The Forecasting Power of the Different Volatility Indicators in Indian Capital Market

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Key Words:

1.Attitudes and Behaviour
2.Rationality
3.Segmentation

Abstract
This research explores the predictive power of the India VIX (volatility index) in emerging markets from April 2009 to March 2011. The results of the study show that the models including both the volatility indicator and the option market information have a stronger predictive power. With respect to the trading information from different types of investors in option markets, the trading information from the foreign institutional investors in option markets demonstrates a significantly positive relationship with the stock market volatility. In addition, the results of this paper also reveal that the India VIX GARCH volatility forecasting and stock index options are a strong indicator of future stock market volatility. The GARCH outperforms the historical volatility and the VIX volatility forecast in assessing the activities of Indian capital market.

INTRODUCTION

Volatility Index is a measure of market's expectation of volatility over the near term. Volatility is often described as the “rate and magnitude of changes in prices” and in finance often referred to as risk. Volatility Index is a measure, of the amount by which an underlying Index is expected to fluctuate, in the near term, (calculated as annualised volatility) based on the order book of the underlying index options. India VIX is a volatility index based on the NIFTY Index Option prices. From the best bid-ask prices of NIFTY Options contracts, a volatility figure are calculated which indicates the expected market volatility over the next 30 calendar days. India VIX uses the computation methodology of CBOE, with suitable amendments to adapt to the NIFTY options order book using cubic splines, etc.

Volatility Index: Volatility Index is a measure of market's expectation of volatility over the near term. Usually, during periods of market volatility, market moves steeply up or down and the volatility index tends to rise. As volatility subsides, volatility index declines. Volatility Index is different from a price index such as NIFTY. The price index is computed using the price movement of the underlying stocks. Volatility Index is computed using the order book of the underlying index options and is denoted as an annualised percentage. The Chicago Board of Options Exchange (CBOE) was the first to introduce the volatility index for the US markets in 1993 based on S&P 100 Index option prices. In 2003, the methodology was revised and the new volatility index was based on S&P 500 Index options. Since its inception it has become an indicator of how market practitioners think about volatility. Investors use it to gauge the market volatility and base their investment decisions accordingly.

India VIX: India VIX is a volatility index computed by NSE based on the order book of NIFTY Options. For this, 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. India VIX indicates the investor's perception of the market's volatility in the near term i.e. it depicts the expected market volatility over the next 30 calendar days. Higher the India VIX values, higher the expected volatility and vice versa.

As the volatility index has attracted growing attention in recent years, the CBOE has also launched many different volatility indices based on other underlying targets, such as the NASDAQ-100 Volatility Index (VXN), the DJIA Volatility Index (VXD), and the S&P 500 3-Month Volatility Index (VXV), etc. Nevertheless, the VIX still remains to be the most widely-used and discussed information indicator in security markets. For example, in the 1998 LTCM and the 2002 WorldCom bankruptcy, the VIX rapidly increased to a level over 40. In the 2007 worldwide financial tsunami

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caused by the sub-prime mortgage crisis, the VIX even exceeded 80 when the Lehman Brothers filed for bankruptcy. Hence, previous researchers found that the VIX serves as a powerful predictive indicator of the developed derivative markets. Meanwhile, exploring the predictive power and accuracy of different models and volatility indicators regarding the future stock market volatility has become one of the major topics in the field of risk management of financial markets in recent years. This study, intend to compare the predictive performance of the historical volatility, the implied volatility, the volatility index (India VIX) of stock index options, and the GARCH volatility forecasts, regarding the future stock price movements in India.

According to the comparison of the empirical results with the models merely considering the volatility indicator, the predictive performance of the models that incorporate both the volatility indicator and option market information gives a proper response. Among all of the volatility indicators, GARCH Volatility would generates the best predicative performance, followed by India VIX, Implied Volatility Aggregate, Implied Volatility Call, Implied Volatility Put and Historical Volatility. Further, some inclusion to option market information (trading volume and open interest of option markets) was made, and found that among all of the models, the model using the India VIX as an independent variable achieves the greatest predictive performance, followed by the models using the GARCH Volatility and IVP. Finally, the trading information of different types of investors from option markets into the models was incorporated and verifying the applicability of the volatility index to the emerging markets. Therefore, the results of our study show that the VIX is a powerful predictive indicator for the stock market volatility in the emerging markets. Investors can thus make use of the volatility index to further understand the stock market movement and adjust their national/international portfolios accordingly.

REVIEW OF LITERATURE

Christensen and Prabhala (1998) utilized the non-overlapping samples to restudy S&P 100 index options and documented that the implied volatility is superior to the historical volatility in predicting the future market volatility.

Blair, Poon and Taylor (2000) compared the implied volatilities and intraday returns, in the context of forecasting index volatility over horizons from one to twenty days. Forecasts of two measures of realised volatility are obtained after estimating ARCH models using daily index returns, daily observations of the VIX index of implied volatility and sums of squares of five-minute index returns. The in-sample estimates show that nearly all relevant information is provided by the VIX index and hence there is not much incremental information in high-frequency index returns. For out-of-sample forecasting, the VIX index provides the most accurate forecasts for all forecast horizons and performance measures considered. The evidence for incremental forecasting information in intraday returns is insignificant.

Wu and Xiao (2002) conducted a close examination of the relationship between return shocks and conditional volatility, where the impact of return shocks on conditional volatility is specified as a general function and estimated non parametrically using implied volatility data—the Market Volatility Index (VIX). They provide a good description of the impact of return shocks on conditional volatility, and it appears that the news impact curves implied by the VIX data are useful in selecting ARCH specifications at the weekly frequency. They found that the Exponential ARCH model of Nelson is capable of capturing most of the asymmetric effect, when return shocks are relatively small. For large negative shocks, our nonparametric function points to larger increases in conditional volatility than those predicted by a standard EGARCH. Their empirical analysis further demonstrates that an EGARCH model with separate coefficients for large and small negative shocks is better able to capture the asymmetric effect.

Yu (2002) examine the performance of nine alternative models for predicting stock price volatility using daily NZSE40 (New Zealand) data. The main results are the following: (1) the stochastic volatility model provides the best performance among all the candidates; (2) ARCH-type models can perform well or badly depending on the form chosen: the performance of the GARCH(3,2) model, the best model within the ARCH family, is sensitive to the choice of assessment measures; and (3) the regression and exponentially weighted moving average models do not perform well according to any assessment measure, in contrast to the results found in various markets.

Aboura, and Villa (2003) deals with the accuracy of international volatility indexes (VX1, VDAX and VIX). First, they find that VX1, VIX and VDAX are good tools for predicting future realized volatility and they also show that past implied volatility informs more about future implied volatility than past realized volatility. They, also, embed each of the implied volatility indexes as an exogenous term in the GARCH variance equation and find that all of them dominate the GARCH terms. Secondly, they compute parameters of a stochastic volatility model using implied volatility indexes. Thirdly, they studied the transmission mechanisms of implied volatility indexes.

Szakmary et al. (2003) explored 35 major futures and options markets in the U.S., and their findings corroborated the fact that the implied volatility predicts the future market volatility better than the historical volatility.

Mark (2003) indicated that the VIX is generally 3.8% lower than the VXO. The VIX and VXO have been shown to have similar analytical capabilities in predicting the future market volatility.

Mayhew and Stivers (2003) studied the top 50 most heavily-traded options of the CBOE and demonstrated that the VXO contains more information. However, no consensus was reached with respect to the lightly-traded options. Whaley (2000) analyzed the S&P 100 index and the VXO and suggested that the relation between stock market returns and VXO variation is asymmetric.

Koopman, Jungbackera and Hol (2004) explores the forecasting value of historical volatility (extracted from daily return series), of implied volatility (extracted from option pricing data) and of realised volatility (computed as the sum of squared high frequency returns within a day). They consider unobserved components and long memory models for realised volatility which is regarded as an accurate estimator of volatility. The predictive abilities of realised volatility models are compared with those of stochastic volatility models and generalised autoregressive conditional heteroskedasticity models for daily return series. Their results show convincingly that realised volatility models produce far more accurate volatility forecasts compared to models based on daily returns. Long memory models seem to provide the most accurate forecasts.

Carr and Wu (2006), who showed that the VIX outperforms the historical volatility and the volatility estimated from GARCH models in forecasting the S&P 500 index volatility.

Banerjee, Doran and Peterson (2007) investigate the relationship between future returns and current implied volatility levels and innovations. They found that the VIX-related variables have strong predictive ability.

Hung, Tzang and Hsyu (2009) compared the efficacy of high low range volatility and implied volatility indexes in volatility forecasting. Their result shows that in less liquid option trading markets, the high low range volatility, in combination with VIX, can be used as an alternative tool in investment decisions and risk management.

Wiphatthananthakul and McAleer (2009) By using Thailand's SET50 Index Options data, they modify the apparently complicated VIX formula to a simple relationship, which has a higher negative correlation between the VIX for Thailand (TVIX) and SET50 Index Options. Their results show that TVIX provides more accurate forecasts of option prices than the simple expected volatility (SEV) index, but the SEV index outperforms TVIX in forecasting expected volatility. Therefore, the SEV index would seem to be a superior tool as a hedging diversification tool because of the high negative correlation with the volatility index.

Szado (2009) reported that the potential diversification benefits of adding a long VIX and VIX futures to the base portfolio are significant. Although the VIX derivatives have achieved widespread recognition, it is still challenging on the pricing of VIX options and futures.

Degiannakis and Christos (2010) Investigate the possible incremental information incorporated in the VIX index in an ARCH framework, where an inter day dataset is considered, as well as in an ARFIMAX framework, where the realized volatility computed from an intraday dataset is the dependent variable and found that VIX index is incorporated as exogenous variable either in an inter day or in an intraday model specification, it provides incremental predictive ability.

Yu et al. (2010) studied the exchanges and OTC markets in Hong Kong and Japan and concluded that the implied volatility is a better predictor of the future volatility in the exchanges and OTC market's than the GARCH volatility forecasts and the historical volatility.

Chung, and Tsai (2011) investigate the informational roles played by these two option markets with regard to the prediction of returns, volatility, and density in the S&P 500 index. Their results reveal that the information content implied from these two option markets is not identical. In addition to the information extracted from the S&P 500 index options, all of the predictions for the S&P 500 index are significantly improved by the information recovered from the VIX options.

Konstantinidi and Skiadopoulos (2011) investigated the information efficiency of the VIX futures.

Shu and Zhang (2011) suggested that although the VIX futures have some price-discovery function, overall the VIX futures market is still considered informationally efficient.

Yang and Liu (2012) explores the predictive power of the volatility index (VIX) in emerging markets. The results of the study show that the models including both the volatility indicator and the option market information have a stronger predictive power. Their results also reveal that the volatility index (TVIX) of Taiwan stock index options is a strong indicator of future stock market volatility.

DATA AND METHODOLOGY

Daily data of Volume and open interest, India VIX, daily data of nifty, important transaction data of nifty index option for different type of investors' viz. FII, DII and other investor were collected from official website of National Stock Exchange. Study period for this research was 01/04/2009 to 31/3/2011.

Model And Methodology

Present study uses different type of volatility, to measure daily realized volatility for Indian capital market. As the India VIX and implied volatility is annualized volatility and measured by using total trading days. The Models used for realized volatility (RV) Annualized and historical volatility (HV) at day t are as follows,

$$Hv_t = \frac{Ht - i- Lt - i}{Ct - i} * \sqrt{n} \quad \text{................1}$$

$$Rv_t = \frac{Ht - Lt}{Ct} * \sqrt{n} \quad \text{................2}$$

Where,

Ht = Highest price of the day of nifty,

Lt = Lowest price of the day of nifty,

T = Total Trading day in a year of nifty,

Ct = Closing price of the day of nifty.

n= no. of trading days

Present study focuses on mainly 2 issues; firstly: to examine the impact of different volatility on stock index return. Secondly, to explore whether India VIX is good predictor of future market volatility or not, in comparison to implied volatility, historical volatility and GARCH volatility forecasting.

For this purpose the following equations were estimated:

$RV_t = \alpha 0 + \alpha 1\, HV_{t-i} + \epsilon_t$...................................3

$RV_t = \alpha 0 + \alpha 2 IVA_{t-i} + \epsilon_t$ 4

$RV_t = \alpha 0 + \alpha 3\, IVC_{t-i} + \epsilon_t$ 5

$Rv_t = \alpha 0 + \alpha 4 IVP_{t-i} + \epsilon_t$ 6

$RV_t = \alpha 0 + \alpha 5\, IndiaVIX_{t-i} + \epsilon_t$..........................7

$RV_t = \alpha 0 + \alpha 6\, GfV_{t-i} + \epsilon_t$...................................8

Where, VIXt is volatility index computed by NSE based on order book of nifty options on day t.

GFVt is GARCH volatility forecasting on day t,

IVAt is overall implied volatility on day t,

IVCt is call implied volatility on day t,

IVPt is Put implied volatility on day t,

HVt is historical volatility on day t.

Єt is error term

The equations of Black-Scholes were used to inversely derive the annual volatility implied from the market prices of options. The implied volatility represents investors' expectations of the future volatility of stock returns and helps investors to determine whether the option prices are reasonable or not. The implied volatilities of put and call options may differ because of the differences in moneyness between the call and put options. To mitigate the problems in measuring the implied volatility, we adopted three different measures of the implied volatility in the analysis, including the implied volatility of the (nearest) at-the-money call option (IVC), put option (IVP), and the averages of both call and put that is overall volatility of call and put (IVA) with the shortest maturity (of at least five trading days). To avoid the observation errors generated by the implied volatility when it is an independent variable that may affect the results of regression, this study adopts the log-transformed data of the volatility measures.

Present study was designed primarily, to test the predictive power of the volatility index in terms of the future market volatility in Indian Capital Market. The volatility index, constructed according to the new version of the CBOE VIX computation formulas in 2003, is based on a series of different exercise prices of the nifty index options. Such a volatility index is not derived from any of the option pricing model, and its calculation is also irrelevant to any other option pricing models. Instead, it is derived from the weighted average of the put and call option premiums.

India Vix: Computation Methodology

India VIX uses the computation methodology of CBOE, with suitable amendments to adapt to the NIFTY options order book. The formula used in the India VIX calculation is

$$\sigma^2 = \frac{2}{T} \quad \frac{?\,K}{K2i}\, e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{f}{ko} - 1\right]^2 \text{.....................9}$$

VIX= σ...10a

$?\,K_i = K_i + 1 - K_i - 1$

....10b

India VIX= σ * 100

T = Time to expiration

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

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

$\Delta K_i = K_i+1 - K_i-1 / 2$

ΔK for the lowest strike is simply the difference between the lowest strike and the next higher strike. Likewise, ΔK for the highest strike is the difference between the highest strike and the next lower strike.

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

K_0 = First strike below the forward index level, F.

Time To Expiration (t)

India VIX calculation measures the time to expiration in years, using minutes till expiration. The time to expiration is given by the following expression.

T = {M Current day + M Settlement day + M Other days}/ Minutes in a year

Where,

M Current day = Number of minutes remaining until midnight of the current day (from computation time up to 12.00 am). It is 3.30 pm up to 12.00 am

M Settlement day = Number of minutes from midnight until closing hours of trading (i.e. 3:30 p.m.) on expiry day

M Other days = Total number of minutes in the days between current day and expiry day excluding both the days.

India VIX uses put and call options in the near and next month expiration, in order to bracket a 30-day calendar period. It may be noted that CBOE VIX rolls to the next and far month with less than a week to expiration. However, with 3 trading days left to expiry, India VIX "rolls" to the next and far month.

Risk Free Interest Rate (R)

The relevant tenure of NSE MIBOR rate (i.e. 30 days or 90 days) is being considered as risk free interest rate.

Determination Of Forward Index Level, F

Volatility index is computed using mainly the quotes of the out of the money (OTM) options. The strip of OTM option contracts for computing India VIX could be identified if the at the money (ATM) strike is identified. In case of CBOE, the forward index level is arrived at by using the strike price at which the absolute difference between the call and put prices are minimum. NSE has an actively traded, large and liquid NIFTY futures market. Therefore the latest available traded price of the NIFTY futures of the respective expiry month is considered as the forward index level.

Computation Of K_0

K0 is the strike price just below the forward index level. This is considered as the at-the money strike (K0).

Garch Model

Engle in 1993 claimed that the conditional variance in the GARCH model is more effective in predicting the volatility of stock returns than the historical volatility. For this study, the volatility was estimated from the GARCH model to forecast the future volatility of stock markets. The conditional mean and conditional variance equations of stock returns are defined below

$R_t = \alpha_0 + \alpha_1 Rt\text{-}1 + \epsilon_t$..11

$h_t = \beta 0 + \beta_1 \epsilon^2 t\text{-}1 + \beta_2 h_t\text{-}i$... 12

Where, R_t = are the daily return,

h_t = are the conditional variance of returns, and

ε_t = the residual of returns on the weighted average stock index on day t.

According to Engle (1982) and Bollerslev (1986) a rolling-over method is adopted to obtain the volatility estimated from the GARCH model in equation 41 ht+i is the volatility in period (t+1), which was derived from the parameter estimated of β1 and β2 for total trading days in a year. Similarly, ht+2 is the volatility in period (t+2) derived from the parameter estimated of β1 and β2 for total trading days in a year less 1 day. In order to reconcile the comparative bases, the variance ht estimated by the GARCH model is also adjusted and annualized. We incorporate the results of the estimated GFVt into equation 42 to compare its predictive power with the volatility index, historical volatility, and implied volatility.

Different from the index spot markets, the index option markets are highly-leveraged security markets. After investors pay the option premium, they are entitled to purchase or sell a certain amount of the underlying assets from or to the sellers of contracts based on the exercise prices stipulated on the option contracts. If investors expect future stock prices to be on the rising trend, they would tend to buy call options or sell put options. On the contrary, if they predict future stock prices to be on the downward trend, they would tend to buy put options or sell call options in order to make profits. Researcher included the trading volume and open interest of option market into the model because trading volume and open interest of option markets possess the explanatory power regarding the future volatility of stock prices. The realized volatility of the past five days (RV t-1 to RV t-5) was used as control variable. Study was based on Lag 1 criterion, which is decided by Akaike information criterion. The Model was decided as follows:

$RV_t = α0 + α_1 RV_{t-1} + α2 RV_{t-2} + α3 RV_{t-3} + α4 RV_{t-4} + α5 RV_{t-5} + α6 \text{ Volatility}_{t-i} + α_7 \text{ VOLUME}_{t-I} + α8 \text{ OPEN INTEREST } t_{-i} + ε_t$ 13

Where Volatility $_{t-i}$ refers to IVA $_{t-i}$, IVP $_{t-i}$, IVC $_{t-i}$, India VIX $_{t-i}$, or GARCH Volatility $_{t-i}$,,

Volume refers the trading volume of option contract on the t-i day

Open Interest refers to the total outstanding contracts of the index option on the t-i day.

The put call ratio is good indicator to understand the market behaviour and pattern hence it was added in our analysis. This was added in our analysis only because it clears the position of FII, DII and other investor sentiment towards the volatility in the capital market.

Basic formula used for Put- Call ratio is:

P- C Ratio = $PUT_t / PUT_t + CALL_t$ 14

To strengthen the analysis, study also uses the put-call volume and open interest made by the FII, DII, and other investors. The model proposed for this purpose is as follows.

$RV_t = α0 + α1 RV_{t-1} + α2 RV_{t-2} + α3 RV_{t-3} + α4 RV_{t-4} + α5 RV_{t-5} + α6 \text{ Volatility}_{t-i} + α7 \text{ FII}_{t-I} + α8 \text{ DII}_{t-i} + α9 \text{ Other Investors} + ε_t$.............................15

Where, FII is foreign Institutional Investors,

DII is Domestic Institutional Investors, and

Other Investors are remaining all market players and individual Investors.

From the above equation researcher try to predicted the different volatility indicators and different types of investors toward future market volatility. Correlation coefficient was also estimated to understand the impact of volatility on the stock return index.

Descriptive Statistics

Table 4.1 summarized the descriptive statistics of the realized volatility (RV), implied volatility (IVA, IVC, and IVP), volatility index (TVIX), Volume, Open Interest, Index return and GARCH forecast volatility (GFV). Among the volatility indicators, the IVP had the highest mean value, followed by IVC, IVA, RV, India VIX and GARCH Volatility had the lowest mean value, while GARCH volatility and India VIX mean were negative. The values of skewness were positive for all variables this indicated that that the data distributions were skewed to the right. The statistics of kurtosis shows that the distributions of variables like RV, IVC, IVP, IVA, Open Interest and Index return are leptokurtic while volume GARCH volatility and India were stationary data at its own lag.

Correlation coefficients

Table 4.2 concluded the correlation coefficients for the main variables used in analysis. The correlation matrix demonstrates a negative correlation coefficient of about 0.4 between the Index return and future volatility by options (VIX) and GARCH Volatility, it indicated that if return of index would increase then future volatility and GARCH volatility would decrease. Also, the correlation between IVA, IVP, IVA and VIX was positive but very low; it implied that the implied volatility and the volatility index may had a different pattern to predict the realized volatility (RV). Implied volatility due to call, put and average of both were highly correlated, coefficient of these all three were approx 0.9. Correlation coefficient between open Interest and realized volatility were found to be negative, it indicated that on increase in open interest of option volatility decrease to slight extant. In the end for volume it can be conclude that when selling pressure was in market than volume-Volatility relationship would be very low. Hence it was expected that the predictive power of all volatility indicators would different but pattern may be same.

Comparison Of Different Volatility Indicators

The results of predictive power of each type of volatility indicator regarding the future market volatility were given in table 4.3, for this purpose Log transformed data had been used. The regression coefficient, t- stat, R2 and F value from all models were recorded.

The empirical results reveal that all volatility indicators were used independently. The coefficients of all indicators were positive which means that volatility would increase in near term and it can remain for long time. All t-stat were significantly positive for all indicators and were statically significant at 1% level of significance. The highest t-stat were reported in GARCH volatility forecasting (10.60190), followed by India VIX (9.24683), Implied volatility average of call and put (7.45630), Implied volatility of call (5.68718) and finally lowest in Implied volatility of put (4.820108).

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Results And Discussions

Table 1 : Descriptive Stats

Variable	RV	IVA	IVC	IVP	VIX	GARCH VOL	Volume	OI	Return
Mean	0.29328	0.32016	0.35216	0.39508	-0.11734	-0.1793	209630466	52596	0.141923
SD	0.188499	0.1924	0.1863	1.69	5.1975	4.08	86739950	19324	1.5741
Skewness	4.603353	2.018	2.931	3.53	0.184652	0.9123	1.2755287	1.89264	2.782
Kurt	45.29337	36.15	30.17	7.08	0.481727	2.701	2.314197	5.381	31.34

Table 2 : Correlation Coefficients

Variable	RV	IVA	IVC	IVP	VIX	GARCH VOL	Volume	OI	Return
RV	1								
IVA	0.12	1							
IVC	0.119	0.94	1						
IVP	0.132	0.926	0.904	1					
VIX	0.154	0.22	0.172	0.169	1				
GARCH VOL	0.163	0.274	0.199	0.237	0.883	1			
Volume	0.226	0.241	0.218	0.263	0.070	0.201	1		
OI	-0.139	-0.29	-0.270	-0.211	0.663	0.509	0.59	1	
Return	0.213	0.169	0.191	0.114	-0.418	-0.516	-0.11	-0.261	1

Log Transformed Data

Table 3 : Historical Volatility Versus Implied Volatility, Vix Volatility And GARCH Forecasting Volatility

Intercept	HV	Implied volatility			VIX	GFV	R2	Adjusted R^2	F
		IVA	IVC	IVP					
0.01162 (8.79182)	0.281436 (4.10891)						0.13821	0.1296	41.7343
0.00614* (4.88136)	0.436* (8.639)	0.31384* (7.45630)					0.4234	0.4213	81.162912
0.00438* (8.63418)	0.10701* (4.148)		0.31131* (5.68718)				0.17870	0.1776	67.10398
0.00990*	0.40130*			0.24969*			0.1565	0.15499	71.20185
(5.43982)	(9.83143)			(4.82108)					
0.00498* (3.8721)	0.45089* (8.37983)				0.36920* (9.24683)		0.2957	0.2949	67.79146)
0.00488** (2.9429)	0.17178* (7.26814)					0.39921* (10.60190)	0.1644	0.1637	69.2949

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Table 4 :volatility Versus VIX volatility and GARCH Forecasting volatility with control variable

Intercept	Realized volatility					Implied volatility			VIX	GFV	R^2	Adjusted R^2	F
	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	IVA	IVC	IVP					
0.00501* (3.26897)	0.27191 (2.1256)	0.0284 (0.5312)	0.36845 (0.4992)	0.62344 (0.79241)	0.11509* (12.43216)	0.45569 (4.19034)					0.3201	0.3122	81.4214
0.00871* (5.36569)	0.2594** (2.45962)	0.0676 (0.6222)	0.43517 (0.81879)	0.56361 (0.52184)	0.19214* (8.24180)		0.92860 (6.18780)				0.2186	0.2079	92.8 86
0.00583* (6.62090)	0.19076*** (1.92534)	0.0257 (0.8172)	0.24418 (0.4189)	0.72979 (0.89978)	0.24589* (9.71639)			0.53772 (8.27815)			0.2941	0.2931	22.3719
0.00685* (4.18174)	0.18477 (2.29321)	0.0134 (0.4084)	0.25741 (0.52184)	0.71363 (0.87641)	0.30415* (8.16213)				0.41585 (9.82143)		0.1186	0.1142	24.0149
0.00896* (8.25484)	0.28014 (7.19541)	0.146 (0.3002)	0.16583 (0.98114)	0.83008 (0.51635)	0.11018* (12.85914)					0.37028 (8.33841)	0.1348	0.1341	139.251

Table 5: Implied Volatility Versus Vix Volatility And Garch Forecasting Volatility With Control Variable, Open Interest And Volume

Intercept	Realized volatility					Implied volatility			VIX	GFV	VOL	OI	R2	Adjusted R^2	F
	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	IVA	IVC	IVP							
0.00492* (3.25316)	0.46265* (8.23557)	0.0427 (0.212)	0.33021 (0.81694)	0.61612 (0.8959)	0.15202* (4.27684)	0.16682 (6.40018)					0.0988 (0.2513)	0.2466 (0.2701)	0.3776	0.3741	82.301
0.00736* (5.21376)	0.30485* (7.98647)	0.0536 (0.881)	0.38140 (0.68156)	0.60861 (0.59865)	0.19263* (9.60522)		0.08986 (4.18591)				(1.99131)	(0.4813)			
0.00630* (4.46275)	0.30485* (7.98647)	0.0443 (0.211)	0.46215 (1.0897)	0.57265 (0.4276)	0.29872* (8.31635)			0.07778 (3.36437)			(0.1023)	(0.3872)			
00.645* (9.38211)	0.16716* (4.13233)	0.0024 (0.181)	0.17093 (0.1246)	0.82897 (0.3154)	0.18653* (9.05952)				0.12735 (8.76345)		0.0152 (0.5321)	0.3112 (0.3811)	0.6767	0.6754	39.153
0.00701* (4.24654)	0.57280* (8.65641)	0.0355 (0.263)	0.17533 (1.0742)	0.56999 (0.5906)	0.25524* (7.8531)					0.16046 (8.36346)	0.0843* (0.3312)	0.1121 (0.4041)	0.4633	0.4620	31.692

LAG = 1

Table 6: Table 4.6: Implied Volatility Versus Vix Volatility And Garch Forecasting Volatility With Control Variable With Investor Sentiment

Intercept	Realized volatility					volatility Implied			VIX	GFV	FII_{t-i}	MF_{t-i}	$Other_{t-i}$	R^2	Adj. R^2	F
	RV_{t-1}	RV_{t-2}	RV_{t-3}	RV_{t-4}	RV_{t-5}	IVA	IVC	IVP								
0.00792 (6.49617)	0.35063 (8.1275)	0.0494 (0.938)	0.42931 (0.2293)	0.54978 (0.4963)	0.13772 (8.35890)	0.04719 (8.9787)					-0.00756 (-3.8158)	0.5173 (1.164)	-0.0484 (-0.011)	0.1923	0.1892	40.196
0.00813 (5.23996)	0.29837 (5.3759)	0.0896 (0.934)	0.40499 (0.1925)	0.58954 (0.5129)	0.6413 (5.43271)		0.0944 (2.429)				-0.00728 (-4.5251)	0.5287 (1.160)	-0.925 (-0.593)	0.4319	0.4301	80.940
0.00958 (7.24680)	0.45724 (4.3259)	0.0365 (1.211)	0.43627 (0.39708	0.56281 (0.6385)	0.21961 (11.26571)			0.1707 (4.548)			-0.00488 (-3.1932)	0.2795 (0.494)	-0.624 (-0.245)	0.3922	0.3920	44.259
0.00603 (2.41963)	0.43248 (8.2953)	0.0596 (0.583)	0.64221 (0.37183	0.34897 (0.8944)	0.12991 (10.18943)				0.1936 (4.5321)		-0.00431 (-2.5486)	0.6921 (0.874)	-0.936 (-1.020)	0.1640	0.1624	41.078
0.00440 (2.71539)	0.51665 (8.1289)	0.0459 (0.876)	0.29990 (0.39784	0.60510 (0.5635)	0.21671 (12.19654)					0.0824 (10.102)	-0.00715 (-2.5670)	0.5229 (1.139)	-0.843 (-0.841)	0.7823	0.7611	55.921

LAG = 1

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Also Historical Volatility in equations was included to determine whether the model combining the historical volatility and other types of volatility indicators could enhance the explanatory power. The empirical results show that the coefficients of volatility indicators in each model were positive and statically significant at the 1% level of significance. In general, when a single volatility indicator was adopted as an independent variable in the model, (If Lag kept constant) GARCH Volatility would generate the best predicative performance, followed by India VIX, IVA, GFV, IVC, IVP and HV. Previous research confirmed the fact that the predictive performance of the implied volatility was better than that of the historical volatility. Also, the predictive power of the India VIX was very close to that of the implied volatility. Previous research stated that the volatility index was an effective predictive indicator of the future market volatility. It might be possible that the explanatory power (adjusted R2) of all models was reduced when the number of lag periods increased, but for this research only 1 lag had been used. The models with the lag period equal to 1 (i=1) had the higher explanatory power. It implied that the ability of volatility indicator to reflect market information was better in shorter time periods. Overall, the results suggest that the volatility indicators adopted in this study had impacts in determining the future realized volatility.

Incorporation of the Control Variables

The results of implied volatility Versus VIX volatility and GARCH Forecasting volatility with control variable were reported in table no 4.4. After the complete analysis it was found that each type of volatility indicator was able to reflect the market information regarding volatility of future periods.

Thus, the realized market volatility of the past 5 days was added into the models as the controlling variables to test whether the results would be affected by including the recent realized volatility. The result shows that the realized volatility of day one and five were statically significant at 1%, 5%, and 10% level of significance which indicated that explanatory power of the model would be enhanced when it compared to single model of volatility indicator

The maximum value of model adjusted R2 is 0.3122 with the lag length equal to 1 were found maximum in IVA. The coefficients of IVA, IVC, IVP, India VIX, and GFV were all significantly positive and t-stat was statically significant at 1% level of significance. The RVt-1 to RVt-5 was added to the regression models, the coefficients of the all RV t-i significantly positive. These results confirmed that the market information from the recent periods can effectively reflect the future volatility. The overall results of Table 4 were similar to those previously analyzed. The model confirmed that the GARCH Volatility as an independent variable achieves the greatest predictive performance, and the performance of India VIX volatility indicators was quite close to that of GARCH Volatility. It suggested that the implied volatility and the volatility index were good indicators in predicting the future volatility of stock markets. The results also suggest that the models including RVt-1 to RVt-5 perform better than those without RVt-1 to RVt-5 in terms of predicting the future realized volatility.

Inclusion of the Option Market Information

Many previous researches confirm that the option market information might reflect the future market volatility. Table 4.5 reported the empirical results generated upon the inclusion of option market information, such as the trading volume and open interest of option markets. The empirical results show that the coefficient of each volatility indicator was statistically significant at the 1% level.

The coefficients of Volume was found positive but t-stat of volume with IVC accepts the null hypothesis that volatility patterns would change in future but volatility in most of the models were not statistically significant at the 1%, 5%, and 10% level. It proved that the option trading volume could not reflect the future market volatility. As the empirical results of the open interest of option were same as option trading volume, the information covered in the option trading volume might included the information set covered in the open interest, but it was not reflecting in option volume contract traded in the market. Incorporating the option market information in the model could slightly enhance the explanatory power of the models. The maximum value of model adjusted R2 is 0.6767 in India VIX. Based on the data with the lag length equal to 1 (i=1), among all the models, the model using the India VIX as an independent variable achieves the greatest predictive performance, followed by the models using the GARCH Volatility and IVP.

Incorporation of the Information from Different Types of Investors

The trading volume of put and call options will affect the volatility of stock markets. This dataset was given in www.nseindia.com and collected on daily basis that enable us to further classify the types of option transactions. the investors were divided into three types: the foreign institutional investors, domestic institutional investors, and other investor (remaining investors like individual investors, market makers etc. kept under this criterion). There was use of the information variables of put-call ratios developed

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by to conduct our analysis. The put-call ratio could be measured on two basis, first, different types of investors were measured based on the volume of long call and long put option contracts, second, the number of put and call option contracts purchased by different types of investors to open new positions on date t.

Table 4.6 lists the empirical results, from the above table it could be concluded that the positive coefficient was found between the volatility indicators (IVA, IVC, IVP, India VIX, and GARCH Volatility) and the realized volatility (RV), and the all t-stat of volatility indicators were statically significant. The trading information from different types of investors was likely to generate different results. All coefficients of the put-call ratios of foreign institutional investors (FII) were significantly positive at the 1% level; it indicated that FII contracts leaves an impression on the volatility of capital market and volatility pattern changes in proper manner, whereas all coefficients of the put-call ratios of other investors were negative and confirm that the contracts of other investor did not had any impact on the volatility of capital market and patterns of volatility were highly irregular as it accept the null hypothesis. While DII had all coefficients positive but accept null hypothesis. The results indicate that foreign institutional investors were able to predict the market volatility more precisely than the other types of investors. The reason for negative coefficient in other investor might be the matchmaking or revising quotes. When market volatility was high, the need for matchmaking or revising quotes would tend to be reduced. Hence the coefficients of other investor were significantly negative with respect to RV. Finally, it was found that the explanatory power of the models was significantly enhanced through the incorporation of the trading information variables (put-call ratios) of different types of investors.

CONCLUSION

The predictive power of different types of volatility indicators in Indian Capital Market, including the historical volatility, the implied volatility, the India VIX, and the GARCH forecast volatility was investigated. Different models were developed to examine the explanatory power of the volatility indicators in predicting the stock market volatility. Further, the detailed trading information compiled in the dataset of the NSE was used to explore the influence of the information from option markets on the stock market volatility. Further, the study compared the various models of volatility indicators, and the result revealed that when a single volatility indicator was adopted as an independent variable in the model, (If Lag kept constant) GARCH Volatility would generates the best predicative performance, followed by India VIX, Implied Volatility Aggregate, Implied Volatility Call, Implied Volatility Put and Historical Volatility. Further, some inclusion to option market information (trading volume and open interest of option markets) was made, and found that among all of the models, the model using the India VIX as an independent variable achieves the greatest predictive performance, followed by the models using the GARCH Volatility and IVP. Finally, the trading information of different types of investors from option markets into the models was incorporated and verifying the applicability of the volatility index to the emerging markets, in an attempt to fill the gap in the research. The empirical results of this study suggest that foreign institutional investors are able to predict the market volatility more precisely than the Domestic institutional investor and other types of investors. The reason for negative coefficient in other investor may be the matchmaking or revising quotes. When market volatility was high, the need for matchmaking or revising quotes would tend to be reduced. Hence the coefficients of other investor were significantly negative with respect to Realized Volatility. It was found that the explanatory power of the models was significantly enhanced through the incorporation of the trading information variables (put-call ratios) of different types of investors.

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