly. Hence, all the slope coefficients of Inflation, IIP, GDP, RBI's Monetary Information, Manpower Survey, Fiscal Deficit and BOP's Current A/c balance should be positive and statically significant.
- After the announcements of scheduled news, IVIX goes its normal level, i.e. it declines up to certain days. Hence, all the slope coefficients of Inflation, IIP, GDP, RBI's Monetary Information, Manpower Survey, Fiscal Deficit and BOP's Current A/c balance should be negative, and should be statistically significant.

To analyse the impact of such announcements Dummy variable technique with ordinary least square, GARCH (1,1) and EGARCH (1,1) is employed. The findings of the study reveal that:

- **OLS Regression Results**: The results of the OLS regression demonstrate that on the report day the release of RBI's Monetary Information and Employment Survey Report influences the behaviour of IVIX. The Monetary Information news leads to a 2.059% decline in IVIX. Whereas the Employment survey release increases the IVIX by 2.1044% on report day. All other announcements are found to be statistically insignificant. The one day before results indicates no slope coefficients to be statistically significant except the RBI Monetary Information. This indicates that investors closely monitor the release of monetary news. If the behaviour of IVIX one day after the release is observed, none of the slope coefficients appear statistically significant and bears the expected sign, indicative of the fact that the behaviour of IVIX is not influenced by macroeconomic announcements one day after their release. The intercept appears non-zero and negative in all the three scenarios. This could mean that the markets to do experience high degree of volatility because of the forthcoming announcements.

- **GARCH (1,1) Model Results:** The GARCH (1,1) model results for report day indicate that only RBI Monetary Information and Employment Survey releases are found to be statistically significant at 1% and 5% level of significance respectively. Thus confirming that monetary policy of the RBI news and employment report news is observed by the market participants in their financial planning. RBI disclosure of Monetary Information leads to a decrease in IVIX by 1.993%. This could be indicative of the fact that the monetary policy of RBI was in favour of the markets which resolved much of the uncertainty prevalent present. Whereas it can be said that unfavourable employment figures lead to an increase of 1.918% in IVIX on employment report day. The one day before results show that RBI Monetary Information is positive and statistically significant at 1% level of significance. This confirms that investors over react to forthcoming RBI monetary information, release thus leading to a rise in IVIX levels none of the other variables show an impact on IVIX. The one day after results indicate that the market movement is more mechanical a day after the macroeconomic announcements as none of the slope coefficients appear to be statistically significant.

- **EGARCH (1,1) Results**: The EGARCH (1,1) model results show that slope coefficients of the GDP, IIP, Inflation, Fiscal Deficit, and BOP Current A/C Balance are found to be statistically insignificant. This reveals that these macroeconomic announcements do not influence the IVIX and the reaction of investors is indifferent to them. Whereas only the slope of RBI's Monetary Information and Employment are found to be positive and negative respectively and statistically significant at 1% level of significance. The behaviour of IVIX during a day before the macroeconomic announcements indicate RBI's Monetary Information influences IVIX. The coefficient is significant at 1% level of significance. The One day after results reveals no influence of macroeconomic announcements on IVIX. The EGARCH (1,1) results also demonstrate that IVIX exhibits positive and statistically significant leverage effects at one percent level, indicating that positive shocks (good news) have greater impact on this market than the negative shocks (bad news).

7.2.2 Extent of Volatility in the Indian Equity Market before and after Introduction of India VIX:

In this study we make an attempt to estimate the volatility in the Indian equity market by employing the GARCH family of models. The researcher further explores the changes in volatility of returns on NSE before and after introduction of the India VIX (IVIX). Thus the time series for capturing the volatility has been split into two periods i.e. the Pre- IVIX introduction period (1-1-2000 to 31-3-2008) and the Post-IVIX introduction period (1-4-2008 to 31-8-2016). The sample comprises of daily data of CNX Nifty for the period from 1st January 2000 to 31st August 2016 compiled and published by NSE India. A GARCH (1,1) model across the two periods is employed and its parameters are compared. Further a GARCH (1,1) model with dummy is employed to validate the influence of IVIX on NSE returns.

- **GARCH(1,1) Model Results:** After Comparing parameters of the GARCH (1,1) models across the two sub-periods, it is observed that estimated coefficient α_1 increases from 0.0591 to 0.0780 in the post-IVIX introduction period, which confirms that the impact of recent news has a greater impact on price changes. This implies that the information is being impounded more quickly following the onset of IVIX. Besides, the persistence coefficient β_1 has decreased from 0.7905 to 0.7144 in the post-IVIX introduction period which suggests that an increase in the rate of information flows reduce the uncertainty about previous news. In other words, following the onset of Indian VIX, the 'old news' have lesser impact in determining the volatility of the Indian spot market. This is also confirmed by the sum of coefficients α_1 and $\beta_{1,}$ ($\alpha_1 + \beta_1$), that changes from 0.9231 (pre-IVIX) to 0.7924 (post-IVIX) suggesting persistence of shocks from the Pre-IVIX introduction period to the Post-IVIX introduction period is reduced.

- **GARCH (1,1) Model with Dummy Results:** Further the IVIX Dummy coefficient (DIVIX**)** in GARCH(1,1) model which takes the value of 0 for the Pre-IVIX introduction period (1-1-2000 to 31-10-2007) and takes the value 1 for the Post-IVIX introduction period (1-11-2007 to 31-8-2016) is introduced. The IVIX Dummy coefficient (DIVIX) is found to be negative and statistically significant at one percent level, implying that the volatility of the spot market has declined after the introduction of IVIX in India.

7.2.3: To examine the predictive ability of symmetric and asymmetric GARCH models in forecasting India VIX

In this objective the forecasting ability of symmetric and asymmetric GARCH models have been examined. The performance of the basic GARCH, EGARCH and TGARCH models is evaluated in forecasting the India VIX. The daily closing levels of India VIX are considered from 2nd March 2009 to 31st August 2016 and for the purpose of the study the data has been split into two parts i.e. the In-sample and the Out-sample data. The predictive ability of the competing models was evaluated using standard (symmetric) errors namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Theils Inequality Coefficient for out-sample forecasts.

GARCH(1,1, EGARCH(1,1), and TGARCH(1,1) Results: The estimates of parsimonious GARCH (1,1), EGARCH(1,1), and TGARCH(1,1) models reveal that the ARCH and GARCH terms in conditional variance equations are positive and significant at one per cent level in all estimations, implying a strong support for the ARCH and GARCH effects. Besides, the results show that the sum of $\alpha + \beta$ coefficients in the conditional variance equations of GARCH (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models were all were close to unity, implying that innovation to the conditional variance is highly persistent and takes longer time to dissipate. In the EGARCH (1, 1) model, the dependence of volatility on its past behaviour is confirmed, as α_1 and δ_1 coefficients appear to be statistically significant. Besides, the asymmetric coefficient γ_1 (0.202547) shows that the VIX index exhibits statistically significant asymmetric effects at one percent level. This indicates that positive shocks (good news) have greater impact on this VIX Index than the negative shocks (bad news). The results of the TGARCH(1,1) model reveals that asymmetric effect captured by the parameter estimate δ (-0.214376) is less than zero confirming that the volatility to positive innovations (good news) is larger than that of negative innovations (good news).

Overall, using the minimum Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) values as model selection criteria for the GARCH models, the preferred model is the GARCH (1,1) model based on the minimum Akaike Information Criteria and Schwarz Information Criteria.

Evaluation of Forecasting ability of Models: The models were then evaluated in terms of their forecasting ability of future India VIX index. The standard (symmetric) loss functions were employed to evaluate the forecasting performance of the competing models: the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Mean Absolute Percent Error (MAPE) and the Theil Inequality Coefficient. The results show that the GARCH (1,1) model outperformed all the other models in forecasting India VIX series with the lowest error measurements. This is followed by the TGARCH (1, 1) model that performed better in forecasting the India VIX series.

7.2.4: To study the dynamic linkages between International equity markets through volatility Indices:

Through this objective the dynamic linkages between select developed equity markets and emerging markets were studied. An attempt was made to investigate whether there is market integration in terms of implied volatility spillovers. The sample consists of daily changes in the values of implied volatility indices from March 2009 to August 2016. The dynamic linkages between implied volatilities of selected countries i.e. US (VIX), Germany (VDAX) representing developed markets and India (IVIX), China

(VXFXI), and South Korea (VKOSPI) were taken as a proxy for emerging equity markets. The VAR (p) system followed by Impulse Response Function and Variance Decomposition analysis was employed to ascertain the lead-lag effects in examining the transmission of shocks of the implied volatility series of one index over the other. The results of the study show that:

Correlation Analysis result: The Pearson's Correlation Coefficient analysis results on the implied volatility series indicate moderate level of correlation can be observed amongst the five volatility indices. The lowest degree of correlation is observed between the US and Korean Index (0. 2032) However, the highest degree of correlation is observed between US and China (0.6604).

VAR Results: The F-statistics indicate that the estimated VAR (2) model is statistically highly significant. And the Adjusted R^2 ranges from 0.0136 for VXFXI to 0.182 for VKOSPI. The stability of the estimated VAR model with 2 lags is tested by examining the inverse roots of the character AR polynomials. All the inverse roots should lie within the unit circle and should have modulus of less than one for the VAR model to be stable. The results reveal that estimated VAR model with 2 lags is stable as all roots lie within the unit circle

Impulse Response Function: The impulse response function was employed to measure the responses of the variables—IVIX, VIX, VDAX, VKOSPI, VXFXI—in the dynamic VAR system to a shock to each variable. A total of 25 impulse responses could be calculated since there are 5 variables in the system. A unit shock is applied to IVIX, VIX, VDAX, VKOSPI, VXFXI and the corresponding impulse responses of IVIX on Day 1 are observed. Similarly, the same unit shock is applied to each volatility index and responses of IVIX on Day 2 are noted and so on.

The effects of the shock on IVIX are both positive and negative. The IVIX seems to be affected most by the US index. The impulse response function confirms our previous results. From Day 4 onward up to Day 6, the effect of the same shock each time gradually dies out and thus induces no more change in the IVIX index.

Variance Decomposition Results:

USA: The variance decomposition results for VIX indicate that the 1 day ahead forecast error variance of VIX is explained by it alone and it explains 97.77644 % of its 10 day ahead forecast error variance. Neither the Asian nor the German markets hold strong explanatory powers. It is seen that the volatility in the US market is largely driven by domestic innovations.

South Korea: VKOSPI explains 92.84% of its own 1 day ahead forecast and 78.55% of its 10 day ahead forecasts. It is noted that VIX contributes to explaining 7.16% of 1 day ahead forecast of VKOSPI and 20.109% of 10 day ahead forecast error variance of the South Korean Index. VXFXI explains around 1.027% of 10 day ahead forecast error variance of VKOSPI. The South Korean market volatility seems to be influenced largely by domestic factors. Of the four markets examined it seems highly influenced by shocks from the US market. The results also indicates delayed reaction of the South Korean market to innovations in the US market, as the percentage share of the US market innovations increases from 7.16259% on day 1 to 20.109% on day 10.

China: It is seen that domestic factors explain 51.361% of 1 day ahead forecast error variance of VXFXI. It is significantly integrated with VIX as it explains 44.70601% of 1 day ahead forecast error variance of VXFXI. The Chinese volatility index is minimally integrated with the other Asian indices. The VKOSPI explains 3.932521% of 1 day ahead forecast error variance, whereas IVIX and VDAX show absolutely no influence on the volatility of the Chinese market. If we look at the 10 day ahead forecasts for VXFXI then it may be noted that VXFXI explains 50.36% of its own Forecast Error Variance. VIX explains 44.23%, VKOSPI 5.32%, IVIX 0.072%, and VDAX 0.004 % of 10 day ahead Forecast Error Variance for VXFXI.

India : The results for IVIX show that the 81.5527% 1 day ahead forecast error variance of IVIX is explained by it alone, whereas 8.512867%, 7.912169%, and 2.022799% is explained by VKOSPI, VIX and VXFXI respectively. If we observe the 10 day ahead forecast error variance of IVIX, 75.72929% is explained by itself, 13.14896% by VIX, 8.499503% by VKOSPI, and 2.59635% by VXFXI. Of the four markets examined it seems highly influenced by shocks from the US market. But a delayed reaction is noticed in the Indian market to innovations in the US market, as the percentage share of the US market innovations increases from 7.912169 % on day 1 to 13.14896 % on day 10.

German: VDAX explains 68.67231% of its 1 day ahead forecasts, followed by VIX explaining 27.89226 % and VXFXI explaining 1.974267% forecast error variance respectively. The 10 day ahead forecast show that VDAX explains 65.2049 % of its forecast error variance whereas VIX and VXFXI explains 31.34698% and 1.808851% respectively. None of the other indices play a significant role.

Variance Decomposition Analysis reports that the volatility in the five markets seems to be driven mainly by shocks in their respective domestic markets. Of the five indices examined, The US index emerges as an influential Volatility Index which explains 20.109%, 44.23006%, 13.14896%, 31.34698% of 1 day ahead forecast error variance for VKOSPI, VXFXI, IVIX, and VDAX respectively. The South Korean market exhibits properties of leading market in the Asian region. Explaining 3.932521% forecast error variance on day 1 and 5.326382% on day 10 of China, whereas

8.512867% forecast error variance on day 1 and 8.499503% on day 10 of India. The innovations in the German market fail to explain the forecast error variance in the other four markets. It is also interesting to note that the India VIX is not influenced much by other volatility indices (especially the US Index) compared to China which though in the same stage of development as India is more integrated with international markets

7.3 CONCLUSION:

In recent times the implied volatility indices have received a lot of attention from the academic community, policy formulators, and investors. The implied volatility index derived from the option prices is the forward-looking expectation of the future stock market volatility. It is also referred to as investor’s fear or greed index as it is considered a barometer of investor sentiments. The importance of implied volatility index increases day-by-day among the market participants and analysts, the rational is that agents can predict the trend of market with short horizon. The scholarly works of (B.J.Christensen & Prabhala, 1998) suggest implied volatility to be the best estimate among all other estimates of future realized return. The recent interest of analysts and academics in stock market returns and forecasting of future volatility based on implied volatility index has laid the foundation for the present study.

In the light of the popularity and usefulness of implied volatility indices in the world, this study makes an attempt to analyse the behaviour of the Indian Implied Volatility Index. Though extensive literature is available on the implied volatility indices of developed countries, limited work in this area is done in the context of emerging economies like India. The Impact of scheduled macroeconomic announcements on IVIX has been examined. The researcher has made a novel attempt to study the extent of volatility in the Indian equity market before and after implementation of IVIX and examine the predictive ability of symmetric and asymmetric GARCH models in forecasting IVIX. Lastly, in this era of globalisation, the dynamic linkages between international equity markets have been studied through implied volatility indices.

In studying the behaviour of IVIX around scheduled macroeconomic announcements, the Scheduled releases of INFLATION, IIP, GDP, RBI Monetary Information, Employment, Fiscal Deficit, and BOP Current A/C Balance are considered. No significant influence of macroeconomic news on report day and day before on India VIX is reported, except RBI Monetary Information disclosure and Employment survey report. Besides, the findings demonstrate indifferent response of India VIX one day after the scheduled news announcements. We also expect the investors to observe these news releases in their portfolio selection and management. However, the findings of the study reveal that investors need not consider the scheduled macroeconomic announcements, except the RBI Monetary information disclosure and employment report in their financial planning as they have no significant influence on market volatility. The results are also indicative of the inefficiency of the Indian options market.

Further, the study explores the changes in volatility of returns on NSE before and after implementation of IVIX. In addition, the results provide the evidences that the volatility of the spot market has declined after the introduction of IVIX in India and the impact of recent news has a greater impact on the spot market changes in the post-IVIX introduction period. At the same time, the persistence of volatility shocks has declined in the post-IVIX scenario indicating increased efficiency of the Indian stock market. Hence, the study suggests that the introduction of post-IVIX have improved the speed and quality of information flow in the Indian stock market and has helped curb spot market volatility in India.

Since volatility forecasting holds great significance to market players, we make an attempt to forecast IVIX using the GARCH family of models. We test the predictive ability of symmetric GARCH (1,1), and Asymmetric TGARCH (1,1) and EGARCH (1,1) models in forecasting the India VIX index and evaluate their performance by employing standard (symmetric) loss functions. The GARCH (1,1) model is considered the most suited for the Indian market as it outperform all the other models in forecasting the India VIX price series.

In an integrated market, Volatility spillovers in terms of implied volatility can have far reaching implications for risk managers, market regulators, traders, and international portfolio managers. It is important for them to know which market leads the other and which market is the prime source of implied information. For constructing volatility forecasts and taking accurate investment decisions it becomes essential to be well informed about dependencies in implied volatilities. Through this study the dynamic linkages between five implied volatility indices i.e. IVIX, VIX, VDAX, VKOSPI and VXFXI are examined. The study reveals that there exist linkages between all five international volatility indices. The ever expanding globalization in the finance and investment industry is the main reason behind these linkages. The US VIX appears to bear the highest explanatory power. Therefore, this index should be closely observed by overseas regulatory authorities as an early warning signal for future turbulence in their domestic markets. The India VIX is moderately influenced by the US index. The IVIX seems to be also integrated minimally with its Asian equivalents. It is observed that none of the sample market's Volatility Index has a substantial influence over the

IVIX. A possible reason for this could be that the Indian equity markets bear a lesser degree of integration to the global financial system. But this is likely to change once India expands its financial systems and brings it on par with the global financial system.

7.4 IMPLICATIONS AND RECOMMENDATIONS:

The implications of this kind of study for the investment community and regulatory bodies are rather multifaceted. Few implications suggested by the researcher of the present work are listed below:

The study gives a fair idea to the investors as to which macroeconomic variable they should consider and observe in their financial planning since the RBI monetary policy and employment report have a significant impact and are key indicators revealing the health of the economy. These have to be monitored closely by investors who plan their investment strategy.

The results highlight the importance of the volatility index by suggesting that the introduction of IVIX has improved information flow in the Indian stock market and has helped to reduce market volatility. Thus a model has been suggested which could provide accurate forecasts of short term volatility in the market, which could help option traders get a directional view as to where the market is heading.

The study also examines linkages between global markets in terms of implied volatility Indices. This can have significant implications for risk managers, market regulators, traders and international portfolio managers. It helps them understand which market leads the other and which market is the prime source of implied information. Being well informed about the manner in which implied volatility dependencies assist in constructing accurate volatility forecasts and taking investment decisions.

Volatility Indices can provide volatility trading and hedging opportunities to investors. The volatility indices can be used for profit booking in the market by developing trading strategies like a volatility long position in times of rising volatility and a short position when volatility declines.

7.5 SCOPE FOR FUTURE RESEARCH:

The present study has focused on domestic macroeconomic announcements and their impact on India VIX. The study could be extended in a globalized setup by observing the behaviour of IVIX around the economic news of Europe, the US, and other emerging economies. Another area that remains to be explored in the context of India VIX is the macroeconomic announcement surprises and investor expectations.

The volatility contagion between IVIX and other global volatility indices can be further extended by studying the co-movement of India VIX and with other major markets like UK, Japan, other Eurozones, and emerging South East Asian economies. Complex analytical tools such as multivariate GARCH models could also be employed for this purpose.

Analysing the significance of volatility derivatives in the Indian market as a tool for Hedging could also make an interesting area for research.

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