

Comparative Performance of Volatility Forecasting Models in Indian Markets

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Volatility forecasting is an important area of research to financial markets and lot of effort has been expended in improving volatility models since better forecasts translates into better pricing of options and better risk management. In this direction, this paper attempts to evaluate the ability of ten different statistical and econometric volatility forecasting models to the context of Indian stock and forex markets. These competing models are evaluated on the basis of two categories of evaluation measures – symmetric and asymmetric error statistics. Based on an out - of - sample forecasts and using a majority of evaluation measures we find that G-J ARCH 11, 1 and EW 1 L4 methods will lead to better volatility forecasts in the Indian stock market and G-ARCH (5, 1) will achieve the same in the forex market. The same models perform better on the basis of 'asymmetric error statistics' also.

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Introduction

Volatility is the variability of asset price changes over a particular period of time and it is very hard to predict it correctly and consistently. In financial markets, volatility presents a strange paradox to market participants, academicians and policy makers. Without volatility superior returns cannot be earned, since a risk free security offers meager returns. On the other hand if it is 'high', it will lead to losses for the market participants and represent costs to the economy. Therefore, volatility estimation is an essential part in most finance decisions, be it asset allocation, derivative pricing or risk management (Poon and Granger, 2003) . However, there is no easy answer to the question of which model should be used to calculate volatility since different volatility models which are being used by practitioners lead to different volatility estimates. In the past two decades, this has been a fertile area for research in financial economics for both academicians as well as practitioners. Unfortunately, most of the work was done in developed markets in the context of stock and forex markets. This paper is an attempt to examine the efficacy of the competing volatility forecasting models in the Indian market.

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The works of Mandelbrot (1963) and Fama (1965) were the first few works that examined the statistical properties of stock returns. In the same strand, Kiray's (1989) work proceeds further which not only investigates the statistical properties but also presents evidence on the forecasting ability of ARCH (autoregressive conditional heteroskedastic) and GARCH (generalized ARCH) models. Also is EWMA (exponentially weighted moving average) and the Historic Simple Average method. Pagan and Schwert (1990) report that GARCH I and EGARCH (exponential general autoregressive conditional heteroskedastic) models enhanced results suggested by nonparametric methods yields significant increases in explanatory power. In the same year, Dimson and Marsh (1990) came up with rather interesting finding that simple models perform better than the exponential smoothing or regression based methods. Of course, it has to be noted that their study does not include the popular ARCH family of models. In contrast to this, Tse (1991), Tse and Tung (1992) find that EWMA models provide better forecasts than the GARCH models. These studies were conducted in different markets – the former was carried out in the US stock market while the later was conducted in Japanese and Singapore markets respectively. Franses and Nan Dijk (1996) examined the forecasting ability of the GARCH I family of models against random walk model in five European stock markets and found that the random walk model fares better even when the period of the 1987 crash was included. Brailsford and Faff (1996) investigated the forecasting models in the Australian market and found that though the ARCH I class of models and simple regression provide better forecasts the rankings were sensitive to the error statistic used to assess the accuracy of the forecast. In the context of foreign exchange markets, West and Cho (1995) find evidence in favour of the GARCH model over shorter intervals and in the longer horizon no model fares better. Some of the more recent works were by Loudon *et al.* (2000), Alcmillan *et al.* (2000), Yu (2002), Klaassen (2002), Vilasuso (2002) and Balaban (2004).

In the Indian context, Varma (1999) investigated the volatility estimation models comparing LARCH and the EWMA models in the risk management setting. Pander (2002) explored the extreme value estimators and found that they perform better than the traditional close to close estimators although his study does not consider the performance of extreme value estimators versus time varying volatility models. Kaur (2004) examined the nature and characteristics of stock market volatility in India.

From the literature review the following points emerge:

1. There is no conclusive evidence as to the supremacy of any volatility forecasting model in the literature on developed markets.
2. In the Indian context, research on this important topic is fragmented as there is no work that compares the ability of all the important competing models. Though, to some extent, the work by Varma (1999) is an important contribution, it considers only the stock market and that too with a different objective.
3. In the context of foreign exchange market, this topic is not addressed at all.
4. Evidence in the form of out-of-sample forecasting has not been used and the question of how the simple models fare against sophisticated models is still unanswered in Indian literature.

In this context, the present work sets out to investigate the relative ability of various forecasting models ranging from naive models to relatively advanced models in both stock and forex markets of India.

Data Description

In this study, we considered the NIFTY index as a proxy for the stock market and accordingly, the closing index values were collected from June 3, 1990, till December 31, 2005. The exchange rate data was pertaining to the Indian rupee/US dollar exchange rate over the period January 3, 1994, till December 31, 2005, and the same was collected from the Pacific Exchange Rate Service (<http://fx.sauder.uhc.cal>). Out of the total observations the data pertaining to July, 1990, till December, 2000, totaling 126 monthly observations of NIFTY were used for estimation of the model parameters and the remaining observations will be used for out-of-sample forecasting also known as hold out sample. In the case of foreign exchange market, the data pertaining to the January 1994 till December, 2000, totaling 85 monthly observations were used for estimation of the model parameters and the remaining observations will be used for out of sample forecasting. Therefore the first month for which out-of-sample forecasts are obtained is January 2001, and the out-of-sample forecasts were constructed for 60 months till December, 2005. The daily observations were converted into continuous compounded returns in the standard method as the log differences:

$$r_t = \ln \left(\frac{I_t}{I_{t-1}} \right)$$

here I_t stands for the closing index value/exchange rate on day 't'. Following Merton (1980) the monthly volatility is obtained as the sum of the squared daily returns in that month which is shown below:

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$$0. = E r_t,$$

$$r=1$$

Where r_t is the daily return on day 't' and N is the number of trading days in the month under question. The descriptive statistics of the data are presented in Table 1 and Figures 1 and 2 plot the return series of NIFTY and exchange rate respectively. The mean daily return for NIFTY was 0.0631% while for exchange rate it was 0.0119% and the annualized volatility for NIFTY is around 27.88% and for the exchange rate it was 4.278%. Both the series exhibit excess kurtosis indicating that the unconditional return distributions are not normal. The Jarque-Bera (JB) statistic confirms that normality is rejected at a p-value of almost 1. The plot of return series in Figures 1 and 2 shows that there is persistence and volatility clustering is a feature of both the markets which suggests that the volatility is predictable. From Figures 3 and 4 we can note that the returns exhibit fat tails which is more prominent for the exchange rate series. The Ljung-Box Q statistics for the return and squared return series show that the null hypothesis of no serial correlation cannot be rejected at 36th lag for both series. To test for possible unit roots the Augmented Dickey-Fuller (ADF) statistic is calculated and the results are presented in the last row of Table I. The null hypothesis of unit root can be rejected in both the cases at 1% level of significance.

Table 1: The Descriptive Statistics of the Data

	NIFTY returns	Exchange rate returns
Mean	0.000631	0.000119
Standard Error	0.000291	0.000049
Standard Deviation	0.017633	0.002706
Kurtosis	5.918042	28.63223
Skewness	-0.12005	0.887248
Minimum	-0.13054	-0.02187
Maximum	0.120861	0.034755
J B	5347.902(0.000)	10295.91(0.000)
Q(36)	145.15(0.000)	63.004(0.004)
Q'(36)	2240.1(0.000)	517.78(0.000)
ADF statistic**	25.83543	21.86964

* The McKinnon critical value at 1% level of significance is 3.4356 and the test is conducted for 4 lags. The inferences remain the same for the Phillip-Perron test also. For an explanation of Augmented Dickey Fuller test, see Hamilton (1994)

Markets

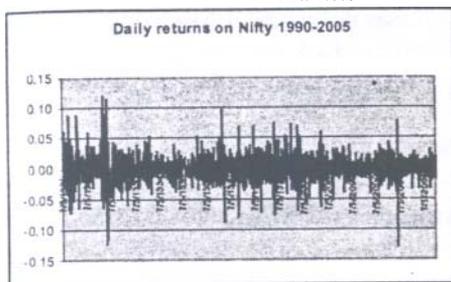


Figure 3

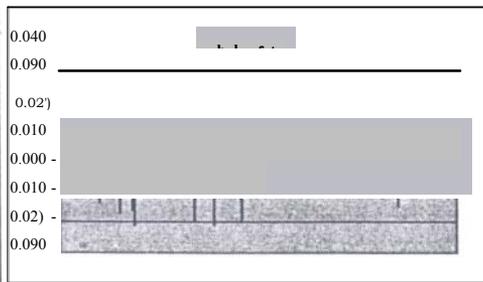
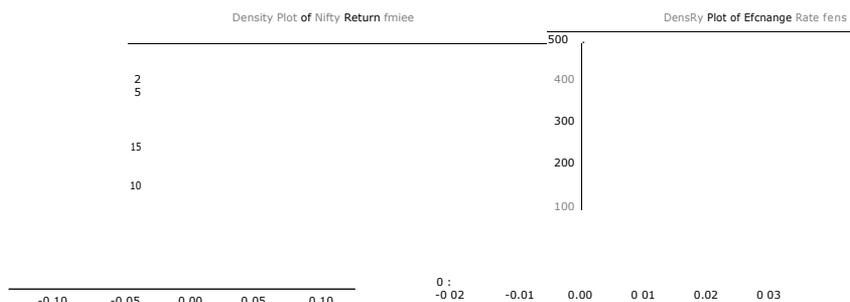


Figure 4

Figure 1

Figure 2



The absence of unit root means the series is stationary, and combined with the phenomenon of volatility clustering implies that volatility can be predicted and the forecasting ability of the different models can be generalized to other time periods also.

Competing Models

Taking cues from the literature review, this work examines the forecasting capabilities of the following models:

1. Random walk
2. Historical mean
3. Moving average
4. Simple regression
5. Exponential weighted moving average
6. Simple and higher order GARCH models

The models that were considered in this particular study are not exhaustive but cover a very large variety of models ranging from naive models to the advanced models like GARCH and the model preferred by practitioners. We tried to include those models whose efficacy has not been examined earlier in the Indian context. We were also

guided by the researcher's assessment of the models used by practitioners like exponential smoothing (RiskMetrics™ which uses this model is being used by more than 625 institutions worldwide. Source: Web site of Risk metrics).

In the following paragraphs, we attempt to give a brief description of all the candidate models:
Random Walk Model

As per this model, the best forecast for this period's volatility is the last period's realized volatility

$$\sigma_t = \sigma_{t-1} + u_t$$

where $t = 127 \dots 186$ for Nifty and $t = 85 \dots 144$ for the exchange rate series. *Historical Mean Model*

Assuming the conditional expectation of the volatility constant, this model forecasts volatility as the historical average of the past observed volatilities

$$\sigma_t = \frac{1}{t-1} \sum_{i=1}^{t-1} \sigma_i$$

where $t = 127 \dots 186$ for Nifty and $t = 85 \dots 144$ for the exchange rate series. *Moving Average Model*

in the historic mean model, the forecast is based on all the available observations and each observation, whether it is very old or immediate, is given equal weight. This may lead to stale prices affecting the forecasts. This is adjusted in a moving averages method which is a traditional time series technique in which the volatility is defined as the equally weighted average of realized volatilities in the past 'm' months.

$$\sigma_t = \frac{1}{m} \sum_{i=t-m}^{t-1} \sigma_i$$

The choice of 'm' is rather arbitrary and in this paper we investigate five models of 3, 6, 12, 24 and 60 months.

Simple Regression

In this method, the familiar regression of actual volatilities on lagged values is run. In other words, autoregression is first performed on the first part of data which is meant

for estimating the parameters and the estimates thus obtained were used for forecasting the volatility for the next month. Accordingly, the first part involves running the following regression:

$$\sigma_t = a + \beta \sigma_{t-1}$$

'a' and β are estimated over the 11 year period from July 1990 till December 2000 for NIFTY and for the exchange rate it was done for 7 year period from January 1994 to December 2000. Now for the next forecast the volatility for February 2001, the parameters 'a' and β are re-estimated by omitting the most distant past observation i.e., July 1990 and including the January 2001 actual volatility observation. This process is repeated and thus the estimation window moves forward. The same process is carried out for exchange rate series also. By following this methodology, we actually utilize the time-varying parameters for each month.

Exponential Weighted Moving Average'

Exponential smoothing is an adaptive forecasting method that gives greater weight to more recent observations so that the finite memory of the market is represented. This method adjusts the forecasts based on past forecast errors and the forecast is calculated as a weighted average of the immediate past observed volatility and the forecasted value for that same period i.e.,

$$\hat{\sigma}_t = a \sigma_t + (1-a) \hat{\sigma}_{t-1}$$

Here a is known as smoothing factor and is constrained to $0 < a < 1$. The smoothing factor determines the weight that is given to actual volatility observed in the immediate past month and as $a \rightarrow 1$ it means more recent observations get more weight and a can be chosen based on the analyst's intuitive judgement or can be objectively determined so as to produce the best fit by minimizing the sum of the squared deviation between actual and forecasted volatilities in the estimation period i.e., using insample data. Past studies viz., Dimson and Marsh (1990) estimate optimal a for each year but, in this study, we re-estimate it on a monthly basis.

ARCH and GARCH

ARCH stands for 'autoregressive conditionally heteroskedasticity' and these models

strictly speaking, this method is exponential smoothing smoother. some practitioners and in particular, RiskMetrics™ call it as exponentially smoothed moving average. Hence to avoid confusion they are also calling this approach the same name

are a sophisticated group of time series models initially introduced by Engle (1982). ARCH models capture the volatility clustering phenomenon usually observed in financial time series data. In the linear ARCH (q) model, the time varying conditional variance is postulated to be a linear function of the past 'q' squared innovations. In other words, variance is modeled as a constant plus a distributed lag on the squared residual terms from earlier periods

$$r_t = \mu + \epsilon_t, \text{ and } \epsilon_t = r_t - \mu + a \sum_{i=1}^q \epsilon_{t-i}^2$$

Where $\epsilon_t \sim iid N(0,1)$ For stability $\sum a_i < 1.0$ and "...theoretically q may assume any number but generally it is determined based on some information criteria like Akaike information criteria (AIC hereafter) or Bayesian information criteria (BIC hereafter). In financial markets the ARCH(1) model is used most often and this is a very simple model that exhibits constant unconditional variance but non-constant conditional variance. Accordingly the conditional variance is modeled as

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2$$

As with simple regression, the parameters in ARCH and GARCH models (discussed next) are estimated at monthly intervals using a rolling window of monthly 1 year window.

The problem with the ARCH models is that it involves estimation of a large number of parameters and if some of the parameters become negative they lead to difficulties in forecasting. Bollerslev (1986) proposed a Generalized ARCH or GARCH (p, q) model where volatility at time t depends on the observed data at t-1, t-2, t-3 ... t-q as well as on volatilities at t-1, t-2, t-3 ... t-p. The advantage of GARCH formulation is that though recent innovations enter the model it involves only estimation of a few parameters and hence there will be little chance that they will ill-behaved. In GARCH there will be two equations — conditional mean equation given below,

$$r_t = \mu + \epsilon_t$$

and the conditional variance equation shown below,

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^p \beta_i \sigma_{t-i}^2$$

The parameters in both the equations are estimated simultaneously using maximum

it is assumed that they are Gaussian. The simplest and most commonly used member of the GARCH family is the GARCH (1, 1) model shown below

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

6-~ GARCH

forecast for the next day is computed given as

$$\hat{\sigma}_{t+1}^2 = \omega + \alpha_1 e_t^2 + \beta_1 \sigma_t^2$$

If the forecast is required for more than one day for instance 'n' day forecast is given as

$$\hat{\sigma}_{t+n}^2 = \omega \left[\frac{1 - \beta_1^n}{1 - \beta_1} \right] + \alpha_1 \beta_1^{n-1} e_t^2 + \beta_1^n \sigma_t^2$$

Following Schwarz Information Criteria and Akaike Information Criteria' we found that the best model in the GARCH (p, q) class for 1 For conserving space and to maintain the flow the values are not presented and are available up on request was a GARCH (4, 1) in the stock market and GARCH (5, 1) in the forex market. We also tested for whether the GARCH (4,1) adequately captured all the persistence in the variance of returns by using Ljung-Box Q- statistic at the 36th lag of the standardized squared residuals was 38.496 (p = 0.357) indicating that the residuals are not serially correlated. However, in this study, we evaluated the performance of the GARCH (1, 1) model also that is often used in financial economics literature.

In our forecasting exercise, first we estimated the GARCH parameters using the estimation period i.e., July, 1990, to December, 2000, for NIFTY and January, 1994, to December, 2000, for exchange rate series and then used these parameters to obtain the forecasts for the trading days in January, 2001, and these daily forecasts were aggregated to obtain the forecast for the month of January 2001. Then the beginning and end observations for parameter estimation were adjusted by including the data for January 2001 and omitting the data pertaining to July 1990. The procedure is repeated for every month using a rolling window of 11 years for NIFTY data and 7 years rolling window for the exchange rate data.

Empirical Results

We compare the forecast performance of each model using the following error statistics used in past studies viz., Yu (2002) and Brailsford and Faff(1996).

¹ For conserving space and to maintain the flow the values are not presented and are available upon request

Mean absolute error (MAE). Root Mean Square Error (RMSE). Theil's U (TU) and MAPE. These are defined as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - \hat{a}_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - \hat{a}_i)^2}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|a_i - \hat{a}_i|}{a_i}$$

In all the above statistics, 'n' stand for number of out of sample forecasts which is equal to 60 as the same was done over a five year period. Theil's U is a statistic that uses the random walk as a benchmark for comparing the quality of forecast models. Behind this notion is the belief that if a forecasting model cannot do better than a naive forecast, then the model is not doing an adequate job. These statistics are generally termed as symmetric forecast error statistics as they penalize both over forecast and under forecast equally. Since over forecast and under forecast may lead to different profit/cost consequences to buyers and sellers differently they have to be treated differently i.e., a differential weighting is required since under forecast of volatility may be desirable for an option buyer since the resulting price will be less but it will be undesirable for the seller as the buyer's gain will be the seller's loss. Following Brailsford and Faff (1996) the below mentioned asymmetric error statistics mean absolute error statistics MME(U) and MME(0) were constructed

$$MME(U) = \frac{1}{60} \sum_{i=1}^n (|a_i - \hat{a}_i| + U \cdot |a_i - \hat{a}_i| \cdot I_{a_i < \hat{a}_i})$$

$$MME(0) = \frac{1}{60} \sum_{i=1}^n (|a_i - \hat{a}_i| + |a_i - \hat{a}_i| \cdot I_{a_i > \hat{a}_i})$$

Where 0 is the number of over predictions and U is the number of under predictions. MME(U) penalize more the under predictions and MME(0) penalizes more the over predictions.

Results and Discussions

Table 2 presents the results of the error statistics explained in the earlier section. In this table we present the actual statistic along with the relative ranking of that particular method among the competing models. From the results we can make the following observations. Firstly, based on Theil's-U and MAE the GARCH models outperform other models in both the markets viz., stock and forex markets. While on the basis of MAPE there is unanimity of the superiority of EWMA method in both the markets, on the basis of RMSE, EWMA method fares well in the stock market and in the forex market. Again GARCH (5, 1) model ranks the best. In the stock market, EWMA is found to perform better on the basis of two measures – RMSE and MAPE while on the basis of MAE, though it is ranked second, the difference in forecast error as per GARCH (4, 1) and EWMA is very nominal. On the other hand, the GARCH models perform clearly ahead of EWMA in the forex market on the basis of three measures.

Second, all the measures indicate historical mean model as the worst performing model in the forex market and in the stock market. Historical mean model is ranked worse by two measures i.e., MAE and MAPE while random walk model is categorized as the worse by RMSE and Theil's U. It is customary for Theil's U to compare the performance of competing models against the simplest of the forecast methods — termed the "naive" model, the random walk, which usually consists of a forecast repeating the most recent value of the variable – but in forex market three other models historic mean model, 5-yr moving average, and simple regression were found to produce worse results than the random walk model. The performance of the popular simple regression method is rather not encouraging in either of the markets - in forex market it was ranked as ninth by two measures and an equal number ranked it as eighth.

Third, in the stock market, the forecast accuracy increases on an average of 70% by using the GARCH models vis-a-vis the worse performing models and in the forex market this improvement is to the extent of 80%. In other words, if we consider the forecast error of last ranked model on the basis of one of the measures (for instance) RMSE as the base then by using the top ranked model EWMA the forecast error reduces by around 49% which is a significant reduction in forecast error.

Fourth, the higher order GARCH models like the GARCH (4, 1) and GARCH (5, 1) perform better vis-a-vis the simple GARCH (1, 1) and other competing models and the improvement in forecast accuracy as indicated by Theil's-U, MAE or MAPE is quite significant. Finally, on the basis of asymmetric loss error statistics, one can note that only random walk model provides unbiased forecasts. The probability of over predictions is equal to the probability of under predictions which is equal to 50% and the null hypothesis of an equal number of under and over forecasts cannot be accepted for any other model but for random walk model at conventional levels of significance. In both the markets the superior ranked models viz., EWMA or GARCH (5, 1) models have

a tendency to produce over forecasts but with relatively small errors. On the basis of MME (U) the best fit GARCH (5, 1) emerged better model in the forex market while the simple GRACH (1, 1) model ranked higher and on the basis of MME (0), the exponential smoothing method comes out as the best model.

Table 2
Forecast Error Statistics: Symmetric Loss Function
Forex Market

	TI'	Rank)LaE	Rank	RISE	Rank)LIPE	Rank
F.II)1A	0.371 ² _0684	3	0 00003886	2	0 000076 ² _ 1	3	0.69837091	1
LARCH (1,1)	0.34314795	2	0 00003898	3	0.00007327	2	1 0732953(3
GARCH(5,1)	0.19417391	1	0.00002618	1	0.00005512	1	0.7215696:	2
Hist mean	1.40357378	10	0.00013247	10	0.00014819	10	9.02841 ²² 292	10
MA 0.25	0.78727372	5	0 00006012	4	0.0001 1098	5	1.4604538:	5
NIA1	0 71895733	4	0 00006442	5	0.00010606	4	2 1588523_	6
MA3	0 8301 8970	6	0 00006819	6	0 0001 1397	6	2.94984062	7
MtA5	1.04221655	9	0.00009297	8	0.00012769	9	5.39745416	8
Random Walk	1 00000000	7	0.00006936	7	0 00012497	7	128499625	4
Simple reg	1.00425344	8	0.0001097 ² _9	9	0 000/2535	8	6 3159135-1	9
Stock Market								
EII)IA	0 27 ² _24587	2	0 00182689	2	0.00375781	1	0.43634152	1
GARCH (1,1)	0.36603526	3	0 00205138	3	0 00453581	3	0 66207931	3
GARCH (4.1)	0.18421407	1	0.00181562	1	0 00442270	2	0 4434'-738	2
Hist mean	0.67727683	8	0 00447397	10	0 00601602	7	1.90841812	10
-IA0.25	0 70598849	9	0 00299082	4	0	8	0 787-H4084	5
NIA1	0 59060266_4	4	0 00314696	6	0 00561790	4	11 ² _509497	7
)L13	0 62189710	6	0 00347056		0 00576481	6	1 35809469	8
MA5	0 61518752	5	0 0037 ² _339	8	0 00573363	5	153291,122	9
Random Walk	100000000	10	0 0031423'	5	0 007 ² _ 9752	10	0 7.3871 373	4
Simple reg	0 65787628		0 00380932	9	0 00637964	9	1 09204205	6

Table 3
Forecast Error Statistics: Asymmetric Loss Function

Forex Market

	MME (U)	Rank	MME(0)	Rank	*UF	*OF	Binomial Probability
E~S1A	0.00026037	5	0.002453762	1	25	35	0.0405
GARCH (1,1)	0.00032763	9	0.003343912	4	18	42	0.0008
GARCH(5,1)	0.00002198	1	0.00363254	6	3	57	0.0000
Hist mean	0.00020415	4	0.008542411	10	9	51	0.0000
MA 0.25	0.00037696	10	0.002953131	2	25	35	0.0450
MA1	0.00032036	7	0.003532308	5	24	36	0.0313
MA3	0.00027142	6	0.003715157	7	19	41	0.0018
MA5	0.00032264	8	0.005337611	8	16	44	0.0001
Random Walk	0.00003259	2	0.00318197	3	28	32	0.0900
Simple reg	0.00014919	3	0.00789716	9	9	51	0.0000

Stock Market

EWMA	0.01528793	7	0.017317598	1	24	36	0.0313
LARCH (1,1)	0.010776017	1	0.029168636	5	14	46	0.0000
LARCH (4,1)	0.017671237	9	0.019619105	2	25	35	0.0405
flirt mean	0.011655316	2	0.056495534	10	6	54	0.0000
MA 0.25	0.012127 ² ₂	4	0.027,36292 ₈	4	19	41	0.0018
MA1	0.012789144	6	0.033654615	6	20	40	0.0036
MA3	0.012475947	5	0.041711653	7	14	46	0.0000
BIA5	0.01 ² ₅ _00327	3	0.047648542	9	8	52	0.0000
Random Walk	0.021915472	10	0.023570821	3	30	30	0.1026
Simple reg	0.016527291	8	0.042020027	8	11	49	0.0000

*CF and OF stand for number of under forecasts and number of over forecasts

Conclusion

Volatility forecasting is an important area of research in financial markets and in this paper, we evaluate the comparative ability of different statistical and econometric volatility forecasting models in the context of Indian stock and forex markets. Total often different models were considered in this study and these competing models are evaluated on the basis of two classes of evaluation measures – symmetric and asymmetric error statistics. Based on the out of sample forecasts and the number of evaluation measures that rank a particular method as superior 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. These findings are contrary to the findings of Brailsford and Faff (1996) who found no single method as superior. But the results in stock market are similar to the findings of Akigray (1989) and McNillan *et al.* (2001) and Anderson and Bollerslev (1998) and Anderson *et al.* (1999) in the forex market. The inferences remain same even on the basis of asymmetric error statistics i.e., GARCH (4, 1) and GARCH (5, 1) models when under forecasts are penalized heavily in the stock market and forex market respectively and EWMA when over forecasts are penalized heavily.

References

- Akigray, V. 1989. Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecasts, *Journal of Business*, 62: 55-80.
- Andersen, T. G. and T. Bollerslev 1998. Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. *International Economic Review*, 39: 885-905.
- Andersen, T. G., T. Bollerslev and S. Lange 1999. Forecasting Financial Market Volatility: Sample Frequency vis-a-vis Forecast Horizon. *Journal of Empirical Finance*, 6: 457-477.
- Balaban, E. 2004., Comparative Forecasting Performance of Symmetric and asymmetric Conditional Volatility Models of an Exchange Rate. *Economic Letters*, 83: 99-105
- Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics*, 31: 307-327.
- Bollerslev, T. R., Y. Chou and K. F. Kroner 1992. ARCH Modeling in Finance. A Review of the Theory and Empirical Evidence, *Journal of Econometrics*, 52: 5-59
- Bollerslev, T., R. F. Engle and D. B. Nelson 1994. ARCH Models. in R.F. Engle and

- D. McFadden, Eds.. *Handbook of Econometrics*, Vol. 4. North-Holland: Amsterdam.
- Brailsford, T. J. and R. W. Faff 1996. An Evaluation of Volatility Forecasting Techniques, *Journal of Banking and Finance*, 20: 419-438.
- Dimson. E. and P. Marsh 1990. Volatility Forecasting Without Data-Snooping, *Journal of Banking and Finance*. 14: 399-421.
- Engle. R. F 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of U.K. Inflation, *Econometrica*, 50: 987-1008.
- Fama Eugene F. 1965. The Behavior of Stock-Market Prices, *Journal of Business*. 38:1: 34-105.
- Franses. P. H. and Dick Van Dijk 1996. Forecasting stock market volatility using (nonlinear) GARCH Models, *Journal of Forecasting* 3: 229-235
- Hamilton, James D 1994. *Time Series Analysis*. Princeton University Press
- Kaur, H. 2004. Time varying volatility in the Indian Stock Market, *Vikalpa* 29(4): 25-42
- Klassen. F. 2002. Improving GARCH Volatility Forecasts. *Empirical Economics*. 27: 363-94.
- Loudon. G. W. Watt and P. Yadav 2000. An Empirical Analysis of Alternative Parametric ARCH Models, *Journal of Applied Econometrics*, 15: 117-36.
- Mandelbrot. B. 1963. The variation of certain speculative prices, *Journal of Business*. 36:394-414
- McMillan. D. A. Speight and O. Gwilym 2000. Forecasting UK Stock Market Volatility. *Applied Financial Economics*, 10: 435-448
- Merton. Robert 1980. On estimating the expected return on the market: An explanatory investigation. *Journal of Financial Economics*, 8: 323-61
- Pagan. A. R. and G. W. Schwert 1990. Alternative Models for Conditional Stock Volatility. *Journal of Econometrics*, 45:267-290
- Pandey A 2002. The Extreme Value Volatility Estimators and Their Empirical. Performance in Indian Capital Markets, *VSE Working Paper No. 52* downloadable from www.nseindia.com
- Poon, S. and C. Granger 2003. Forecasting Volatility in Financial Markets: A Review, *Journal of Economic Literature*. 41: 478-539
- Tse. S. H. and K. S. Tung 1992. Forecasting Volatility in the Singapore Stock Market. *Decision*, Vol. 33,

Comparative Performance of Volatility Forecasting Models in Indian Markets

Asia Pacific Journal of Management, 9: 1-13.

Tse, Y. K. 1991. Stock Returns Volatility in the Tokyo Stock Exchange, *Japan and the World Economy*, 3: 285-298.

Yu, J. 2002. Forecasting Volatility in the New Zealand Stock Market, *Applied Financial Economics*, 12: 193-202.

Varma, J. R. 1999. Value at risk models in the Indian stock market *IIAL4 Working Paper no. 99-07-05* downloadable from www.iimand.ernet.in

Vilasuso, J. 2002. Forecasting Exchange Rate Volatility, *Economic Letters*, 76: 59-64.

West, K. D. and D. Cho 1995. The Predictive Ability of Several Models of Exchange Rate Volatility, *Journal of Econometrics*, 69: 367-391.