American Journal of Applied Sciences 7 (11): 1487-1494, 2010
ISSN 1546-9239

Suitability of Volatility Models for Forecasting Stock Market Returns: A Study on the Indian National Stock Exchange

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Abstract: Problem statement: Measuring volatility is an important issue for stock market traders. Also, volatility has been used as a proxy for riskiness associated with the asset. This study aims to compare the different volatility models based on how well they model the volatility of the India NSE. **Approach:** The study has made use of five models which are Historical/Rolling Window Moving Average Estimator, (ii) Exponentially Weighted Moving Average (EWMA), (iii) GARCH models, (iv) Extreme Value Indicators (EVI) and (v) Volatility Index (VIX).The data includes the daily closing, high, low and open values of the NSE returns from 2005-2008. The model comparison was done on how well the models explained the ex-post volatility. Wald's constant's test was used to test which method best suited the requirements. **Results:** It was concluded that the AGARCH and VIX models proved to be the best methods. At the same time Extreme Value models fail to perform because of the low frequency data being used. **Conclusions:** As other research suggests these models perform best when they are applied to high frequency data such as the daily or intraday data. EVIs give the best forecasting performance followed by the GARCH and VIX models.

Key words: Volatility models, Volatility Index (VIX), Exponentially Weighted Moving Average (EWMA), historical/rolling window, garch models, Chicago Board Options Exchange (COBE), Extreme Value Indicators (EVI), currency market

INTRODUCTION

All financial markets have numerous participants in the form of investors, fund managers and policy makers. Every investor has a different risk appetite and wants to make returns according to the same. Few do this on their own and many consult fund managers. All their attempts are affected by the decisions of the policy makers. But the underlying aim of all participants is to see that the financial markets move in their favor. All of them use past data to see how the asset prices have varied and how the prices will be the next working day. In this context, volatility and the measure thereof play a very important role to equity and derivatives traders as well. They are interested in the present and future direction and the degree to which the market is moving. Historically, volatility has been defined as the variation in asset prices. Volatility has been used as a proxy for riskiness associated with the asset. And hence volatility estimation is of central importance to risk management, pricing (especially options) and portfolio construction both from investors and the perspective of fund managers.

Volatility has remained the central concept in finance, whether in derivative pricing, asset allocation, or risk management. A number of attempts have been made to find the best measure of volatility through a diversified family of models. The success or failure of these volatility measuring models depends crucially on the ability to generate accurate volatility forecasts. There are a wide array of ARIMA models, which have been used in forecasting the equity value and measuring the volatility in the equity markets. However there is quite a strong body of literature advocating the use of the GARCH family of models to forecast volatility (Batra, 2004; Chong *et al*., 1999; Chuang *et al*., 2007; Floros, 2008; Poon and Granger, 2003; Walsh and Tsou, 1998; Akgiray, 1989, Corhay and Rad, 1994; Magnus and Fosu, 2006; Nazar *et al.*, 2010). Despite the importance of conditional volatility, the existing literature has not yet reached an agreement on whether implied GARCH or stochastic volatility estimators provide better and more accurate forecasts of volatility.

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Furthermore, there are also wide array of other models beyond the GARCH family, which are also claiming their supremacy over others in measuring volatility in the equity markets. One of such models is the Chicago Board Options Exchange (COBE) VIX model. The CBOE introduced a new VIX to the world of volatility measurement. The research paper published by the CBOE describes the methodology for calculating the new Volatility Index (VIX) of the stock markets. It is a robust and an efficient method of forecasting volatility and considers the entire range of option prices (Index Options) available. One of the most important features of VIX, as the study points out, is that, historically, VIX hits its highest levels during times of financial turmoil and investor fear. As markets recover and investor fear subsides, VIX levels tend to drop.

Against this back drop an attempt has been made to (i) examine different volatility models and (ii) compare these volatility models forecasting ability. In the study five models have been estimated and analyzed and their volatility forecasting ability has been compared. These models are (i) Historical/Rolling Window Moving Average Estimator, (ii) Exponentially Weighted Moving Average (EWMA), (iii) GARCH models, (iv) Extreme Value Indicators (EVI) and (v) Volatility Index (VIX).

Before explaining the types of models used in this study it is imperative to discuss some important properties of stock returns, as only a few models cater to these important properties. These properties are: (a) Time varying volatility: the volatility of stock markets varies with time, (b) Volatility clustering: There is high serial correlation between squared returns. It has been found that there are stretches of time when volatility is relatively high and stretches of time when it is relatively low and (c) Leverage effect: Volatility is high on bad days when compared to good days in the stock market. Therefore, this exercise has chosen the methods for estimating volatilities that fulfill the three aforementioned properties.

The study first reviews the literature on the various types of volatility measuring models and their ability to forecast the volatility of the stock return. Next we present the methodology adopted and data set used in the study. It follows the empirical results derived from the various forms of aforesaid volatility models under study and their comparisons for best volatility measurers. Finally, the study concludes and recommends the model that is capable of forecasting the volatility especially in the contest of NIFTY returns in the Indian scenario.

Literature review: We make here an extensive attempt to review the literature on different volatility forecasting models. (Pang *et al*., 2007) Using the weekly closing price of the Shenzhen Integrated Index, the volatility of the Shenzhen Stock Market has been attempted through three different models: Logistic, AR (1) and AR (2). The investigation shows that the AR (1) model exhibits the best predicting result, whereas the AR (2) model exhibits predicting results that is intermediate between the AR (1) model and the Logistic regression model.

A study (Brandt and Kinlay, 2005) considered the properties of a wide range of statistical measures of volatility, from the common standard deviation metric to less widely used range-based measures. This research indicates that the efficiency of the methods depends on properties such as the sample size and frequency, process drift, opening gaps and time-varying volatility. It shows that the extreme value estimators provide the best results when compared to other methods but even these methods are faulty when the frequencies are very high. The performance of these estimators further deteriorates in the presence of other exceptions such as stochastic volatility and opening gaps. None of the estimators achieves anything close to the levels of efficiency expected from theory or those seen in simulation studies. One more finding is that the classical estimator performs significantly worse than any of the other estimators on every criterion.

Bali (2005) introduces a conditional extreme value volatility estimator (EVT) based on high-frequency returns. The relative performance of the extreme value volatility estimator is compared with the discrete time GARCH and implied volatility models. The authors have used intraday data for their research study. They find that the forecasting ability of various discrete time GARCH models turns out to be inferior to VIX and EVT. Of the three they find that the EVT provides the best forecast for high frequency data. Suganuma (2000) looks mainly at VAR which in turn depends on the volatility. He considers that different volatility measures such as rolling window, EWMA, GARCH and stochastic volatility GARCH and EWMA type models that incorporate the dynamic structure of volatility and are capable of forecasting future behavior of risk should perform better than constant, rolling window volatility models. The study finds that the models might not be consistent in performance in different time periods. They use White’s bootstrap method to confirm the above findings. No model consistently outperforms the benchmark. This helps to explain the observation that practitioners seem to prefer simple models such as constant volatility rather more complex models such as GARCH.

Kumar (2006) made an attempt to examine the comparative performance of volatility forecasting models in Indian Markets i.e., Indian stock and forex markets. It was observed from the out of sample forecasts and the number of evaluation measures that rank a particular method as superior that we can infer that EWMA will lead to improvements in volatility forecasts in the stock market and the GARCH (5.1) will achieve the same in the FOREX market.

Ajay (2005) made an attempt to model and forecast volatility in Indian capital markets comparing the performance of various unconditional and conditional volatility models. He used daily data of Nifty series for 3 years (1999-2001). As far as forecasting ability of models and estimators is concerned, the authors find that the conditional volatility models fare extremely poorly in forecasting five-day (weekly) or monthly realized volatility. In contrast, extreme value estimators, except the Parkinson estimator, perform relatively well in forecasting volatility over these horizons.

Banerjee and Sarkar (2006) attempted to model volatility in the daily return of the NSE using data which has been collected over a five-minute interval. This study shows that GARCH models predict the market volatility better than the other models such as historical average, EWMA. Also, among the GARCH models they find that the asymmetric GARCH models provide a better fit than the symmetric GARCH models. They also conclude that the change in volume of trade positively affects market volatility.

One of the research papers on smoothing factors (Taylor, 2004) uses intraday volatility models to compare the different volatility methods. The samples have been compared based on their out-of-sample predictive ability. Out of all the volatility models GARCH (1,1) provides the best forecast. Nevertheless this author points out the fact that it largely depends on the asset as well. In this case GARCH (1,1) provided the best results for the exchange rate volatility, but for other asset classes such as stock market returns, other methods might outperform GARCH(1,1). Also, he emphasizes that the models that include intraday information may provide better forecasts.

Lu *et al*. (2007) compared different models based on the underlying distribution patterns assumed by the methods. In the study they analyze the volatility forecasting performance of the GARCH models based on various distributional assumptions in the context of stock market indices and exchange rate returns. The zero down to the logistic (LOG), the Scaled Student's T (SST) distributions and the Risk metrics model are the most efficient methods for volatility forecasting of stock markets. Risk metrics and normal distributions provide some of the most accurate forecasts for the exchange rate forecasts.

Vilder and Vilder (2007) provide a theoretical basis for the comparison and optimization of volatility proxies, based on intraday data. In this study a volatility proxy is the result of applying a positively homogeneous functional to the intraday return process. This is a limitation that rules out, for instance, volatility predictors. On the other hand, it offers the possibility of developing a simple theory for comparing and optimizing proxies. Equivalently, the correlation with daily volatility is large. For the S and P 500 data a combination of the high-lows over ten-minute intervals and the absolute returns over ten-minute intervals yields a good proxy.

Finally, Mapa (2004) proved that GARCH (1,1) is not the best method for forecasting the exchange rate volatility. He shows a comparative analysis of all the ARCH-type models. The authors have used the exchange rates data to forecast the volatility of the American Currency Market. They find that the TARCH (2, 2) and EGARCH models perform the best because they accommodate the leverage effects. They also emphasize on the distribution used in estimating the parameters of the model.

MATERIALS AND METHODS

Data: The present study is conclusive in nature, where various volatility models have been used in forecasting the volatility by making use of the secondary data. The daily closing values of the NSE index from Jan 1st, 2005-Dec 31st, 2007 have been drawn from the NSE website. The forecasting period has been chosen from Jan 1st, 2008-Oct 31st, 2008. The data from 1st November, 2008-31st December, 2008 has been kept for out of sample forecasting.

Models used: The study has made use of five different models for volatility estimation and the methodologies associated with these aforesaid models have been briefly discussed sequentially hereunder.

Historical/rolling window moving average estimator: The historical or n-period rolling window moving average estimator of the volatility corresponds to the average standard deviation of the returns over the recent window of size n. It is given by the square root of the expression:

$$\sigma_{t+1}^{2} = \frac{1}{n}\sum_{s-t-n+1}^{t}(r-\mu)^{2}$$

Where:

r = Represents the weekly market return

μ = Indicates the average return of the selected period

This method is the easiest of all the methods, though the final value of volatility depends a lot on the size of the window. If the size is very small and if there is a black swan in the small window selected then the effect would be very high. Moreover this estimate measures only the unconditional volatility of time series and does not take into account the dynamic properties of the model. In this method all the returns are given equal importance and no special importance is given to the time of occurrence. However in the present exercise, the weekly variance is calculated using the formula stated above. By making use of the first 156 weekly returns and variances the variance for the 157th week has been calculated by using the formula. For the next week (158th week) the above two steps are repeated using 2nd-157th weekly returns.

Exponentially Weighted Moving Average (EWMA): This method is an improvement over the historical moving average estimator in which the returns are given weights according to the time of occurrence. The most recent observation is given the highest weight and the last observation in the window is given least weight. The weights decrease exponentially. In this way the current events have a higher effect on the volatility being estimated. Suppose there is a large and unwarranted move in the market, the higher weight age given to that variable helps in moving the volatility upward. A smoothing factor λ is chosen and declines exponentially. Here the value of λ determines how much of the move is transferred to the next day's volatility. A low value of λ makes sure that the volatilities respond faster when compared to higher value of λ. It usually lies between 0.94 and 0.97 (daily to monthly respectively).Various research papers have shown that the best results are obtained when λ is equally to 0.94 when calculating weekly volatility. EWMA estimate is calculated as a square root of the following expression:

$$\partial_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)(r-\mu)^2$$

One drawback of the EWMA model is that it can perform only a one period forecast and not h-period ahead forecasts. However in the present exercise, the weights series is calculated with λ = 0.94. The variance (for the 157th week) is calculated using the formula stated above. The variance for the next week is calculated using the 2nd-157th observations. A sensitivity test can be performed using different values of lambda.

GARCH models: GARCH models capture the dynamic nature of volatility and cater to the problem of volatility clustering (periods of large returns are followed by periods of small returns).They also takes into account the leverage effect (volatility is higher in a falling market than in a rising market). GARCH models can take into consideration the fat tails observed in the distribution of stock return series, where large changes occur more often than implied in normal distribution. The three most famous GARCH distributions are (i) A-GARCH, (ii) E-GARCH and (iii) T-GARCH. The general formulation of these GARCH class models is given here under:

$$\sigma_{t+1}^2 = \omega + \sum_{1}^{q}\alpha(r-\mu)^2 + \sum_{s=1}^{p}\beta_s\sigma_{t+1-s}^2.$$

GARCH models give the best volatility estimates but they are not very frequently used because of the complexity involved in calculations. In estimating GARCH models the following strategies have been adopted in the study: (i) fitting a GARCH, EGARCH, TGARCH, AGARCH model with the first 156 data points, (ii) using this model forecast the 157th GARCH variance, (iii) repeating the same for 158th data point with 2nd-157th data points and (iv) generating a separate variance series for all the three GARCH models.

Extreme value indicators: Many studies have shown that the presence of heavy tails in the financial asset returns and for frequencies higher than monthly frequencies there might be deviations from the normal distribution. These studies indicate the presence of extreme values rather than normal distributions. The Extreme Value Theory (EVT) provides a formal framework with which to study the tail behavior of the fat-tailed distributions. This theory has advantages over other distributions such as normal distributions, ARCH, GARCH-like distributions (except E-GARCH) which assume symmetric distributions. Unlike these methods, which basically consider only the closing values, extreme value indicators do calculations based on the high low values of the day. We next describe the following extreme value estimators.

Historical high-low volatility: Parkinson: The Parkinson formula (Parkinson, 1980) for estimating the historical volatility of the underlying high and low prices:

$$\sigma^2 = \left(\frac{z}{n^4 \ln 2}\right)\sum_{i=1}^{n}\ln\left(\frac{H_i}{L_i}\right)^2$$

Historical open-high-low-close volatility-Garman class: Yang and Zhang (2000) derived an extension to the Garman Glass historical volatility estimator that allows for opening jumps. It assumes a Brownian motion with zero drift.

$$\sigma^2 = \frac{z}{n}\sum\left[\ln\left(\frac{O_i}{C_{i-1}}\right)^2 + \frac{1}{2}\ln\left(\frac{H_i}{L_i}\right)^2 - (2\ln 2 - 1)\ln\left(\frac{C_i}{O_i}\right)^2\right]$$

Historical open-high-low-close volatility-Rogers satchel: The Roger and Satchell (1991) historical volatility estimator allows for non-zero drift, but assumed no opening jump:

$$\sigma^2 = \sum\left[\ln\left(\frac{H_i}{Ci}\right)\ln\left(\frac{H_i}{Oi}\right) + \ln\left(\frac{H_i}{O_i}\right)\ln\left(\frac{H_i}{Oi}\right)\right]$$

Historical open-high-low-close volatility-yang Zhang: Yang and Zhang (2000) were the first to derive a historical volatility estimator that has a minimum estimation error, is independent of the drift and independent of the opening gaps. This estimator is maximally 14 times more efficient than the close-to-close estimator:

$$\sigma^2 = \sigma_o^2 + k\sigma_c^2 + (1-k)\,\sigma_{rs}^2$$

Where:

$$\sigma_o^2 = \frac{z}{n-1}\sum\left(\ln\frac{O_i}{C_{i-1}} - \mu_o\right)^2; \quad \mu_o = \frac{1}{n}\sum\ln\frac{O_i}{C_{i-1}}$$

$$\sigma_c^2 = \frac{z}{n-1}\sum\left(\ln\frac{C_i}{O_i} - \mu_c\right)^2; \quad \mu_c = \frac{1}{n}\sum\ln\frac{C_i}{O_i}$$

$$\sigma_{rs}^2 = \frac{z}{n}\sum\left(\ln\frac{H_i}{C_i}\ln\frac{H_i}{O_i} + \ln\frac{L_i}{C_i}\ln\frac{L_i}{O_i}\right); \quad k = \frac{0.34}{1+\frac{n+1}{n-1}}$$

Volatility Index (VIX): The fundamental features of VIX remain the same. VIX continues to provide a minute-by-minute snapshot of expected stock market volatility over the next 30 calendar days. VIX uses a newly developed formula to derive expected volatility by averaging the weighted prices of puts and calls of both near and next months. This simple and powerful derivation is based on theoretical results that have spurred the growth of a new market where risk managers and hedge funds can trade volatility and market makers can hedge volatility trades with listed options. The new VIX calculation conforms more closely to industry practice. It is simpler and also yields a more robust measure of expected volatility. The new VIX is more robust because it pools the information from option prices over the whole volatility skew, not just from at-the-money options. The generalized formula used in the new VIX calculation is:

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

where, σ = VIX/100 and therefore VIX = 100*σ and T is the maturity of the options. The options can either be near-term options or next-term options. The difference between them is that "near-term" options must have at least one week to expiry; a requirement intended to minimize pricing anomalies that might occur close to expiry. When the near-term options have less than a week to expiry, VIX "rolls" to the second and third contract months." Going back to the formula, F is the forward index level from the index prices or the spot (current) price of the index in question. K_i is the strike price of i^{th} out-of-the-money option; it is a call if $K_i > F$ and a put if $K_i < F$. ΔK_i is the interval between the strike prices calculated by halving the difference of the two strikes surrounding K_i as shown here:

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

K_0, in particular, is the first strike below the spot price F. R is the risk-free interest rate and Q (K_i) is the mid-quote price for each out-of-the-money option with strike K_i, whether it is for a call or a put.

To calculate VIX it is required to follow these steps (i) identify both the put and call option contracts for the near month and the next month, (ii) calculate the time to expiration for both the months, (iii) calculate the difference between call and put option prices for each strike price for both near and next month contracts. Select the strike price corresponding to the minimum difference that was finally used, (iv) use the above values, F1 and F2 are calculated, (v) K_0 is calculated by finding out the strike prices just below F1 and F2 for near and next months, (vi) sort all the options in ascending order by strike price. Select call options that have strike prices greater than K_0 and a non-zero bid price. Next, select put options that have strike prices less than K_0 and a non-zero bid price. Select both the put and call with strike price K_0. Then calculate the average quoted bid-ask prices for each option, (viii) ΔK is calculated by averaging the distance between the strikes on either side of each strike price K_i, (ix) Risk free interest rate is taken, (x) Calculate σ_1 and σ_2 and (xi) using the same calculate VIX.

We need the ex-post volatility for comparing the performance of all the volatility models. This is because this can be used as a proxy for the volatility experienced by the stock market participant. So, for calculating the ex-post weekly volatility first the daily returns were calculated using the formula ln (C_i / C_{i-1}) where C_i is the closing value of nifty and C_{i-1} is the closing value of the previous day. After that the weekly average of daily returns was calculated which would help in calculating the daily variance. The variance was multiplies by 5 to get the weekly volatility. Square root of the same gave us the weekly volatility.

Test used: Which model is a better fit? The ex-post volatilities are used as the dependent variables in the regression equations. So the regressions are run with ex-post weekly volatility as the dependent variable and the different volatility series as the independent variable. One regression equation is run for one type of model. Then for every equation using the Wald's Coefficient test, the constant and the coefficient are checked to see if they are statistically equal to zero and one respectively. The R^2 can also be checked to see the explanatory power of the model.

RESULTS

To investigate the ability of various volatility forecasting methods, we carried out comparative analyses across five models such as Rolling Variance, EWMA, GARCH, VIX and Extreme Value Indicators. The following regression equation is used in calculating ex-post volatilities for each of the aforementioned models. In the process, the volatility estimations were carried out for each of these models and presented in Table 1. It shows how well these estimated variances explain the ex-post volatilities,

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

where the y_i`s are the ex-post volatilities and the x_i's are the volatilities estimated through various models.

After each regression we use the Walt's Coefficient test to check if a =0 and β=1. The idea behind this test is to see if the specific method is able to explain the ex-post volatilities completely. In the estimated equation; α = 0 tells us that there is no unexplained part left and β = 1 tells us that the method is contributing completely in explaining the dependent estimated volatility (Table 1).

Rolling variance results: The rolling volatility fails to explain the dependent variable completely. There is a significant AR (1) term involved in the equation, which shows us that the volatility series is auto-regressive. Also the constant is insignificant and is not equal to zero which means that there remains some unexplained part. Also the coefficient of the dependent term is not equal to one so it can be inferred that the rolling variance does not explain the dependent variance completely. The adjusted R^2 is around 22% which is not a very satisfactory result.

EWMA: It also has an AR (1) term but has a constant equal to zero which means that there is no unexplained part in the dependent variable. But like the Rolling variance, it has a coefficient which is not equal to one which means that the EWMA volatility does not completely explain the movement in dependent variable.

GARCH models: The GARCH models give a better fit than the other models because of their ability to meet the special properties of the stock returns. GARCH, EGARCH and TGARCH are better than the other models in the way that they have a better adjusted R^2 and they have a constant which is equal to zero. But the major problem with these GARCH models is that they do not cater to the asymmetric nature of the returns series. AGARCH performs better than other models including the other GARCH models because it accommodates the asymmetric nature of returns series and hence provides the best modeling facility. This is proved by the fact that both the constant and the coefficient are equal to zero and one respectively. These models also have better R^2 when compared to the other models.

Table 1: Walt coefficient estimated across the volatility models

Methods	Constant (α)	Coefficient (β)	Adjusted R-Squared	Rank
Rolling variance	Not equal to zero	Not equal to one	0.2252	9
EWMA	Equal to zero	Not equal to one	0.2248	2
GARCH	Equal to zero	Not equal to one	0.2831	5
EGARCH	Equal to zero	Not equal to one	0.4075	3
TGARCH	Equal to zero	Not equal to one	0.3188	4
AGARCH	Equal to zero	Equal to one	0.3440	1
Garman klass	Not equal to Zero	Not equal to one	0.4147	6
Rogers satchell	Not equal to Zero	Not equal to one	0.4369	7
Yan zang	Not equal to Zero	Not equal to one	0.4371	8
Parkinson's	Not equal to Zero	Not equal to one	0.1696	10
VIX	Equal to zero	Equal to one	0.0239	11

Source: Compiled by the authors from the estimated results

Table 2: Model wise out-of-sample forecasting results

Method	Bias proportion	Variance proportion	Covariance proportion	Method	Bias proportion	Variance proportion	Covariance proportion
Rolling variance	0.00	0.3003	0.6997	GARCH	0.00	0.2824	0.7173
EWMA	0.00	0.2799	0.7201	EGARCH	0.00	0.2032	0.7963
Yang zhang	0.00	0.0623	0.9377	TGARCH	0.00	0.2540	0.7450
Garman klass	0.00	0.0773	0.9227	AGARCH	0.00	0.1763	0.8237
Rogers satchell	0.00	0.0455	0.9549	VIX	0.00	0.1935	0.8065
Parkison	0.00	0.3737	0.6263				

Source: Compiled by the authors from the estimated results

Extreme value indicators: Parkinson's performance is the lowest of all the extreme value methods. They fail to perform better than the other methods, the only consolation being a high adjusted R^2. Many studies have shown that these methods perform best with high frequency data and this research confirms the findings that these methods do not beat the GARCH methods when compared to the other methods. For data with higher frequency their assumptions of jumps and gaps fit in very well whereas other models do not make this consideration and hence these models are better than the other models in those cases.

Volatility Index (VIX): It also has a constant and coefficient equal to zero and one which means that it explains the dependent variable completely. But AGARCH has a better R^2 when compared to VIX so it might be thought that it is superior to VIX. Looking into the complexity of calculations involved in AGARCH, VIX may be considered to be better. At the same time VIX uses the options data which, in a way, reflect the prices being anticipated in the market and hence are a proxy of the future expectations. AGARCH uses the past data to forecast the future and hence VIX can be considered superior to AGARCH.

DISCUSSION

While comparing the forecasting models, it is essential to examine the bias proportion, variance proportion and the covariance proportion associated with each of the models. The bias proportion indicates how far the mean of the forecast is from the mean of the actual series. The variance proportion indicates how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. It is always desirable in a good forecast that the bias and variance proportions should be as small as possible so that most of the bias should be concentrated on the covariance proportions. In a good forecast, the covariance proportion, which is indicative of unsystematic error, should be larger than the bias and variance proportions (Table 2). The results indicate that the extreme value indicators have small values of the bias and variance proportions, implying a good forecast. This can be attributed to the fact that they provide to the leptokurtic tendency of the returns series.

CONCLUSION

This study aims to compare the different volatility models based on how well they model the volatility of the India NSE. The models include a variety of approaches starting from rolling variance to the latest VIX method (released by CBOE).The data include the daily closing, high, low and open values of the NSE from 2005-2008. For VIX all the option details from January 2008 till October 2008 have been considered. All the methods have a rolling window concept and have used the past 156 weeks (3 year data) to forecast the following week's data. To make the rolling window process easier programming concept of Eviews has been used. A comparison was made on how well the models explained the ex-post volatility (the volatility experienced by the market participants). Wald's constant's test was useful in testing which method best suited the requirements. Finally it was concluded that the AGARCH and VIX models proved to be the best methods, followed by the EWMA method. EWMA outperforms the other two methods because of the simplicity and minimum requirement of information. At the same time the Extreme Value models fail to perform because of the low frequency data being used. As other research suggests they perform best when they are applied to high frequency data like the daily or intraday data. EVIs give the best forecasting performance followed by the GARCH and VIX models.

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