



INDIA VIX AND FORECASTING ABILITY OF SYMMETRIC AND ASYMMETRIC GARCH MODELS



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ABSTRACT

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Volatility forecasting plays an important role in decisions concerning risk assessment, asset valuation and monetary policy formulation. Forecasting implied volatility is a key parameter in pricing of options. Thus, through this paper we attempt to model and test the predictive ability of symmetric GARCH(1,1) and asymmetric TGARCH(1,1) and EGARCH(1,1) models in forecasting the India Volatility Index (VIX). The estimated results confirm the dependency of volatility on its past behavior. It discloses that conditional variance takes longer to disintegrate and the innovations to it are highly persistent in nature. The predictive ability of these models to forecast the direction of the VIX series is evaluated by employing a standard (symmetric) loss function, such as the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and Theil's inequality coefficient. The results show that the GARCH(1,1) provides superior forecasts compared to other models.

Contribution/Originality: The study contributes to the existing body of literature on forecasting equity market volatility. It offers market participants a model that can assist them in reliably predicting the future direction of NSE's volatility index (i.e., the India VIX).

1. INTRODUCTION

Uncertainty faced by investors is the starting point for every financial model and investigating the effects of uncertainty on investor sentiments and on share price movements is the aim of every financial model. Uncertainty is the foundation for the very existence of financial economics as a discipline. The study of risk and return trade-offs 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 indicators of market inefficiency and a potential threat to the very integrity of market mechanisms. 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 out on important foreign investment. This, in turn, hampers economic progress.

Hedge funds, banks' proprietary and other professional option traders keenly observe the volatility implied by an option's market price as it supplements their research when making vital buying and selling decisions. An overpriced option is indicated by higher levels of implied volatility (IV) and vice versa. Furthermore, movements in implied volatility largely influence the earnings from volatile positions in complex options, such as straddles.

To gauge the market anxiety and to serve as a proxy for overall market uncertainty, the Chicago Board Options Exchange (CBOE) introduced the implied volatility-based Volatility Index (VIX) in 1993. It serves as a reference point for short-term volatility and 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. Researchers globally have been interested in studying the accuracy and quality of estimates provided by the VIX. [Giot \(2002\)](#) attempted to ascertain if very high levels of volatility or the CBOE Nasdaq Volatility Index (VXN) imply oversold markets and could thus be viewed as a short-term or medium-term opportunity to buy stocks. He concluded that investors interested in entering oversold markets should wait until very high levels on these indices are witnessed but they should restrict their strategy strictly to the short term. [Becker, Clements, & White \(2007\)](#) compared VIX forecasts with the forecasts from the GARCH model, stochastic volatility model, realised volatility class model and models following the MIDAS (mixed data sampling) approach. They concluded that the VIX does not provide any additional information necessary for forecasting volatility. [Hung, Ni, & Chang \(2009\)](#) analyzed the S&P 500 VIX information content and range-based volatility by comparing their benefits to the forecasting performance of the GJR-GARCH volatility model. The author adopted a symmetric loss function to assess the efficiency and bias problem.

Of late, volatility forecasting has occupied the attention of academicians and practitioners as it plays a vital role in many areas of security analysis, portfolio management, economic policy formulation and risk evaluation. In the past, historical volatility methods were employed to estimate future volatility, but in recent times, more refined and advanced time series models are being advocated by experts for accurate evaluation of options. [Balaban, Bayar, & Faff \(2003\)](#) analyzed volatility prediction approaches across fourteen different Asian, Scandinavian and European countries along with the UK and US. The results of their research revealed that, based on symmetric error statistics, the volatility forecasts provided by exponential smoothing methods (ESMs) are the most superior and those by ARCH type models are the worst. [Majumdar & Banerjee \(2004\)](#) compared the forecasting ability of econometric models, namely GARCH, EGARCH, GJR-GARCH, APARCH & IGARCH in predicting volatility. They revealed that the asymmetric EGARCH model, which Nelson proposed in 1991, performed the best among the different models that were tested. [Degiannakis \(2008\)](#) employed a fractionally integrated ARMA model with the VIX as the dependent variable, and volatility measures based on interday and intraday forecasts as explanatory variables to investigate whether they provide incremental information in the forecasting of volatility. The results revealed that all the forecasting information was provided by the VIX. They realized volatility as well as conditional volatility does not provide significant predictability information and, therefore, do not provide any added value to the predictions. [Fernandes, Medeiros, & Scharth \(2014\)](#) examined the statistical properties of the CBOE daily market volatility index. The findings revealed that the VIX has a negative relationship with the S&P 500 index returns and it displays a positive relationship with the volume of the S&P 500 index. Credit spread has a negative long-term implication on the VIX. [Kownatzki \(2016\)](#) examines the precision of VIX and implied volatility in general as a proxy for risk. In normal market conditions the VIX overestimates volatility and underestimates it in times of financial crisis. Therefore, he concluded that the VIX cannot be considered a reliable tool for risk management. [Miljkovic & SenGupta \(2018\)](#) proposed a novel K-component type of regression model to analyze the S&P 500 market fluctuations through the VIX. They employed the scholastic Barndorff-Nielsen and Shephard models and their model gave a new dimension to building an indicator of non-Gaussian jumps using a mixture of Gaussian regression analyses for financial volatility data. [Allen & Hooper \(2018\)](#) captured the daily realized volatility of the S&P 500 to understand the casual relationship between the US implied volatility index and the S&P 500. Through the application of the artificial neural network (ANN) model they attempted to forecast the future daily values of the VIX. The results of their study suggest that the ANN method is successful in predicting the future direction of VIX using lagged daily realized volatility and the lagged daily S&P 500 index. They also concluded that causality runs between lagged realized volatility and lagged compounded daily returns. [Siriopoulos](#)

& Fassas (2019) analyzed the information content of 50 different publically traded implied volatility indices. They examined their forecasting power and the return volatility relation and their findings showed that implied volatility has information about future volatility beyond that contained in past volatility. These findings are consistent across assets. They also found a significant contemporaneous relationship between implied volatility and underlying assets. Saha, Malkiel, & Rinaudo (2019) constructed a model with explanatory variables exogenous to the index and examined the model prediction errors. Their results show that daily changes in the VIX can be explained by market factors and are not manipulated. In the Indian context, Kumar (2010) investigated the behavior of the India VIX. His research concluded that the IVIX reflects all the stylized facts of volatility. He also made a proposition for the introduction of exchange traded volatility derivatives in India as it mirrors most of the empirical regularities. Fernandes et al. (2014) investigated the performance of the India VIX as a refined measure of market volatility compared to traditional approaches and explored the use of the India VIX as an appropriate tool for timely trading and risk management in the market. Their results demonstrated that the India VIX provides better estimates of market volatility compared to conditional volatility models, such as GARCH and EGARCH. Analysis of the timing strategy indicates that when the India VIX 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. Kownatzki (2016) attempted to determine the forecasting quality of the India VIX and his work revealed that it accurately predicts short term volatility and its prediction power is higher for upward market movements. He concluded that the VIX estimates are precise for low magnitude future price movements.

Though there have been numerous studies on the information content, efficiency and predictive ability of the India VIX, developing an appropriate model for predicting short-term volatility is an unexplored area in the Indian context. This is the first study that aims to evaluate the forecasting performance of symmetric/asymmetric GARCH models for the India VIX. Thus, through this paper an attempt has been made to model and forecast NSE's implied volatility index (i.e., the India VIX). Over the years, academicians and econometricians have developed numerous models to forecast market volatility and applied them 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 are regarded to provide superior forecasts on volatility and have amassed a huge following in financial literature. The objective of the current study is to examine the forecasting ability of symmetric and asymmetric GARCH models, and the performance of the basic GARCH, EGARCH and TGARCH models is evaluated in forecasting the India VIX.

2. METHODOLOGY

Data: The daily closing levels of the India VIX are considered from March 2, 2009 to August 31, 2016. The India VIX data was extracted from the NSE India website. For the purpose of the study, the data was split into two parts – the in-sample and the out-sample data.

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

Out-sample data: The period from June 1, 2016 to August 31, 2016 is considered as the out-sample period and 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 the India VIX.

2.1. Methods of Volatility Forecasting

The most commonly applied class of time-varying models are the generalized autoregressive conditional heteroskedasticity (GARCH) models. Ever since their introduction by Engle (1982) and subsequent generalization by Bollerslev (1986) these advance models have been modified, refined and stretched in several ways to make them best suited for exploring the volatility process. ARCH class models help in capturing the volatility clustering

phenomenon in financial time series. Their first two moments -the mean and the variance – define these models. The mean equation describes the behavior of the dependent variable over time. The functional forms of different models have been expressed below.

The ARCH (q) model is expressed as:

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

Tim Bollerslev (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:

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_q u_{t-q}^2 + \beta_1 h_{t-1}^2 + \beta_2 h_{t-2}^2 + \dots + \beta_p h_{t-p}^2$$

The GARCH(1,1) model can be extended to GARCH(p,q) where the current conditional variance is modeled as a function of q lags of the squared error term and p lags of the conditional variance. 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 a 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 Zakoian (1994), and the GJR-GARCH model was named after its developers, Glosten, Jagannathan, & Runkle (1993). The model includes an additional term to capture the asymmetries in data sets and is an extension of the GARCH vanilla model. 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 $I_{t-1} = 1, \text{ If } u_{t-1} < 0$

$$= 0, \text{ otherwise}$$

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

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 implies a negative relationship between volatility and returns in the series.

2.2. Forecast Performance Evaluation

An important element of an exhaustive forecasting exercise encompasses comparing the forecast performance of competing models. We evaluated the predictive ability of the competing models using popular evaluation measures used in previous studies – root mean square error (RMSE), mean absolute error (MAE), mean absolute

percentage error (MAPE) and Theil's inequality coefficient. These are termed as symmetric forecast error statistics as they treat over-predictions and under-predictions equally. These are defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=n}^n |\hat{\sigma}_i - \sigma_i|^2}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=n}^n |\hat{\sigma}_i - \sigma_i|$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=n}^n |(\hat{\sigma}_i - \sigma_i) / \sigma_i|$$

$$\text{Theil's inequality coefficient} = \frac{\sum_{i=n}^n (\hat{\sigma}_i - \sigma_i)^2}{\sum_{i=n}^n (\hat{\sigma}_{i-1} - \sigma_i)^2}$$

The evaluation techniques discussed above were employed in this study and the model with the fewest forecast errors was ranked as the best model. The out-sample forecasts given by these three models were compared with the actual India VIX and the one producing the fewest deviations was selected.

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 the India VIX index for the sample period are reported in Table 1. The mean value of the daily India VIX was found to be 21.37, and the maximum and minimum values using the study period seem to be 56.07 and 11.56, respectively. Figure 1 shows the daily India VIX closing price during the sample period and it seems to have an upward and downward trend. The standard deviation was found to be higher (7.33) as it largely deviated from the mean value of 21.37. The India VIX closing price series is positively skewed (1.68) and the Kurtosis value is more than 3 (6.33), i.e., excess kurtosis, thus they are leptokurtic. Likewise, the non-normality of the distribution is confirmed by a highly significant and large Jarque Bera statistic. It was found to be statistically significant at the 1% level, rejecting the null hypothesis that the India VIX closing price series is normally distributed, confirming the non-normal distribution of data series.

Table-1. Descriptive Statistics of Daily Closing Price of the India VIX.

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 parenthesis () indicates p-value. * denotes significance at the 1% level.

Given the time series nature of the data, the initial step in the analysis was to test whether the series is stationary or not. The paper employed the augmented Dickey–Fuller (ADF) unit root test for the daily closing price of the India VIX series and the results are reported in Table 2. The ADF statistics result indicates that the price series is stationary. The ADF test statistics reject the hypothesis of a unit root at the 1% level of significance in the price series, implying that the VIX series is stationary.

Actual VIX

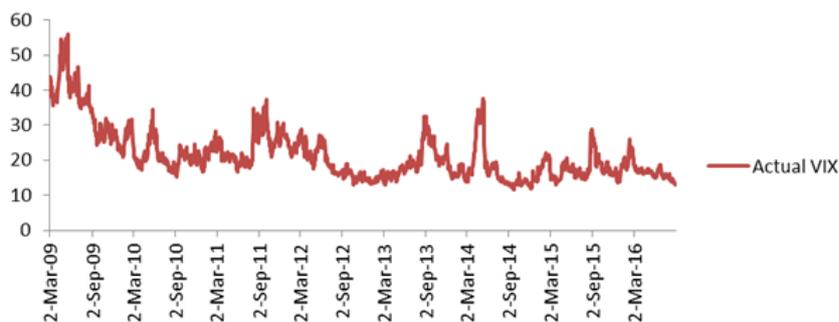


Figure-1. Daily Closing Price of the India VIX for the period from March 2009 to August 2016.

Table-2. Augmented Dickey-Fuller Test Results.

Variable	Intercept	Intercept & Trend
VIX	-4.251616*	-5.095607*

Notes: * indicates significance at the 1% level. Optimal lag length is determined by the Akaike Information Criterion (AIC).

To test whether there is an ARCH effect in the Indian VIX price series, the Ljung Box Q^2 statistical test was used on squared residual series of the mean model and the results are presented in the Table 3. $Q^2[1]$, $Q^2[4]$, $Q^2[12]$ and $Q^2[24]$ represent 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 tested the null hypothesis of no ARCH effect against the alternative hypothesis of the existence of an ARCH effect. From the test of all lags, it was observed that the null hypothesis was rejected at the 1% level of significance, indicating the existence of an ARCH effect in the India VIX during the sample period. Furthermore, to test the null hypothesis of no ARCH effect on the India VIX series, the Engle (1982) ARCH-LM test was conducted. The test results are shown in Table 3. The ARCH-LM test statistics were highly significant at the 1% level, confirming the existence of significant ARCH effects on the India VIX data series during the study period. Hence, the results of both the tests confirmed the presence of ARCH effects in the residuals of time series models in the VIX series and hence the results warrant the estimation of GARCH family models.

Table-3. Ljung & Box (1978) Q^2 statistics and ARCH-LM Test Results for Indian VIX Closing Price.

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

Notes: * indicates significance at the 1% level. $Q^2[1]$, $Q^2[4]$, $Q^2[12]$, and $Q^2[24]$ represent the Ljung Box Q^2 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).

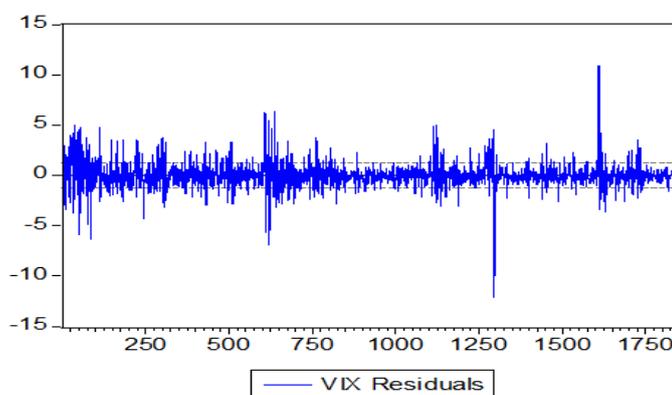


Figure-2. Volatility Clustering of India VIX from March 2009 to August 2016.

Figure 2 exhibits the residual series of the India VIX. 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 effect, in some periods. Statistically, a strong autocorrelation in squared returns is implied by volatility clustering.

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

Table-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_1	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	γ_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): 3.023511 Schwarz Information Criteria (SIC): 3.005897						
Estimates of TGARCH(1,1) Model						
A	B	α_0	β_1	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 values, respectively. * denotes significance at the 1% level. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects in the residuals (Engle, 1982).

The symmetric GARCH(1,1) and asymmetric EGARCH(1,1) and TGARCH(1,1) estimations for the daily closing price of the India VIX are shown in Table 4. The results reveal a strong support for ARCH and GARCH effects in the estimation, which is suggested by the positive and significant ARCH and GARCH terms in conditional variance equations at the 1% level in all estimations. In addition, the results reveal that the equations of conditional variance of the symmetric GARCH(1,1) and asymmetric EGARCH(1,1) and TGARCH(1,1) models were all close to one. This implies that the innovation in conditional variance takes a longer time to die down and is exceedingly persistent in nature. The results are also suggestive of a model that is covariance stationary with long memory and a high degree of persistence in the conditional variance. The α_1 and δ_1 coefficients appear to be statistically significant in the EGARCH(1,1) model, which confirms the dependency of volatility on its past behavior. The asymmetric coefficient γ_1 (0.202547) shows that the VIX exhibits statistically significant asymmetric effects at the 1% level. This indicates that positive shocks (good news) have greater impacts on this VIX than the negative shocks (bad news). This implies that during market upward movement, the impact of volatility is larger compared to market downward movement of the same magnitude, i.e., the volatility caused by positive news is higher than that caused by negative news. This could be attributed to the large impact on volatility caused by the activity of noise traders in the Indian equity market. The TGARCH(1,1) model results also support the finding that the impact of positive news is higher compared to that of negative news as the parameter estimate δ (-0.214376), which captures the asymmetric effect, is less than zero.

The robustness of the estimated mean equations of the GARCH-type models and the presence of the remaining ARCH effects in the standardized residuals was tested with the Lagrange multiplier (ARCH-LM) test. The ARCH-LM(1,1) test results revealed no ARCH effects in the standardized residuals of variance equation of the model, thus indicating that the mean and the variance equations of the GARCH models are appropriately defined.

The Akaike Information Criteria (AIC) and Schwarz Information Criteria (SIC) were employed for the selection of the most fitted GARCH model for predicting the India VIX price series. Overall, the GARCH(1,1) was the most preferred based on the minimum AIC and SIC. Despite the presence of an asymmetric response to news, as suggested by the minimum AIC and SIC, the GARCH(1,1) produced an unbiased estimate leading to consistent and precise inferences pertaining to the modeling and forecasting of the India VIX price series.

Table-5. Forecast performance of estimated models for the out-sample period.

Forecast Error Statistic	GARCH Model	EGARCH Model	TGARCH Model
Root Mean Square Error	2.063653 ¹	3.275960 ³	3.198215 ²
Mean Absolute Error	1.779888 ¹	2.754733 ³	2.699817 ²
Mean Absolute Percentage Error	12.01555 ¹	18.77567 ³	18.39514 ²
Theil's Inequality Coefficient	0.063757 ¹	0.097448 ³	0.095257 ²
Overall Rank			

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

The forecasting ability of the models in predicting the future VIX series was evaluated. The standard (symmetric) loss functions, such as the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE) and Theil's inequality coefficient were employed to evaluate the performance of the competing models. In Table 5, the results of the out-sample forecast performance of the estimated models are shown for the last 64 observations from June 1, 2016 to August 31, 2016. The model displaying the fewest error measurement values is considered to be the best one and the results show that the GARCH(1,1) model is the most fitted and provides superior forecasts of the India VIX price series compared to other models. The TGARCH(1,1) model is considered second best in forecasting the India VIX price series. To summarize, the empirical results revealed that, despite a leverage effect being present in the data series, the performance of the symmetric GARCH model in forecasting the India VIX price series is better than the asymmetric GARCH models.

4. CONCLUSION

Volatility forecasting plays an important role in investment decision, security valuation, risk management and monetary policy formulation. There is extensive literature available on volatility forecasting for implied volatility indices of developed markets, but very limited work has been done in terms of emerging economies. Moreover, Kumar (2010) and Shaikh & Padhi (2015) examined the behavior and forecasting efficiency of the India volatility index, respectively, but this is the first study that attempts to test the predictive ability of the symmetric GARCH(1,1) and asymmetric TGARCH(1,1) and EGARCH(1,1) models in forecasting the India VIX. The estimated results from the models confirmed the dependency of volatility on its past behavior and revealed that innovation to the conditional variance is highly persistent and takes longer to dissipate.

The asymmetric coefficients of the EGARCH(1,1) model show that at that 1% level of significance the VIX series displays statistically significant asymmetric effects. According to the results, positive innovation (good news) has a greater impact on the India VIX than negative innovation (bad news). This implies that the volatility is larger during market upward movement as compared to market downward movement of the same magnitude. This may be attributed to the activity of noise traders in the Indian equity market.

Table-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

The results of the TGARCH(1,1) model confirm that positive shocks have a greater impact than negative shocks, as suggested by the asymmetric coefficient. The models were evaluated in terms of their forecasting ability of future volatility by employing standard (symmetric) loss functions. The results showed that the GARCH(1,1) model gives a superior performance in forecasting the Indian VIX price series compared to the other models.

Finally, Table 6 shows the comparison of actual VIX along with the forecasted values of the Indian VIX, which were predicted through the GARCH(1,1), EGARCH(1,1) and TGARCH models for the last 64 observations from June 1, 2016 to August 31, 2016. The results reveal that forecasted series of VIX from the GARCH(1,1) model has the lesser deviation from the realized VIX.

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