Delhi Business Review ✠ Vol. 17, No. 2 (July - December 2016)

IMPLIED VOLATILITY Vs. REALIZED VOLATILITY

A FORECASTING DIMENSION FOR INDIAN MARKETS

Karam Pal Narwal*
Ved Pal Sheera**
Ruhee Mittal***

PURPOSE
THE aim of the present study is to examine the forecasting efficiency of implied volatility index of India in predicting the future stock market volatility. Therefore, the forecasting efficacy of implied volatility index is compared with intra high-low price range volatility in providing volatility forecasts for S&P CNX Nifty 50 index.

Design/Methodology/Approach: *The generalized autoregressive conditional heteroskedasticity model (GJR-GARCH) is used for the Indian markets as this model captures the asymmetric effect of good news and bad news on conditional volatility. The GJR-GARCH model is augmented with implied volatility and high-low price range volatility.This model is used to compare the forecasting efficiency of implied volatility index with the realised volatility represented by high-low range price volatility, to find out which is a better measure of forecasting the future stock market volatility. For measuring the forecasting performance of IVIX on various forecasting horizons (1-, 5, 10- and 20-days), the test for in-sample and out-of-sample data is done.*

Findings: *The results of in-sample regression show that both implied and high-low volatility contains significant information about the conditional volatility. On the other hand, the overall ranking given to the different models on the basis of out-of-sample forecasting evaluations show that the GJR-GARCH model with IVIX consistently performs better than other models, over various forecast horizons. This shows that IVIX is able to provide incremental information about future volatility forecasts and is a better measure of predicting future volatility than the high-low range volatility.*

Research Limitations: *The major limitation of the study is the data period. Further, more countries can be included in this research to compare the predictive abilities of volatility indices of international markets.*

Practical Implications: *The major implication of this study is for the investors who can use implied volatility indices for forecasting the future volatility, thus can be used as a market timing tool.*

Originality/Value: *In this study a novel approach is developed for examining the predictive ability of Indian Implied volatility index. To the best of authors knowledge no research of this kind has been conducted using Indian stock markets has been carried out.*

Key Words: *Indian VIX, S&P CNX Nifty, GJR-GARCH Model, Indian Stock Markets.*

* *Professor, Haryana School of Business, Guru Jambheshwar University of Science & Technology, Haryana, India.*
** *Professor, Haryana School of Business, Guru Jambheshwar University of Science & Technology, Haryana, India.*
*** *Associate Professor, Rukmini Devi Institute of Advanced Studies, New Delhi, India.*

Introduction

Modelling and predicting financial market volatility has played an important role for market participants as it enables them to anticipate the risks they will face and to implement appropriate hedging policies. A great amount of research work has been carried out to predict and forecast financial market volatility. Different classes of models have been developed for estimating volatility, which can be broadly classified into GARCH-type models (Bollerslev *et al.*, 1992), stochastic volatility models (Taylor, 1986) and realized volatility models (Andersen *et al.*, 2001). All these models use historical stock prices to predict future volatility.

Another strand of research has focused on the informational role of options in predicting volatility. Option markets are often considered as markets for trading volatility. It is widely believed that the implied volatility, derived from an option's price, is the market's forecast of future volatility over the remaining life of such option. Under the assumption of rational expectations, a market uses all the available information to form its expectations on future volatility, and hence option price reveals market's true volatility estimate. Furthermore, if a market is efficient, the estimated implied volatility is considered to be the best possible forecast of the currently available information. It means information generated by all other explanatory variables in the market information set is necessary to explain future realized volatility and should be subsumed in the implied volatility.

A number of studies in the past tried to examine the hypothesis that implied volatility is a superior forecast of subsequent realized volatility. Mixed results were reported by these studies regarding whether the implied volatility is superior to the forecasts based on historical prices, such as ARCH/GARCH volatility, Risk metrics volatility, high-low range volatility etc. Latane & Rendleman (1976) and Chiras & Manaster (1978) did a cross sectional analysis and concluded that implied volatility is a superior forecast of future volatility than ex post standard deviations calculated from historical returns data. Jorion (1995) concluded that an implied volatility form currency option outperforms volatility forecasts from historical price data.

However, several other studies have casted doubts on the above mentioned form of efficiency hypothesis and have found implied volatility to be a weak predictor of future realized volatility. Day and Lewis (1992) found that weekly implied volatility contains information, but it is not a superior forecast of subsequent realized volatility. Lamoureux & Lastrapes (1993) and Canina & Figlewski (1993) reported that implied volatility has little predictive power relative to historical volatility. Christenson and Prabhala (1998) demonstrated that these weaknesses are due to methodological issues, such as overlapping and mismatched sample periods. They found that implied volatility from one-month at-the-money OEX call options is an unbiased and efficient forecast of ex-post realized index volatility. The validity of these concerns was supported by Fleming (1998) and Fleming *et al.,* (1995), who found that implied volatilities from S&P 100 index options yield efficient forecasts of month-ahead S&P index volatility. Further, the studies of Fleming *et al.,* (1995), Christenson and Prabhala (1998) and Fleming (1998) also concluded that implied volatility forecasts are upwardly biased, but dominate volatility in terms of ex ante forecasting power. Furthermore, Blair *et al.,* (2001) reported that implied volatilities from S&P 100 index options provide a more accurate forecast than the realised volatilities obtained from either low-or-high frequency index returns.

Recently, Corrodo & Troung (2007) examined the in-sample and out-of-sample volatility forecasts and revealed that neither implied volatility nor intraday high-low range volatility consistently outperforms the other. Hung *et al.,* (2009), using the implied volatility index of Taiwan for small in-sample data, found the volatility index to be more efficient than the volatility forecasts obtained from other models.

The present study seeks to compare the forecast quality of the India VIX with the realised volatility obtained from historical prices in predicting future stock market volatility. The empirical methodology of Corrado & Troung (2007) has been followed to examine the information content of implied volatility indices in forecasting future volatility. They extended the GJR-GARCH models by adding implied volatility index and/or Parkinson (1980) volatility as exogenous variables. In this study the generalized autoregressive conditional heteroskedasticity model developed by Glosten, Jagannath, & Runkle (1993) (GJR-GARCH) is used for the Indian markets as this model captures the asymmetric effect of good news and bad news on conditional volatility. The GJR-GARCH model is augmented with implied volatility and high-low price range volatility. The GJR-GARCH model is used to compare the forecasting efficiency of implied volatility index with the realised volatility represented by high-low range price volatility, to find out which is a better measure of forecasting the future stock market volatility. For measuring the forecasting performance of IVIX on various forecasting horizons (1-, 5-, 10- and 20-days), the test for in-sample and out-of-sample is used in line with the methodology followed by Blair, Poon & Taylor (2001).

Thus, the present study is focussed to examine the forecasting efficiency of implied volatility index in predicting future stock market volatility. Further an attempt is made to compare the forecasting efficacy of implied volatility index with intra high-low price range volatility in providing volatility forecasts for S&P CNX Nifty 50 index.

For the purpose of research three main types of data: daily index returns, intraday high and low price of stock index and daily implied volatility have been examined. The data spanning from March 2, 2009 to June 30, 2012 has been taken for analysis. The first 550 daily observations for the in-sample period are from March 2, 2009 to May 18, 2011, followed by out-of-sample period from May 19, 2011 to June 29, 2012 which includes280 observations.

Model Specification

The following approach for model specification while comparing implied volatility and realized volatility in forecasting stock market volatility:

Volatility Measures: This study is based on daily volatility data for the S&P CNX Nifty 50 stock market index. The three measures of volatility employed are:

(i) Realized volatility based on the squared daily returns computed from the natural logarithms of closing levels of the S&P CNX Nifty 50.

(ii) Intraday high-low range volatility based on squared range of natural logarithms of intraday high-low levels for the S&P CNX Nifty 50.

(iii) Implied volatility measure India VIX (henceforth, IVIX), based on the option prices of S&P CNX Nifty 50.

Daily Squared Returns: Daily squared returns are calculated as the square of the natural logarithms of the ratio of consecutive daily closing index levels:

$$r_t^2 = ln^2(P_t/P_{t-1}), \ldots \ldots (1)$$

Where, r_t^2 denotes the closing index return for day t based on index levels and day*t-1,* that is, P_t and P_{t-1} respectively.

Daily High-Low Price Range: Parkinson (1980) suggested intraday high-low price range as a measure of return-volatility in financial markets. Equation (2) specifies intraday high-low range volatility, in which hi_t and lo_t denote the highest and lowest index levels observed during trading on day t:

$$RNG_t^2 = \frac{ln^2(hi_t/lo_t)}{4 \ln 2} \ldots \ldots (2)$$

Implied Volatility Index (India VIX): The implied volatility index of India which measures the implied volatility of S&P CNX Nifty returns based on the call and put options of Nifty 50. To be consistent with other daily volatility measures, the implied volatility index of India is squared and divided by 252, the assumed number of trading days in a calendar year.

Structure of the model

In the existing literature, two types of models are applied to measure the forecast quality of various volatility measures which include in-sample model and out-of-sample forecasting evaluations technique. The study employs the same approach for the Indian markets, which is described as follows:

In-sample Models: The methodology adopted by Corrodo & Truong (2007) and Hung *et al.* (2009) for comparing the forecasting efficiency of the implied volatility and high-low range realized volatility for the US and Taiwan stock market respectively is used for the Indian markets. In these studies the standard GARCH model is expanded by exogenous variables: implied volatility index and /or Parkinson (1980) volatility. The information content embedded in IVIX and /or Parkinson volatility is examined by the sign and significance of their GARCH model coefficients. The generalized autoregressive conditional heteroskedasticity model developed by Glosten *et al.* (1993) (GJR-GARCH) is used to capture the asymmetric effects of good news and bad news on conditional volatility.

This model is augmented with implied volatility and high-low range volatility.

Augmented GJR-GARCH Model

Equation (3) specifies the augmented GJR-GARCH model, in which the dummy variable $s_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and 0 otherwise:

$$r_t = \mu + \varepsilon_t$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma IVOL_{t-1}^2 + \delta RNG_{t-1}^2 \qquad (3)$$

where, $r_t =$ return on day *t*, $h_t =$ conditional volatility on day *t*, $IVOL_t =$ implied volatility at the end of options trading on day *t*, and RNG_t intraday high-low range volatility on day *t*.

In the above model, s_t is an indicator function to account for differential effect of the good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) on conditional variance. The effect of the good news is measured by the coefficient α_1, and the effect of bad news is measured by the sum of coefficients $\alpha_1 + \beta_1$. As a priori, it is expected that β_2. and the sum of $\alpha_1 + \beta_2$.is positive. The marginal contributions of implied volatility and high-low range volatility to predict conditional volatility h_t are measured by the coefficients and , respectively.

To assess and compare the incremental information provided by the implied volatilities and high-low price range, the following four models are examined:

Model A: GJR-GARCH (1, 1)

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (4)$$

This model applies the restriction = = 0 to equation (3) to yield a model with no exogenous regressors.

Model B: Parkinson's (1980) High-Low Rrange Volatility is Excluded

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma IVOL_{t-1}^2 \qquad (5)$$

The single restriction applied to equation (3) is $\delta = 0$ to exclude the intraday high-low range volatility and thereby combining the GJR-GARCH model with lagged implied volatility.

Model C: Implied Variance Excluded

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \delta RNG_{t-1}^2 \quad \text{.... ....(6)}$$

The single restriction applied to equation (3) is $\gamma = 0$ to exclude the implied volatility and combine the GJR-GARCH model with lagged high-low price range volatility.

Model D: Unrestricted Model

This model represents a complete implementation of equation (3) i.e.:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 s_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma IVOL_{t-1}^2 + \delta RNG_{t-1}^2 \quad \text{.... ....(7)}$$

Time series of forecasts are obtained by estimating rolling GJR-GARCH models. Each model (Model A, B, C, and D) is estimated initially over first 550 trading days of the in-sample period, from March 2, 2009 to May 18, 2011, and volatility forecasts are made for the next day, say day T+1, using the in-sample parameter estimates. The model and data are rolled forward one day, deleting the observations at T-549 and adding on the observation(s) at time T+1, re-estimated and a forecast is made for time T+2. This rolling method is repeated until the end of the out-of-sample forecast period. The one-step-ahead forecasts provide predictions for May 19, 2011 to June 30, 2012 and define a time series of length 280. On each day, the forecasts are also made for 5, 10, and 20 day volatility.

The daily forecasts exceeding one day are obtained by recursively filling in the equation:

$$h_{t+n} = \alpha_0 + (\alpha_1 + 0.5\alpha_2 + \beta) h_{t+n-1}$$

To measure the forecasting accuracy, the following forecast evaluation criteria are used. These criteria include MSE (mean squared error), MAE (mean absolute error), HMSE (heteroskedasticity-adjusted mean squared error), and HMAE (heteroskedasticity-adjusted mean absolute error).Hansen & Lunde (2006) and Patton (2006), among others, found that different loss functions were sensitive to the proxy of the unobserved latent volatility. Meanwhile, different loss functions gave different weights to "surprising" observations. For example, unlike the MAE, the MSE gave greater weight to outlier observations. Furthermore, both MSE and MAE placed more weight on the errors associated with the greater realized volatilities, but the HMAE and HMSE put less weight on such errors. Therefore, all of these four loss functions are used to obtain consistent conclusions. With various loss functions, the best predicting measure will be expected to stand out in most cases.

At time $y_{t,N}$ denotes realized volatility measured as squared daily returns over an N-day forecasts period beginning on day t, and $\widehat{y_{t,N}}$ the corresponding volatility forecasts for the same period:

$$MSE: f\left(\widehat{y_{t,N}}, y_{t,N}\right) = \frac{1}{n}\sum_{t=1}^{n} (\widehat{y_{t,N}} - y_{t,N})^2$$

$$MAE: f\left(\widehat{y_{t,N}}, y_{t,N}\right) = \frac{1}{n}\sum_{t=1}^{n} \left|(\widehat{y_{t,N}} - y_{t,N}\right|$$

$$HMSE: f\left(\widehat{y_{t,N}}, y_{t,N}\right) = \frac{1}{n}\sum_{t=1}^{n} (\frac{\widehat{y_{t,N}}}{y_{t,N}} - 1)^2$$

$$HMAE: f\left(\widehat{y_{t,N}}, y_{t,N}\right) = \frac{1}{n}\sum_{t=1}^{n} \left|(\frac{\widehat{y_{t,N}}}{y_{t,N}} - 1\right|$$

Empirical Analysis

Descriptive Statistics

The statistical summary of the variables is reported in Table No. 1 for daily returns and three volatility measures: squared daily returns, squared implied volatilities and squared high-low price ranges. The descriptive statistic shows that daily squared returns are the most volatile among these three volatility series. Their standard deviation is 4.92 times as the IVIX, and 2.26 times as the realized volatility. This statistic suggests the presence of too much noise in the data. It is also seen that the high-low price range volatility is almost twice as volatile as the implied volatility index (IVIX) as judged by their respective standard deviation measures. The result is also consistent with the notion that implied volatility represents average volatility over the remaining life of options. Therefore, it should exhibit less volatility than realized volatility.

According to Table No. 1, the distributions of five volatility series are positively skewed and leptokurtic. The Jarque-Bera test for normality rejects the null hypothesis of normal distributions for the series at 5% level of significance. The results of unit root test with two different approaches i.e. ADF and PP tests with intercept, with intercept and trend and none of these two, indicate that except for IVIX, rest of the three series i.e. the Parkinson volatility, squared daily returns and daily returns are stationary at 1% level of significance. The IVIX has the strongest positive serial correlation. It shows that IVIX has more long memory feature than the range volatility, as suggested by the magnitude of serial correlation. The return series does not exhibit significant serial correlations, which may be due to measurement errors, such as bid-ask bounce.

Table No. 1: Descriptive Statistics for Daily Returns and Three Measures of Volatility

	Daily returns	Squared daily returns	Implied volatility (IVIX)	Parkinson (RNG)
Mean	0.082	2.132	2.952	1.579
Median	0.074	0.639	2.314	0.842
Maximum	16.334	266.810	12.476	112.970
Minimum	-6.022	0.000	0.919	0.033
Std. Dev.	1.459	9.730	1.974	4.288
Skegness	1.665	24.461	2.135	21.574
Kurtosis	21.545	662.482	7.902	551.934
Jarque-Bera	12262.770	15105404.000	1461.380	10485320.00
Probability	0.000	0.000	0.000	0.000
Observations	829	829	830	830
Autocorrelations				
Lag (1)	0.035 (0.315)	0.01 (0.772)	0.977 (0.00)	0.212 (0.00)
Lag (2)	0.001 (0.603)	0.007 (0.942)	0.957 (0.00)	0.078 (0.00)
Lag (3)	-0.03 (0.62)	0.012 (0.969)	0.938 (0.00)	0.076 (0.00)
First Difference	-	-0.498 (0.000)	-0.07 (0.042)	-0.415(0.000)
ADF statistic				
With intercept	-7.960(0.000)	-28.451(0.000)	-3.164(0.023)	-8.912(0.000)
With intercept and Trend	-11.035(0.000)	-28.770(0.000)	-3.452(0.045)	-23.883(0.000)
None	-7.852(0.000)	-6.125(0.000)	-2.238(0.024)	-2.824(0.005)
Phillips-Perron statistics				
With intercept	-27.746(0.000)	-28.553(0.000)	-3.021(0.033)	-25.030(0.000)
With intercept and Trend	-27.922(0.000)	-28.778(0.000)	-3.360(0.058)	-24.750(0.000)
None	-27.665(0.000)	-28.776(0.000)	-2.120(0.033)	-26.309(0.000)

Note: p values are reported in the parenthesis.

The results of autocorrelation test on first difference series of volatility measures *i.e.* squared returns and range volatility are found to be negative and statistically significant at 5% level. It is expected as these series are stationary at level. Thus, both of these series may exhibit a mean reversion phenomenon.

GJR-GARCH model results

In this section the information content of IVIX is evaluated by examining the statistical results of various GARCH specifications.

Table No. 2 reports the GJR-GARCH parameter estimates for the S&P CNX Nifty stock index using the in-sample data which comprises of first 550 observations in the sample. Column 2 through 7 states the parameter estimates, with robust t-statistics in parenthesis below each coefficient estimate. Column 8 represents the log-likelihood values. The Durbin-Waston statistics for the models given in column 9 indicate the absence of autocorrelation in the regression errors.

The log-likelihood statistics in the Column 8 show that Model D has the largest value followed by Model B, Model C and Model A. This shows that the augmented GJR-GARCH model D performs significantly better (as log-likelihood increases by 29.054) than the standard GJR-GARCH model A.

In Table No. 2, the GJR-GARCH coefficients á$_1$ measuring the effect of good news are significant and negative in models B, C and D, but in model A the value of á$_1$ is significant and positive. This shows that when the basic GJR-GARCH model is augmented with implied volatility and high-low range volatility the good news generated in the market has significant impact on conditional volatility. On the other hand, the coefficient á$_1$is not significant in model A, indicating that effect of good news on conditional volatility is not very strong. The coefficient á$_2$ measuring the impact of bad news is significant and positive for Model A, B, and D; and the sum ofcoefficientá$_1$+ á$_2$ is positive for Model A and B but is slightly negative for Model D. This gives evidence in favour of asymmetric effect of past daily returns on conditional volatility in which bad news (å$_{t-1}$< 0) has a stronger effect on conditional volatility and good news (å$_{t-1}$> 0) has comparatively weak effect.

In addition, the in-sample results for Model B and C yields a significant coefficient ã and ä for implied volatility and high-low range volatility respectively, suggesting that both implied volatility and high-low range volatility provide significant information content regarding the conditional volatility.

Table No. 2: Summary of GJR-GARCH in-sample regression for daily S&P CNX Nifty 50 index volatility

	α_0	α_1	α_2	B	γ	δ	Log-L	DW
Model A	0.017 (1.484)	0.061* (3.158)	0.086* (2.391)	0.902* (41.983)			-946.503	1.931
Model B	-0.050 (-0.239)	-0.023* (-2.709)	0.210* (2.660)	0.494** (2.528)	0.293*** (1.751)		-920.655	1.931
Model C	0.004 (0.078)	-0.151* (-4.202)	0.080 (1.466)	0.860* (14.747)		0.325* (4.354)	-928.224	1.931
Model D	-0.119 (-0.489)	-0.148* (-3.144)	0.141*** (1.657)	0.489* (3.360)	0.270 (1.300)	0.299** (2.315)	-917.449	1.931

*Note: This table reports the results for various specifications in Equation (4), (5), (6) and (7) to describe conditional volatility. Parameters are estimated by quasi-maximum likelihood, and t-statistics are robust following Bollerslev and Wooldridge (1992) and presented in parentheses. Significance of coefficients is indicated by *, **, *** for the 1%, 5%, and 10% levels, respectively. In addition, the log likelihood of the model and DW statistic are reported in Column 8 and 9.*

Out-of-sample forecast comparison

The information content and forecasting efficacy of the daily implied volatility and high-low price range volatility is also compared by generating out-of-sample forecasts. The results of out-of-sample tests will be based on the various criterions of forecasting evaluations.

Table No. 3 summarizes out-of-sample forecast accuracy for 1-, 5-, 10- and 20-day forecasts across various GJR-GARCH model by reporting RMSE, MAE, HMSE and HMAE of volatility forecasts of the S&P CNX Nifty index.

Since each loss function treats forecasts errors in different ways, it seems more relevant to consider the overall performance of both the measures. A rank is given to each model on the basis of these loss functions, where one means the best and four means the worst. Table 4 presents the ranking of the various models on the basis of the data reported in Table No. 3. The four models are ranked according to their performance under each loss criterion. In Table No. 4 the row of "total" denotes the sum of rankings order for four models over different forecast horizons. The least number associated with model indicates the best model in forecasting market volatility.

Table No. 3: Out-of-sample forecasts evaluation statistics for the S&P CNX Nifty of the four loss functions

		1-Day Forecast		
	RMSE	MAE	HMSE	HMAE
Model A	5.119	1.533	3.174	1.112
Model B	4.968	1.493	2.715	1.072
Model C	5.111	1.498	3.522	1.205
Model D	5.018	1.485	2.953	1.985
		5-Day Forecast		
	RMSE	MAE	HMSE	HMAE
Model A	5.190	1.542	2.792	1.093
Model B	5.059	1.501	2.383	1.058
Model C	5.456	1.559	3.654	1.226
Model D	5.276	1.532	2.866	1.137
		10-Day Forecast		
	RMSE	MAE	HMSE	HMAE
Model A	5.317	1.547	2.885	1.081
Model B	5.190	1.508	2.702	1.075
Model C	5.616	1.548	4.331	1.244
Model D	5.389	1.519	3.991	1.170
		20-Day Forecast		
	RMSE	MAE	HMSE	HMAE
Model A	5.570	1.599	2.604	1.096
Model B	5.562	1.568	3.426	1.161
Model C	6.124	1.613	6.256	1.445
Model D	5.805	1.605	4.882	1.311

Note: Reported are 1-, 10-, and 20-day volatility forecast evaluations based root mean square errors (RMSE), mean absolute errors (MAE), heteroskedasticity-adjusted mean squared error (HMSE), and heteroskedasticity-adjusted mean absolute error (HMAE).

Table No. 4:Ranking of Models A, B, C and D on basis of values of loss function

1-Day Forecast				
	Model A	Model B	Model C	Model D
RMSE	4	1	3	2
MAE	4	2	3	1
HMSE	3	1	4	2
HMAE	2	1	3	4
Total	13	**5**	13	9
5-Day Forecast				
	Model A	Model B	Model C	Model D
RMSE	2	1	4	3
MAE	3	1	4	2
HMSE	2	1	4	3
HMAE	2	1	4	3
Total	9	**4**	16	11
10-Day Forecast				
	Model A	Model B	Model C	Model D
RMSE	2	1	4	3
MAE	3	1	4	2
HMSE	2	1	4	3
HMAE	2	1	4	3
Total	9	**4**	16	11
20-Day Forecast				
	Model A	Model B	Model C	Model D
RMSE	2	1	4	3
MAE	2	1	4	3
HMSE	1	2	4	3
HMAE	1	2	4	3
Total	**6**	**6**	16	12

Note: This table list the overall performance of each forecast measure. The rankings are based on the data in Table3. The numbers with the least amount in each total row indicate the best performance.

The most interesting aspect of the results reported in Table No. 4 is that for different forecasting horizons, Model B gets rank 1 for maximum number of times on the basis of various loss functions, as model B attains the minimum value for RMSE, MAE, HMSE and HMAE. Therefore, the model B, in which implied volatility is included in the GJR-GARCH model, ranks the highest among the four approached for 1-, 5-, 10-, and 20-days forecast horizon. On the other hand, Model C in which Parkinson range volatility is included gets the worst ranking in maximum number of cases. This shows that Model C is the worst performer. Thus, these results imply that the implied volatility provide significant information content about the future volatility as compared to other measures of realized volatility. When implied volatility index is added to the basis GJR-GARCH model, the value of the various loss function decreases across different forecasting horizons, implying that the incremental forecast information generated by IVIX plays a dominant role in predicting stock market volatility over both standard GARCH model A and model C in which high-low range volatility is added. These results are contrarian to the discussion given by Corrado & Truong (2007).

The empirical results for out-sample forecast evaluations favour that information content of implied volatility dominates that of historical volatility in predicting future market expectations. This suggests that India VIX is a superior forecast of future stock market volatility as compared to the realized volatility generated by high-low price range volatility. IVIX helps in gauging future expectations about volatility. Thus, IVIX can be considered as one of the leading measures of market participants about the future uncertainty.

Conclusion

In this study the forecasting efficiency of implied volatility index is compared with daily high-low range volatility computed using S&P CNX Nifty index. The general regression formula takes the form of GJR-GARCH model which is augmented by adding implied volatility index and high-low range volatility. The results of in-sample regression show that both implied and high-low volatility contains significant information about the conditional volatility.

On the other hand, the overall ranking given to the different models on the basis of out-of-sample forecasting evaluations show that the augmented model B stands first across different forecasting horizons. The results depict that for 550-day in sample data the implied volatility index outperforms high-low range volatility in 1-, 5-, 10-, and 20- day volatility forecasts. The general GJR-GARCH model with IVIX consistently performs better than other models, over various forecast horizons. This shows that IVIX is able to provide incremental information about future volatility forecasts and is a better measure of predicting future volatility than the high-low range volatility.

References

Andersen, T.G., Bollerslev, T., Diebold, F.X., & Ebens, H. (2001). The distribution of stock return volatility. *The Journal of Financial Economics*, *61*(1), 43-76.

Blair, B.J., Poon, S.H., & Taylor, S.J. (2001). Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high frequency index returns. *Journal of Econometrics, 105*(1), 5-26.

Bollerslev, T., & Wooldridge, J.M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time-varying co-variances. *Econometric Reviews, 11*(2), 143-172.

Bollerslev, T., Chou, R.Y., & Kroner, K.F. (1992). ARCH modeling in finance: A review of the theory and empirical evidence. *The Journal of Econometrics, 52*(1-2), 5-59.

Canina, L., & Figlewski, S. (1993). The informational content of implied volatility. *Review of Financial Studies*, *6*(3), 659-681.

Chiras, D.P., & Manaster, S. (1978). The information content of option prices and a test for market efficiency. *Journal of Financial Economics*, *6*(2-3), 213-234.

Christensen, B.J., & Prabhala, N.R. (1998). The relation between implied and realized volatility. *Journal of Financial Economics*, *50*(2), 125-150.

Corrado, C., & Truong, C. (2007). Forecasting stock index volatility: Comparing implied volatility and the intraday high low price range. *The Journal of Financial Research*, *30*(*2*), 201-215.

Day, T.E., & Lewis, C.M. (1992). Stock market volatility and the informational content of stock index options. *Journal of Econometrics*, *52*(1-2), 267-287.

Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices. *Journal of Empirical Finance*, *5*(4), 317-345.

Fleming, J., Ostdiek, B., & Whaley, R E. (1995). Predicting stock market volatility: A new measure. *Journal of Futures Markets*, *15*(3), 265-302.

Glosten, L.R., Jagannathan, R., & Runkle, D.E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48*(5), 1779-1801.

Hansen, P., & Lunde, A. (2006). Realized variance and market microstructure noise. *Journal of Business & Economic Statistics*, *24*(2), 127-161.

Hung, C.H., Tzang, S.W., & Hsyu, D.S.D. (2009). Forecasting efficiency of implied volatility and the intraday high-low price range in Taiwan stock market. *International Research Journal of Finance and Economics*, *27*, 192-202.

Jorion, P. (1995). Predicting volatility in the foreign exchange market. *Journal of Finance*, *50*(2), 507-528.

Lamoureux, C.G., & Lastrapes, W.D. (1993). Forecasting stock return variance: Towards an understanding of stochastic implied volatilities. *Review of Financial Studies*, *6*(2), 293-326.

Latane, H.A., & Rendleman, R.J. (1976). Standard deviations of stock price ratios implied in option prices. *Journal of Finance, 31*(2), 369-381.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, *53*(1), 61-65.

Patton, A.J. (2006). Modelling Asymmetric Exchange Rate Dependence. *International Economic Review, 47*(2), 527-556.

Taylor, S. (1986). *Modelling financial time series.* (1st ed.). New York: Wiley.