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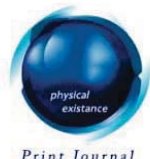
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Comparison of Different Volatility Model on Dhaka Stock Exchange

Imran Parvez ^α, Md. Moyazzem Hossain ^ο & Masudul Islam ^ρ

Abstract- Dhaka stock exchange (DSE) is a very hazardous market, so its volatility forecasting would be a very difficult and necessary task. The behaviour of Stock Market is different from market to market. So a unique time series model couldn't be a best forecasting technique for all stock market because of their varying nature. There are various types of time series model like Expected weighted moving average model, GARCH-type models, Moving Average models, Exponential smoothing model and so on. In this paper our objective is to compare the ability of different types of models to forecast volatility of Dhaka stock exchange.

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I. INTRODUCTION

Volatility in financial markets, particularly stock and foreign exchange markets is an important issue that concerns government policy makers, market analysis, corporate managers, and financial managers and it has held the attention of academics and practitioners over the last two decades.

Volatility is not the same as risk. When it is interpreted as uncertainty, it becomes a key input to many investment decisions and portfolio creations. Investors and portfolio managers have certain levels of risk which they can bear. A good forecast of the volatility of asset process over the investment holding period is a good starting point for assessing investment risk. Volatility is the most important variable in the pricing of derivative securities, whose trading volume has quadrupled in recent years. To price an option, we need to know the volatility of the underlying asset from now until the option expires. In fact, the market convention is to list option prices in terms of volatility units. Nowadays, one can buy derivatives that are written in volatility itself, in which case the definition and measurement of volatility will be clearly specified in the derivative contracts. In these new contracts, volatility now becomes the underlying "asset." So a volatility forecast is needed to price such derivative contracts.[12] Policy makers often rely on market estimates of volatility as a barometer for the vulnerability of financial markets and the economy. So, for the economic development of Bangladesh, the volatility forecasting is a very important issue.

Many econometric models have been used. The Auto Regressive Conditional Heteroscedasticity (ARCH) model introduced by Engel and Bollerslev's Generalized

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ARCH (GARCH) model conveniently accounted for time varying volatility. In ARCH, the conditional variance is equal to a linear function of past squared errors. The GARCH specification allows the current conditional variance to be a function of past variance as well. The GARCH models have been applied to study stock market volatility by Poon and Taylor, Engel and Ng and Kearns and Pagan.

The conditional variance of the current error in the GARCH model is specified as a function of past conditional variances and past errors. Only the magnitude of the errors affects volatility, but their signs do not. The character of asymmetry in the distribution of stock returns allows an unexpected positive return to cause less volatility than an unexpected negative return of the same size. The GARCH model cannot explain asymmetry in distribution of stock returns. A new model is needed to make allowances for asymmetric distribution of stock returns that the GARCH model fails to capture. Nelson proposed the Exponential GARCH (EGARCH) model, Glosten et al. proposed the GJR-GARCH model. A comparison of the GARCH, EGARCH and GJR-GARCH models by Engel and Ng on daily Japanese stock index return data suggests that GJR-GARCH is the best one. Using monthly US stock returns Pagan and Schwert find better explanatory power from the EGARCH model. [11]

However, despite the appeal of complexity and despite their popularity, it is by no means agreed that complex models such as GARCH provide superior forecasts of return volatility. Dimson and Marsh (1990) is a notable example in which simple models have prevailed – although it should be pointed out that ARCH models were not included in their analysis. Specifically, Dimson and Marsh apply five different types of forecasting model to a set of UK equity data, namely, (a) a random walk model; (b) a long-term mean model; (c) a moving average model; (d) an exponential smoothing model; and (e) regression models. They recommend the final two of these models and, in so doing, sound an early warning in this literature that the best forecasting models may well be the simple ones. Other papers however spell out a mixed set of findings on this issue. For example, Akgiray (1989) found in favor of a GARCH (1, 1) model (over more traditional counterparts) when applied to monthly US data. Brailsford and Faff (1996) investigate the out-of-sample predictive ability of several models of monthly stock market volatility in Australia. In the measurement of the performance of the models, in addition to symmetric loss functions, they use asymmetric loss functions to penalize under/over-prediction. They conclude that the ARCH class of models and a simple regression model provide superior forecast of volatility. However, the various model rankings are shown to be sensitive to the error statistics used to assess the accuracy of the forecasts. [1]

Bangladesh is a developing country here the capital formation is so much important for the economic development. For this capital formation the Stock Market plays a crucial role. But the Stock Market of Bangladesh is not an efficient market. So to make the market efficient and to reduce the uncertainty of the investor to invest, the volatility forecast is necessary step for the government and policy makers.

A volatility model must be able to forecast volatility; this is the central requirement in almost all financial applications. In this study, we try to forecast the daily volatility of Dhaka stock market by different well recognized models: Moving Average, GARCH (1, 1), Exponential Smoothing, E-GARCH, GJR-GARCH and rank their ability by different error measurement tools like Mean Sum Square of Error (MSE), Mean Absolute Error (MAE), Theil-U, Linex Loss Functions etc.

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II. DSE GENERAL INDEX

a) Return Series

Here we use the DSE General Index from 1st January 2002 to 19th June 2012, 2639 daily data. In following Fig-1 we depict the return series of DSE General Index, reveals that, as expected, volatility is not constant over time and moreover tends to cluster. Periods of high volatility can be distinguished from low volatility periods. Here the maximum change occurs in 16th November 2009, which is 23 per cent rise. The second largest rise is the 15.5 per cent return on 11th January 2011 and the largest fall is 9.3 per cent return in 10th January 2011.

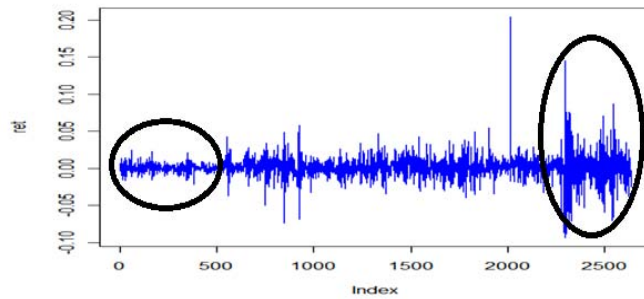


Fig. 1: Return Series. The Oval indicate a low volatility period and a high volatility period

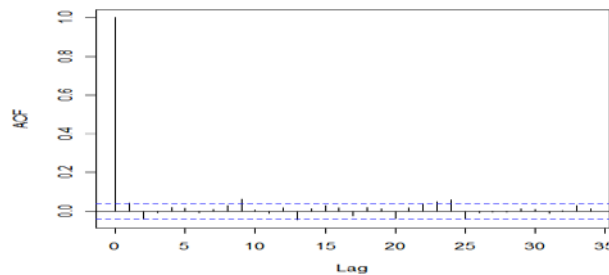


Fig. 2: Correlogram of Return Series

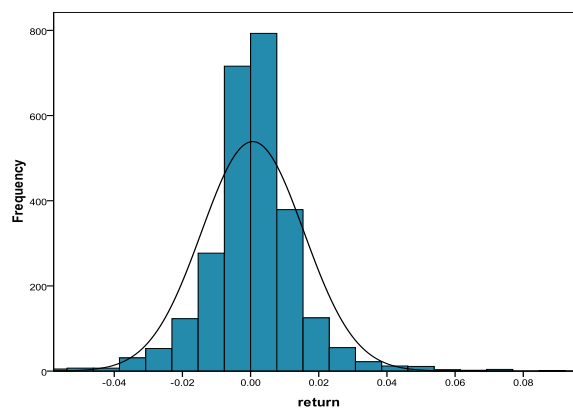


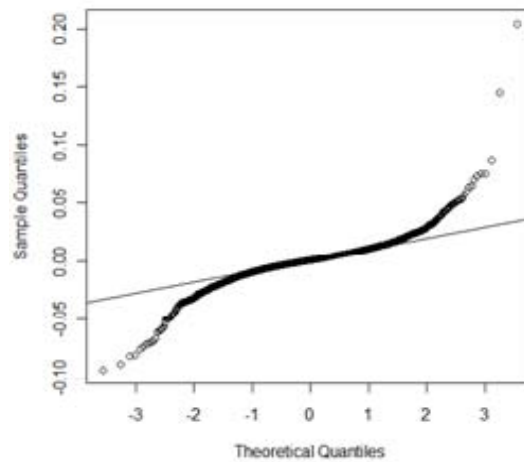
Fig. 3: Histogram of return with normal curve

Table 1: Descriptive Statistics of return

		Statistic
<i>r</i>	Mean	0.00063
	Std. deviation	0.015
	Skewness	0.913
	Kurtosis	20.431
	<i>N</i>	2639

The mean daily return is 0.063 per cent. The standard deviation of the daily returns is 0.015. The series also exhibits a positive skewness of 0.913 and excess kurtosis of 20.431, indicating the absence of normality which also reveals from Q-Q plot, Kolmogorov smirnov test and Shapiro-Wilk normality test. It can be easily seen from the histogram that there are many returns which are above four standard deviation is highly unlikely with the normal distribution.

Using the augmented Dickey-Fuller (ADF) unit root test we can clearly reject, as expected, the hypothesis of a unit root in the return process. The ADF t-statistic is -12.92 which rejects the unit root hypothesis with a confidence level of more than 99 per cent.

*Fig. 4:* Normal Q-Q plot of returnTable 2: Normality Test of return

<i>r</i>	Kolmogorv Smirnov		Shapiro-Wilk	
	Statistic	Sig.	Statistic	Sig.
	5.134	0.00	.8621	0.00
	ADF Test			
	Statistic		Sig	
	-12.92		0.01	

b) Volatility Series

We obtain the daily volatility simply squaring the return series. i.e., $\sigma_t^2 = r_t^2$, Where r_t is the daily return on a day t . From the following Fig-5 we can easily point out the huge volatility periods which are 16th November 2009, 11th January 2011 and the 10th January 2011 which also focuses from the return series. The table-3 and the Fig-6 both show that the first five autocorrelations are significantly different

from zero which suggests that the daily volatility series is apart from randomness and hence predictable. To test for possible unit roots the augmented Dickey-Fuller (ADF) statistic is calculated and the results are also presented in table-3. The ADF statistic for the entire sample is -10.13 with p-value 0.01. Hence the hypothesis that the daily volatility in the DSE General index over the period 1st January 2002 to 19th June 2012 has a unit root has to be rejected.

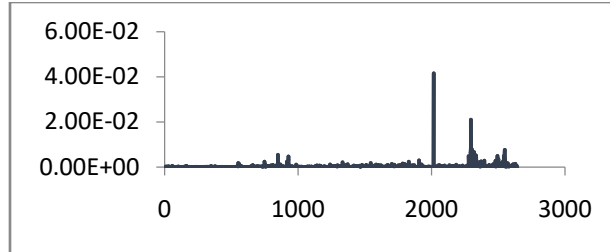


Fig. 5: Daily volatility series

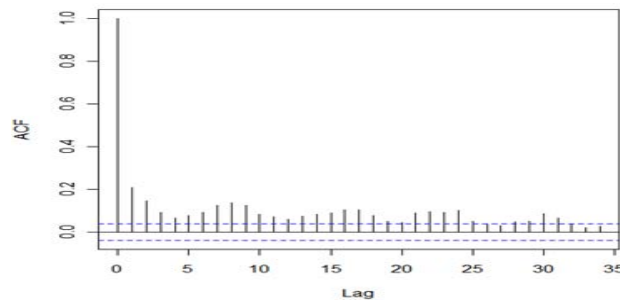


Fig. 6: Correlogram of Daily Volatility

Table 3: Summary statistics and normality test of Daily volatility series

Mean	Maximum	Skewness	Kurtosis	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7
0.0002	0.04	25.128	868.254	.208	0.146	.093	.066	.078	.093	.124
ADF Test					Shapiro-Wilk Normality Test					
Test Statistic		P-value			Test Statistic		P-Vlaue			
-10.13		0.01			0.1508		0.000			

III. VOLATILITY FORECASTING TECHNIQUES

a) Moving average

According to the historical average model, all past observations receive equal weight. In the moving average model, however, more recent observations receive more weight. In the paper, two moving average models are used: a five-year and a six-year moving average. The five-year model is defined as

$$\hat{\sigma}_{T+1}^2 = \sum_{i=1}^{1825} \hat{\sigma}_{T+1-i}^2 T = 2286, \dots 2638 [13].$$

b) Exponential smoothing

Exponential smoothing is a simple method of adaptive forecasting. Unlike forecasts from regression models which use fixed coefficients, forecasts from exponential smoothing methods adjust based upon past forecast errors. Single exponential smoothing forecast is given by $\hat{\sigma}_{T+1}^2 = (1 - \alpha)\hat{\sigma}_T^2 + \alpha\sigma_T^2$ where $0 < \alpha < 1$ is the damping (or smoothing factor). By repeated substitution, the recursion can be rewritten as $\hat{\sigma}_{T+1}^2 = \alpha \sum_{t=1}^T (1 - \alpha)^t \sigma_{T+1-t}^2, 2286, \dots, 2638$ This shows why this method is called

exponential smoothing - the forecast of σ_{T+1}^2 is a weighted average of the past values of σ_{T+1-t}^2 , where the weights decline exponentially with time. The value of α is chosen to produce the best fit by minimizing the sum of the squared in sample-forecast errors. Dimson and Marsh (1990) and BF select the optimal α annually.[13]

c) Generalized Arch (GARCH)

For the ARCH (q) model, in most empirical studies, q has to be large. This motivates Bollerslev (1986) to use the GARCH (p; q) specification which is defined as

$$\begin{cases} r_t = \mu + \sigma_t \epsilon_t \\ \sigma_t^2 = \lambda + \sum_{j=1}^q \alpha_j (r_{t-j} - \mu)^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \end{cases}$$

Define $s_t = r_t - \mu$, $m = \max\{p, q\}$, $\alpha_i = 0$ for $i > q$ and $\beta_i = 0$ for $i > p$. Following Baillie and Bollerslev (1992), the optimal h-day ahead forecast of the volatility can be calculated by iterating on

$$\hat{\sigma}_{t+h}^2 = \lambda + \sum_{i=1}^m (\alpha_i + \beta_i) \hat{\sigma}_{t+h-i}^2 - \beta_h \hat{w}_t - \dots - \beta_m \hat{w}_{t+h-m}, \text{ for } h = 1, 2, \dots, p$$

$$\hat{\sigma}_{t+h}^2 = \lambda + \sum_{i=1}^m (\alpha_i + \beta_i) \hat{\sigma}_{t+h-i}^2 \text{ for } h = p+1, p+2, \dots$$

$$\hat{\sigma}_\tau^2 = s_\tau^2 \text{ for } 0 \leq \tau \leq t,$$

$$\hat{\sigma}_\tau^2 = s_\tau^2 = T^{-1} \sum_{i=1}^T s_i^2, \text{ for } \tau \leq 0$$

$$\hat{w}_\tau = s_\tau^2 - E(s_\tau^2 / I_{\tau-1}), \text{ for } 0 < \tau \leq t,$$

$$\hat{w}_\tau = 0, \text{ for } \tau \leq 0$$

With the daily volatility forecasts across all trading days in each month. Again, the selection of p and q is an important empirical question. Here BIC is used to choose p and q . The GARCH (1, 1) model has been found to be adequate in many applications and hence is used as a candidate model. [13]

d) GJR-GARCH

In order to accommodate the possible differential impact on conditional volatility from positive and negative shocks, Glosten et al. (1992) extended the GARCH model to capture possible asymmetries between the effects of positive and negative shocks of the same magnitude on the conditional variance. The GJR(p, q) model is given by:

$$h_t = \omega + \sum_{j=1}^p \alpha_j \epsilon_{t-j}^2 + \gamma I(\epsilon_{t-1}) \epsilon_{t-1}^2 + \sum_{i=1}^q \beta_i h_{t-i}$$

where the indicator variable, $I(x)$ is defined as:

$$I(x) = \begin{cases} 1, & x \leq 0 \\ 0, & x > 0 \end{cases}$$

for the case $p = q = 1$, $\omega > 0$, $\alpha_1 > 0$, $\alpha_1 + \gamma > 0$, $\beta_1 \geq 0$ are sufficient conditions to ensure a strictly positive conditional variance, $h_t > 0$. The indicator variable distinguishes between positive and negative shocks, where the asymmetric effect ($\gamma > 0$) measures the

contribution of shocks to both short-run persistence $\alpha_1 + \gamma/2$ and long-run persistence $\alpha_1 + \beta_1 + \gamma/2$. The GJR model has also had some important theoretical developments. In the case of symmetry of η_t , the regularity condition for the existence of the second moment of GJR(1, 1) is $\alpha_1 + \beta_1 + \gamma/2 < 1$. Moreover, the weak log-moment condition for GJR(1, 1),

$$E\left(\log\left[(\alpha_1 + \gamma I(\eta_t))\eta_t^2 + \beta_1\right]\right) < 0$$

is sufficient for the consistency and asymptotic normality of the QMLE. In empirical examples, the parameters in the regularity condition are replaced by their QMLE, the standardized residuals, η_t are replaced by the estimated residuals from the GJR model, for $t = 1, \dots, n$, and the expected value is replaced by their sample mean. Gonzalez-Rivera (1998) developed the Logistic Smooth Transition GARCH (LSTGARCH) which allows for a gradual change of threshold parameter in GJR. This model is given by:

$$h_t = \omega + \sum_{j=1}^p \alpha_j \varepsilon_{t-j}^2 + \gamma L(\varepsilon_{t-1}) \varepsilon_{t-1}^2 + \sum_{i=1}^q \beta_i h_{t-i}$$

where the Logistic smooth transition variable, $L(x)$ is defined as:

$$L(x) = \frac{1}{1 + \exp(-\theta x)}$$

Sufficient conditions to ensure a strictly positive conditional variance $h_t > 0$ are the same as those for GJR. The Logistic variable takes any value between zero and one and measures the magnitude of positive or negative shocks.[7]

e) EGARCH

Nelson (1991) proposed the exponential GARCH model, which is given as:

$$\log(h_t) = \omega + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^k \beta_j \log(h_{t-j})$$

As the range of $\log(h_t)$ is the real number line, the EGARCH model does not require any parametric restrictions to ensure that the conditional variances are positive. Furthermore, the EGARCH specification is able to capture several stylized facts, such as small positive shocks having a greater impact on conditional volatility than small negative shocks, and large negative shocks having a greater impact on conditional volatility than large positive shocks. Such features in financial returns and risk are often cited in the literature to support the use of EGARCH to model the conditional variances. Unlike the EWMA, ARCH, GARCH and GJR models, EGARCH uses the standardized rather than the unconditional shocks. Moreover, as the standardized shocks have finite moments, the moment conditions of EGARCH are straightforward and may be used as diagnostic checks of the underlying models. However, the statistical properties of EGARCH have not yet been developed formally. If the standardized shocks are independently and identically distributed, the statistical properties of EGARCH are likely to be natural extensions of (possibly vector) ARMA time series processes [8]

i. *Specification on Conditional Variance*

The strict form of the error distribution plays an important role in estimating the EGARCH(1,1) formulation. We conducted two different functional forms of the conditional density $\psi(\cdot)$, the Gaussian Normal distribution and the standardized Student-t distribution.

IV. EVALUATION OF MEASURES

Four measures are used to evaluate the forecast accuracy, namely, the root means square error (RMSE), the root mean absolute error (MAE), the Theil-U statistic and the LINEX loss function. They are defined by

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

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

$$Theil - U = \frac{\sum_{i=1}^n (\hat{\sigma}_i^2 - \sigma_i^2)^2}{\sum_{i=1}^n (\sigma_{i-1}^2 - \sigma_i^2)^2}$$

$$LINEX = \frac{1}{n} \sum_{i=1}^n \left[\exp(-a(\hat{\sigma}_i^2 - \sigma_i^2)) + a(\hat{\sigma}_i^2 - \sigma_i^2) - 1 \right]$$

where a in the LINEX loss function is a given parameter.

The RMSE and MAE are two of the most popular measures to test the forecasting power of a model. Despite their mathematical simplicity, however, both of them are not invariant to scale transformations. Also, they are symmetric, a property which is not very realistic and inconceivable under some circumstances (See BF).

In the Theil-U statistic, the error of prediction is standardized by the error from the random walk forecast. For the random walk model, which can be treated as the bench mark model, the Theil-U statistic equal. Of course, the random walk is not necessarily a naïve competitor, particularly for many economic and financial variables, so that the value of the Theil-U statistic close 1 is not necessarily and indication of bad forecasting performance. Several authors, such as Armstrong and Fildes (1995), have advocated using U-statistic and close relatives to evaluate the accuracy of various forecasting methods. One advantage of using U-statistic is that it is invariant to scalar transformation. The Theil-U statistic is symmetric, however.

In the LINEX loss function, positive errors are weighted differently from the negative errors. If $a > 0$, for example, the LINEX loss function is approximately linear for $\hat{\sigma}_i^2 - \sigma_i^2 > 0$ ('ove-predictions') and exponential for $\hat{\sigma}_i^2 - \sigma_i^2 < 0$ ('under predictions'). Thus, negative errors receive more weight tan positive errors. In the context of volatility forecasts, this implies that an under-prediction of volatility needs to be taken into consideration more seriously. Similarly, negative errors receive less weight than positive errors than positive errors when $a < 0$. BF argue an underestimate of the call option price, which corresponds an under-prediction of stock price volatility, is more

likely to be of greater concern to a seller than a buyer and the reverse should be true of the over-predictions. Christo Versen and Diebold (1997) provide the analytical expression for the optimal LINEX prediction under assumption that the process is conditional normal. Using a series of annual volatilities in the UK stock market, Hwang et al. (1999) show that the LINEX forecasts outperform the conventional forecasts with an appropriate LINEX parameter, a. BF also adopt asymmetric loss functions to evaluate forecasting performance. An important reason why the LINEX function is more popular in the literature is it provides the analytical solution for the optimal prediction under conditional normality, while the same argument cannot be applied to the loss functions used by BF.[13]

V. RESULTS

Table-4: Forecasting performance of competing models under symmetric loss

	RMSE	Rank	MAE	Rank	Theil-U	Rank
GARCH(1,1)_Student-t	0.001771	1	0.00000314	1	0.958604	1
GARCH(11)_Skew Normal	0.002834	10	0.00000805	10	2.461194	10
GARCH(1,1)_Normal	0.001858	6	0.00000345	6	1.055114	6
MA(5)	0.001817	4	0.0000033	4	1.009108	4
MA(6)	0.001825	5	0.00000333	5	1.017771	5
EGARCH(1,1)_Student-t	0.001883	7	0.00000354	7	1.083849	9
EGARCH(1,1)_Skewed Normal	0.001883	8	0.00000354	8	1.083846	7
EGARCH(1,1)_Normal	0.001883	9	0.00000354	9	1.083847	8
GJR-GARCH(1,1)_Student-t	0.001773	2	0.00000314	2	0.96097	2
GJR-GARCH(1,1)_Skew Normal	0.002844	11	0.00000809	11	2.473141	11
GJR-GARCH(1,1)_Normal	0.00309	12	0.00000955	12	2.918154	12
Exponential Smoothing	0.001789	3	0.0000032	3	0.978268	3

Table-5: Forecasting performance of competing models under asymmetric loss

	Linex	Rank	Linex	Rank	Linex	Rank	Linex	Rank
	$a = 10$		$a = -10$		$a = 20$		$a = -20$	
GARCH(1,1)_Student-t	0.000162669	1	0.000151388	1	0.000676337	1	0.000585645	1
GARCH(1,1)_Skew Normal	0.000405247	10	0.000400391	10	0.001634105	10	0.001594809	10
GARCH(1,1)_Normal	0.000178935	6	0.000166714	6	0.000743415	6	0.000645185	6
MA(5)	0.000171325	4	0.000159274	4	0.000712632	4	0.000615759	4
MA(6)	0.000172781	5	0.000160654	5	0.000718625	5	0.000621147	5
EGARCH(1,1)_Student-t	0.000183852	9	0.000171217	7	0.000764041	9	0.000662482	9
EGARCH(1,1)_Skew Normal	0.000183851	7	0.000171217	8	0.000764039	7	0.00066248	7
EGARCH(1,1)_Normal	0.000183851	8	0.000171217	9	0.00076404	8	0.00066248	8
GJR-GARCH(1,1)_Student-t	0.000163044	2	0.000151787	2	0.000677786	2	0.000587286	2
GJR-GARCH(1,1)_Skew Normal	0.000407189	11	0.000402359	11	0.001641835	11	0.001602747	11
GJR-GARCH(1,1)_Normal	0.000478697	12	0.000476454	12	0.001922861	12	0.001904477	12
Exponential Smoothing	0.000166082	3	0.000154411	3	0.000690787	3	0.000596981	3

Here we rank our models with four evaluation of measures: RMSE, MAE, Theil-U and LINEX loss functions. From the above results it is noted all the evaluation method indicates that the GARCH (1, 1) model with conditional distribution Student-t provides the most accurate forecasts and the GJR-GARCH (1, 1) model which is also with conditional distribution Student-t which ranks two.

In RMSE, Exponential Smoothing which has placed third forecasts 1.01 per cent and 0.9 per cent less accurately then GARCH (1, 1) _Student-t and GJR-GARCH (1, 1) _Student-t respectively. Where the GJR-GARCH (1, 1) _Normal has placed last and forecast 74.47 per cent and 74.28 per cent less accurately then the first and second superior model. So, the GJR-GARCH (1, 1) _Student-t model provides the worse forecast.

In MAE, Theil-u and in all the Linex loss functions the first, second and the third are the same one which are GARCH(1,1)_Student-t, GJR-GARCH(1,1)_Student-t and Exponential Smoothing respectively. The GJR-GARCH(1,1)_Normal is placed last by all the evaluation methods. It forecasts 204.14 per cent, 204.42 per cent, 194.28 per cent, 214.72 per cent, 184.35 per cent and 225.19 per cent less accurately then the GARCH (1, 1) _Student in MAE, Theil-u, Linex (a=10), Linex (a=-10), Linex (a=20) and Linex (a=-20) respectively. Which shows great evidence that the GJR-GARCH (1, 1) forecasts worse among the twelve competing models for the Dhaka Stock Exchange.

Here all the linex loss functions evaluates similarly except few cases such as EGARCH(1,1)-Skew Normal and EGARCH(1,1)-Normal have placed seven and eight in all the Linex loss functions except Linex (a=-10) etc.

VI. CONCLUSION

The stock market is a pivotal institution in the financial system of a country. In the stock market, when share prices fall below the normal, a warning is given out that the economy is running down and may approach the points of collapse. On the other hand, when the prices are abnormally high, it is the indication of fever in the system and danger of possible death. And these ups and downs are the root cause of what is called volatility which indicates the fickleness or the instability of the stock prices in the market.

The volatility is the important issue for the financial market particularly for the stock market. So in this study our main object is to forecast the future volatility by the best model for the Dhaka Stock Exchange. There is a large literature on forecasting volatility, Many econometric models have been used. However, no single model is superior. Using US Stock data, for example, Akgiray (1989), pagan and Schwert (1989) and Brooks (1998) finds the GARCH models outperform most competitors. Brailsford and Fafi (1996) (hereafter BF) find that the GARCH models are slightly superior to most simple models for forecasting Australian monthly stock index volatility. Using data sets from Japanese and Singaporean markets respectively, however, Tse (1991) and Tse and Tung (1992) find that the Exponential Weighted Moving Average models provide more accurate forecasts than the GARCH model Oimson and Marsh (1990) find in the UK equity market more parsimonious models such as the Smoothing and Regression models perform better than less parsimonious models, although the GARCH models are not among the set of competing models considered.

This paper examined twelve univariate models for forecasting stock market volatility of the DSE General Index. After comparing the forecasting performance of all twelve models, it was found that the GARCH (1, 1) with conditional distribution student-t model is superior according to the RMSE, MAE, Theil-U and four asymmetric loss functions.

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