International Journal of Statistical Sciences *ISSN 1683–5603*
Vol. 7, 2008, pp 59-72

On the Comparison of Performance of Different Volatility Models for Bangladesh Exchange Rate

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[Received August 15, 2005; Revised February 17, 2008; Accepted February 25, 2008]

Abstract

Exchange rates are highly volatile. A good prediction of this volatility makes sure the better policy implication in financial market. Our paper aims is to examine the feasibility of a wide variety of popular volatility models to predict the volatility in Bangladesh foreign exchange market. We have fitted Random Walk (RW), Autoregressive Moving Average (ARMA), Generalized Autoregressive Conditional Heteroscedasticity (GARCH), and Extensive GARCH (IGARCH, GARCH-M and AGARCH) models with Normal, Student-*t* and Generalized Error Distribution. Using the daily closing price index for Bangladesh foreign exchange market from January 1, 1999 to February 28, 2005 we have found that the student-*t* distribution into GARCH model improves the better performance to forecast the volatility of exchange rate.

Keywords and Phrases: ARMA Model, Expanded GARCH Model, Student-*t* Distribution, Generalized Error Distribution.

AMS Classification: 62M10.

1 Introduction

Bangladesh adopted the freely floating exchange rate system since May 31, 2003. But the economic environment is still now underdeveloped with weak financial system and inefficient market management, within these features and under freely floating system Bangladesh cannot make the foreign exchange market stable and this will affect the domestic economy in a long term. Since there are import-export unbalances so it is more likely to face some trouble in Taka-Dollar option pricing. Already some shocking consequences are now happening in Bangladesh. Recently, exchange rate fluctuations are very high and the demand is higher than the supply of USD. Importers are loosing their money and import is substantially decreasing day by day. So, the prices of daily essentials are getting higher yielding a lot of misery for general people. If such situations continue, more crises will take place in future in the economy of Bangladesh. In the recent situations, it is important to analyze the volatility and to take necessary steps to prevent the jump. We would like to model the existing volatility in the exchange rate and to recommend a suitable model to explain this volatility. In these aspects, here we estimated different popular volatility models by MLE method. The models considered here are Random Walk (RW) models, Autoregressive Moving Average (ARMA) model, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models, and Expanded GARCH (IGARCH, GARCH-M and AGARCH) models with normal as well as with student-t and GED assumption.

The Random Walk (RW) model was found to out-perform the traditional structural models. In fact, Meese and Rogoff (1983) concluded that for some assets in particular, exchange rate, prices and fundamentals are largely disconnected. However, Fundamentals succumbed significant explanatory power only over long horizons Mark (1995). Goldstein (1998) presented a paper at the International Monetary Fund's seminar on Chinese Foreign Exchange System and discussed about adjusting China's exchange rate policies. But, the policy of exchange rate adjustment accounts the volatility of the exchange rates. Price spiral of essentials are also related to the volatility of exchange rates. Thus, it is very important to know the nature of import-export balance and volatility of exchange rates. Thousands of works have been conducted on volatility models those solved many challenges in real-world problems. Longmore and Robinson (2004) compared the performance of linear GARCH models to forecast the volatility of returns in the Jamaican foreign exchange market. McMillan and Speight (2004) conducted a study on reassessing the performance of GARCH Models. This leads to assess many models and pluck the best one. Tabak et al.(2002) examined the relation between dollar-real exchange rate volatility implied on option prices and subsequent realized volatility. To model the stock market volatility Gokcan (2000) compared linear and non-linear GARCH models. Vlaar and Palm (1993) used conditional heteroscedastic models to examine the weekly exchange rates in European monetary system. Besides these, many authors discussed about the volatility modeling (Chong et al. (1999), Fabozzi et al. (2004), and Hasan et al. (2004)). In Bangladesh, Chowdhury (1994) studied the statistical properties of daily returns from Dhaka stock exchange (DSE). However, a good modeling is necessary to predict the exchange rate volatility. Thus, there exists a scope to fit a class of volatility models and to set up an appropriate volatility model for Bangladesh foreign exchange market. Thus, our aim in this paper is to compare different kinds of volatility models for Bangladesh foreign exchange rate and to recommend a model for better performance.

2 Methodology

The main purpose of this study is to elucidate a comprehensive analysis on the volatility characteristics of the Bangladesh foreign exchange market. This study includes models which are usually used in domestic and international volatility rate studies such as Random Walk model, Autoregressive Moving Average model, Generalized Autoregressive Conditional Heteroscedasticity model, Expanded GARCH (TGARCH, IGARCH, GARCH-M), and student-t, generalized error distribution.

2.1 Random Walk (RW) model

The random walk model was put forward first by Samuelson (1965) at the earliest stage. He believed that stock price is decided by the actual value of the interest on shares to convert into cash; its fluctuation at the present appearance is random walk. Suppose $\{\varepsilon_t\}$ is a random series with mean μ and constant variance σ^2 and is serially uncorrelated. Then the series $\{r_t\}$ is said to be random walk if

$$r_t = r_{t-1} + \varepsilon_t$$

In this paper, we have assumed that the return series of stock price is $\{r_t\}$. Then the random walk model follows the process: $r_t = \mu + \varepsilon_t$

Among them, μ is the model parameter, $E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma^2$, and ε_t follows normal distribution.

2.2 Autoregressive Moving Average (ARMA) model

The Autoregressive Moving Average (ARMA) model is a kind of model that describes the sequence relativity. Proposed by the Box and Jenkins (1970) first, they thought that single value consisting of sequence has the uncertainty, but from the whole variation of sequence there is certain regulation which is usually used for short-term estimate of time sequence. If the series $\{r_t\}$ satisfies $ARMA(p, q)$, then $\{r_t\}$ can be described using the basic form:

$$r_t = \mu + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \xi_j \varepsilon_{t-j} + \varepsilon_t$$

Where ϕ_i $(i = 1,\ 2,\ .....p)$ and $\xi_j (j = 1,\ 2,\ .....,q)$ are parameters, $E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma^2$, and ε_t's follow particular distribution.

2.3 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model

Bollerslev (1986) coined the term generalized autoregressive conditional heteroscedasticity (GARCH). The conditional variance of ε_t is assumed to be constant for random walk (RW) and Autoregressive (AR) models. But in financial time series, data are usually volatility clustering that means ε_t the conditional volatility changes over time. Now, for the stock price return series $\{r_t\}$ the simple $GARCH(p,q)$ model can be described in the following form:

$$\begin{cases} r_t = \mu + \varepsilon_t \\ \quad E(\varepsilon_t \,|I_{t-1}) = 0, \quad E(\varepsilon_t^2 \,|I_{t-1}) = h_t \\ h_t = \alpha + \sum\limits_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum\limits_{i=1}^{p} \beta_i h_{t-i} \end{cases}$$

Here I_{t-1} is the assembly of all information on $t-1$, α, $\alpha_j > 0$, $j = 1, 2, \ldots\ldots, q$, and $\beta_i > 0$, $i = 1, 2, \ldots\ldots p$.
The GARCH-mean (GARCH-M) reflecting the presence of conditional variance in the conditional mean. If we convert regression coefficients in the $GARCH(p,q)$ model to $r_t = \mu + \delta\sqrt{h_t} + \varepsilon_t$ on the basis of the simple $GARCH(p,q)$ model, then the model changes into $GARCH(p,q)-M$ model which is used to catch the phenomenon that the change of conditional variance in pace with time may cause the change of conditional mean pace in time. The GARCH-M model is a natural extension of GARCH model, since it introduces conditional variance (or standard deviation).

2.4 Expanded GARCH (TGARCH, IGARCH)

The relationship between stock return volatility and the sign of stock returns is also one of interest. Engle and Ng (1993) argued that the relationship has a negative sign, that is, when stock return decreases the volatility increases and vice-versa. This phenomenon is termed as the 'leverage effect'. It may be modeled by the asymmetric volatility model or Threshold Autoregressive Conditional Heteroscedasticity (TGARCH) model in which a multiplicative 'indicator' dummy variable is introduced to capture the influence of the sign of stock return on the conditional variance. In addition, Asymmetric model (Bollerslev et al. (1992) and Palm, 1996) includes Exponential GARCH (EGARCH), the component GARCH, and GJR-GARCH (Glosten et al. (1992) models. This study chooses TGARCH model in asymmetric model for discussion only. To explain the leverage effect of volatility, we can change the volatility equation in simple $GARCH(p,q)$ model into

$$h_t = \alpha + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \varphi \varepsilon_{t-1}^2 d_{t-1} + \sum_{i=1}^{p} \beta_i h_{t-i}$$

Where d_t is a dummy variable such that $d_t = \begin{cases} 1, & \varepsilon_t < 0 \\ 0, & Otherwise \end{cases}$ and then the model changes into the TGARCH model.

Integrated GARCH (IGARCH) is a kind of infinite variance model in GARCH branch (Engel and Bollerslev, 1986). Here, it is supposed that the volatility is satisfied with the equation $h_t = \alpha + \lambda\varepsilon_{t-1}^2 + (1-\lambda)h_{t-1}$ where $0 \leq \lambda \leq 1$. When $\alpha = 0$, IGARCH Model equals to an infinite index shift average model, that is, $h_t = (1-\lambda)\sum_{i=1}^{\infty} \lambda^i \varepsilon_{t-i}^2$.

2.5 Error Distribution

The assumption for error distribution is the foundation of the maximum likelihood estimation to the model. Usually we suppose the error follows normal distribution. But the assumption of normal distribution for excess kurtosis and fat tail of financial return series may gives error result of the model. Therefore, we should add some fat tail to describe the characteristic of financial data.

2.5.1 Normal

The Normal distribution is by far the most widely used distribution when estimating and forecasting GARCH models. Considering $\varepsilon_t = z_t\sigma_t$, the log-likelihood function of the standard normal distribution is given by

$$L_T = -\frac{1}{2}\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2\right]$$

where T is the number of observations.

2.5.2 Student-t

For the Student-t distribution, the log-likelihood contributions are of the form:

$$L_T = \ln\left[\Gamma\left(\frac{\upsilon+1}{2}\right)\right] - \ln\left[\Gamma\left(\frac{\upsilon}{2}\right)\right] - 0.5\ln\left[\pi\left(\upsilon-2\right)\right]$$
$$-0.5\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+\upsilon)\ln\left(1+\frac{z_t^2}{\upsilon-2}\right)\right]$$

where υ is the degree of freedom $2 < \upsilon \leq \infty$ and $\Gamma(.)$ is the gamma function. When $\upsilon \to \infty$, we have the normal distribution. So that the lower υ the fatter the tails.

2.5.3 Generalized Error

For the GED, we have:

$$L_T = -\frac{1}{2}\ln\left[\frac{\overline{)(1/\lambda)^3}}{\overline{)(3/\lambda)}\,(\lambda/2)^2}\right] - 0.5\ln(\sigma_t^2) - \left[\frac{\overline{)(3/\lambda)}z_t^2}{\sigma_t^2\,\overline{)(1/\lambda)}}\right]^{\lambda/2}$$

where the tail parameter $\lambda > 0$. The GED is a normal distribution if $\lambda = 2$, and fat-tailed if $\lambda < 0$.

3 Data and Descriptive Statistics

We analyze the daily closing price index for Bangladesh foreign exchange market from January 01, 1999 to February 28, 2005. The analysis is done using the econometric package Gauss window 6.0 for volatility modeling & Eviews. The parameter estimation method that we choose is MLE. In estimation process, the computational method is BHHH*. Taking the significant difference after May 31, 2003 into consideration, we introduce dummy variables to mean and volatility that are represented by μ_D and σ_D, respectively with 0 value after May 31, 2003 and 1 otherwise. Bangladesh has been introduced the floating exchange rate system after May 31, 2003 and the choice of dummy variable has been made based on this date. The return indices for Bangladesh foreign exchange rate have been taken from http://www.oanda.com/convert/fxhistory. Daily returns are calculated by using the following formula:

$$r_{it} = \log(I_t) - \log(I_{t-1})$$

Where I_t is the return index at time t.
Some of the descriptive statistics for daily returns have been displayed in Table 1. Mean return of the Bangladesh foreign exchange rate (Tk/USD) is 0.013 percent where the Volatility (measured as a standard deviation) is 0.35 percent. The returns of Bangladesh foreign exchange market are leptokurtic, that is, 148.28 (kurtosis for normal distribution should be positive three) and the return series also display significant skewness 4.7 (skewness for normal distribution should be zero). According to Jarque-Berra statistics normality is rejected for the return series. We report the Ljung-Box Q (12) statistics for testing that all autocorrelations up to lag 12 are jointly equal to zero. At lag 12 we reject the hypothesis of no autocorrelation at 5% level of significance. Overall, these results clarify supporting the rejection of the hypothesis that Bangladesh foreign exchange market daily returns are time series with independent daily values. Moreover, the statistics justify the use of GARCH specification in

*BHHH is a numerical optimization method from Berndt, Hall, Hall, and Hausman (1974). Used in Gauss, for example. (Econterms)

Figure 15: The Trend of Exchange Rate Return of Bangladesh

4 In-Sample Performance

Our substantial analyses estimate that the parameters of various models by using MLE method and are used to compare the performance of the different kind of models.

4.1 Random walk (RW) and Autoregressive (AR) model

Table 2 listed the estimated result of Random Walk and Autoregressive model with their t statistics as well as log-likelihood values. The estimates of mean of each model are insignificant and the dummy variable is also insignificant, but the volatility and it's dummy is significant and is reflecting the higher volatility after May 2003 (Table 2). AR Model shows significant lag 1 and lag 2 effects and explain better the return series. It is showing the autocorrelation. Although the value of log-likelihood of AR model is bigger than the log-likelihood value of RW model. It does not imply that AR model perform better than RW model because adding lag variables increases the log- likelihood (the log likelihood for RW is 9511 and for AR is 9640). Thus, we need to test whether the AR(2) model explains the internal regularity of return sequence better than RW model.

Table 2: MLE of RW and AR Models with Normal Distribution

Parameters	RW	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
μ	0.00014 (1.1290)	0.000182 (1.5041)	0.000216 (1.7560)	0.000212 (1.7096)	0.000209 (1.6991)	0.000217 (1.7786)
μ_D	-0.000012 (-0.0784)	-0.000015 (-0.1006)	-0.000018 (-0.1184)	-0.000018 (-0.1176)	-0.000017 (-0.1133)	-0.000017 (-0.1140)
σ	0.0032 (3.55555)	0.0031 (6.2000)	0.0030 (7.500)	0.0031 (6.200)	0.0031 (6.200)	0.0031 (0.0005)
σ_D	0.0005 (5.00)	0.0004 (4.00)	0.0004 (4.00)	0.0004 (4.00)	0.0004 (4.00)	0.0004 (4.00)
ϕ_1		-29.1111 (-14.426)	-34.5191 (-16.648)	-34.2680 (-16.245)	-34.2860 (-16.249)	-34.2259 (-16.228)
ϕ_2			-18.5590 (-8.9548)	-18.0927 (-8.2333)	-17.8206 (-7.9855)	-17.7511 (-7.9658)
ϕ_3				1.3462 (0.6354)	1.8711 (0.8336)	1.1546 (0.5100)
ϕ_4					1.4913 (0.7051)	0.1366 (0.0647)
ϕ_5						-3.9322 (-1.8636)
Log Likelihood	9511.6275	9606.3111	9640.9076	9636.3493	9631.7464	9628.5805

Note: The value in the prentices is the t statistics. The six RW and AR models are nested by the following specification: $r_t = (\mu + \mu_D) + \sum_{i=1}^{5} \phi_i r_{t-i} + (\sigma + \sigma_D)\varepsilon_t,\ \varepsilon_t \sim N(0,1)$

4.2 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model

Estimation results of GARCH models including t-statistics as well as log-likelihood value are listed in Table 3. Comparison of log-likelihood value with Random Walk and AR models we found that adding GARCH effect significantly improves the in-sample fit of the models. The log-likelihood increases from 10100 to more than 10200. It demonstrates that GARCH effect increase likelihood values. In Table 3, all estimates of GARCH parameters are significant. The significance of α_1 parameter in the model indicates the tendency of the shocks to persist. The sum of GARCH parameter estimates, $\alpha_1 + \beta$ is less than 1 which reflects limited volatility of Bangladesh foreign exchange market. The dummy variable σ_D is significantly positive and differs from zero, that is, there exists a higher volatility after May 2003.

Table 3: MLE of GARCH Models with Normal Distribution

Parameters	RW-GARCH	AR(1)-GARCH	AR(2)-GARCH	AR(3)-GARCH	AR(4)-GARCH	AR(5)-GARCH
μ	0.000094 (1.085)	0.000177 (1.4750)	0.000095 (1.11764)	0.000089 (1.047059)	0.000085 (1.00)	0.000086 (1.01176)
μ_D	0.000042 (0.396)	0.000047 (0.3197)	0.000060 (0.5769)	0.000072 (0.692308)	0.000085 (0.8173)	0.000086 (0.8269)
α	7.03E-07 (9.7638)	1.836 E-05 (16.149)	6.45 E-07 (9.4852)	6.47 E-07 (9.514706)	6.48 E-07 (9.5294)	6.64 E-07 (9.2222)
α_1	0.1459 (9.11875)	0.0019 (6.3333)	0.1389 (9.0784)	0.1421 (9.050955)	0.1447 (8.9875)	0.1483 (8.9337)
β	0.7891 (62.628)	0.9911 (49.555)	0.7938 (63.504)	0.7910 (61.79688)	0.7878 (60.137)	0.7820 (56.666)
σ_D	0.1959 (4.3923)	0.1347 (3.3095)	0.2224 (4.7931)	0.2270 (4.871245)	0.2333 (4.9638)	0.2308 (4.9002)
ϕ_1		-24.6238 (-12.176)	-33.8428 (-8.4590)	-35.3575 (-8.74991)	-36.3509 (-9.0580)	-36.8727 (-9.2742)
ϕ_2			-25.1080 (-6.0075)	-27.7747 (-6.45308)	-30.7187 (-6.9739)	-32.4989 (-7.3837)
ϕ_3				-12.5644 (-2.85004)	-15.6896 (-3.4773)	-19.3178 (-4.1814)
ϕ_4					-11.8837 (-2.5864)	-14.9935 (-3.3221)
ϕ_5						-16.2222 (-3.8223)
Log Likelihood	10179.29	9645.51	10209.98	10208.840	10206.812	10208.50

Note: The value in the prentices is the t statistics; the six GARCH models are nested by the following specification: $r_t = (\mu + \mu_D) + \sum_{i=1}^{5} \phi_i r_{t-i} + (1 + \sigma_D)\varepsilon_t,\ \varepsilon_t = \sqrt{h_t} z_t$, and $h_t = \alpha + \alpha_1 h_{t-1} + \beta \varepsilon_{t-1}^2,\ z_t \sim N(0,1)$

4.3 Extensive GARCH (IGARCH, GARCH-M, AGARCH)

Parameter estimation results of extensive GARCH models are listed in Table 4 including their t statistics and log-likelihood values. The results show that the extended GARCH especially GARCH-M, AGARCH and IGARCH do not increase the log-likelihood value; even it decreases the log-likelihood value comparing the normal GARCH likelihood. However, compared to RW and AR models, it increases log-likelihood value. Table 4 shows that the mean and their dummies of all expanded GARCH models are significant. The dummy variables μ_D and σ_D are significantly positive and differs from zero that reveals a higher volatility after May 2003. The sum of GARCH parameter estimates, $\alpha_1 + \beta$ is also less than one which indicates to limited volatility of Bangladesh foreign exchange market. Thus, the extensive GARCH is not better choice compared to the general GARCH model.

Table 4: MLE of Extensive GARCH Models with Normal Distribution

Parameters	RW-AGARCH	RW-IGARCH	RW-GARCH-M
μ	0.000056 (0.62222)	0.000256 (3.657143)	-0.000086 (-0.41148)
μ_D	0.000021 (0.198113)	0.001005 (12.10843)	0.000049 (0.462264)
α	7.37 E-07 (9.329114)		7.11 E-07 (9.608108)
α_1	0.1196 (7.035294)	0.1617 (21.27632)	0.1463 (9.086957)
β	0.7847 (58.12593)		0.7881 (61.57031)
σ_D	0.1805 (4.074492)	0.7811 (15.84381)	0.1923 (4.302013)
α_2	0.0719 (2.152695)		
δ			0.000853 (0.952009)
Log likelihood	10181.835	9882.0225	10179.7425

Note: The value in the prentices is the t statistics; the three Extensive GARCH models are nested by the following specification: $r_t = (\mu + \mu_D) + (1 + \sigma_D)\varepsilon_t,\ \varepsilon_t \sim N(0, 1)$

4.4 GARCH Models with student-t Distribution

The estimated parameters of GARCH models with t-distribution have been incorporated in Table 5 including their t statistics and log-likelihood values. The results connote that the mean and their dummy are significant except AGARCH-t . But, all coefficients of GARCH models are significant. The sum of GARCH parameter estimates, $\alpha_1 + \beta$ is less than 1 which elucidates that the volatility are limited and the data are stationary, that is, the models are well fitted.

Table 5: MLE for Extensive GARCH Models with t- distribution

Parameters	RW-GARCH-t	RW-GARCH-M-t	RW-IGARCH-t	RW-AGARCH-t
μ	0.00012 (3.1578)	-0.000176 (-4.292)	-0.00176 (-10.196)	0.000034 (0.680)
μ_D	-0.00011 (-3.078)	0.000175 (4.2682)	-0.00033 (1.3073)	-0.000029 (-0.58)
α	1.200E-07 (8.45)	1.500E-07 (8.94)		2.600E-07 (9.59)
α_1	0.177 (52.23529)	0.1637 (16.370)	0.0937 (8.60)	0.2084 (20.84)
β	0.642 (56.39474)	0.6455 (60.3271)		0.7316 (187.589)
v	3.1018 (31.80)	3.0018 (39.758)	3.975 (34.217)	3.0008 (29.69)
α_2				1.4995 (52.7992)
δ		0.2072 (11.38462)		
Log likelihood	13869.2025	13940.775	12068.195	13526.1675

Note: The value in the prentices is the t statistics, the four Extensive GARCH with t distribution, models are nested by the following specification: $r_t = (\mu + \mu_D) + \varepsilon_t$, ε_t follows t distribution with v degrees of freedom.

4.5 GARCH models with Generalized Error Distribution

Parameter estimation results of GARCH model with Generalized Error distribution and their corresponding t statistics are give in table 6. The results indicate that all of the parameters including their mean and dummy are significant. The sum of the GARCH parameter $\alpha_1 + \beta$ is less than 1 which indicates the models are fitted well but it gives less log-likelihood value than student-t distribution.

To sum up, our in-sample discussion divulges some important stylized facts for modeling volatility of Bangladesh foreign exchange market. These are:

(1) Considering the GARCH can improve the in-sample fit, although some parameters are insignificant. Furthermore, the specification of conditional mean can

Table 6: MLE for Extensive GARCH Models with Generalized error distribution

Parameters	RW-GARCH-g	RW-GARCH-M-g	RW-IGARCH-g	RW-AGARCH-g
μ	0.000202 (4.5182)	-0.000046 (-3.982)	-0.00716 (-15.246)	0.000254 (2.810)
μ_D	0.000041 (7.472)	0.000374 (6.6512)	0.000045 (3.7213)	-0.000037 (-2.58)
α	1.120E-06 (10.52)	1.301E-08 (9.90)		3.240E-05 (10.5)
α_1	0.077 (32.5228)	0.2375 (34.3340)	0.0835 (14.601)	0.2240 (28.24)
β	0.4201 (38.3444)	0.6957 (84.3751)		0.6678 (98.859)
λ	0.9018 (27.805)	0.5614 (54.354)	1.4575 (52.157)	1.0001 (34.92)
α_2				1.5944 (42.9792)
δ		0.4052 (21.3565)		
Log likelihood	12564.2145	12987.2460	11034.1245	12236.7125

Note: The value in the prentices is the t statistics, the four Extensive GARCH with t distribution, models are nested by the following specification: $r_t = (\mu + \mu_D) + \varepsilon_t,\ \varepsilon_t$ follows Generalized error distribution.

affect the estimated results of other parameters such as volatility and level effect.

(2) It is important to model conditional heteroscedasticity through GARCH. Consideration of extended GARCH effect has no help on improving in-sample fit. It is quite different from the estimation results in USA and other developed as well as some of developing countries as well.

(3) GARCH with t distribution helps capture volatility clustering and especially the excess kurtosis and heavy-tails of return series.

(4) Bangladesh foreign exchange market return behaves quite differently during the period from 31 May 2003 to 28 February 2005. The volatility seems significantly higher during this period.

5 Concluding Remarks

To model the volatility of foreign exchange market in Bangladesh, we fit Random Walk, Autoregressive Moving Average, Generalized Autoregressive Conditional Heteroscedasticity and Expanded GARCH models. On the light of the fitting performance of the models, we may draw following remarks.

(1) AR model, which is added into lag, can not improve the performance and error of the model in contrast to Random Walk model. There is no significant difference between the RW and AR model.

(2) Adding the GARCH effect on the basis of random walk model can improve the performance and error of the model to some extent. GARCH model which contains the leverage effect and regime shift, that is, extensive GARCH model do a little help to improve the model performance. Evermore, it can enlarge the specification error of the model. In other words, it means that using the Risk matrices method (Morgan, 1995), is inappropriate in Bangladesh foreign exchange market.

(3) Adding the student t distribution into GARCH model improve the performance of model dramatically although they could not reach adequate specification for foreign exchange rate return dynamics of Bangladesh.

(4) Adding generalized error distribution into GARCH model increases the log-likelihood but it also give less log-likelihood than student-t distribution.

References

[1] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics*, 31, 307-327.

[2] Bollerslev, T., Chou, Y. R. and Kroner, F. K. (1992). ARCH modeling in finance, *Journal of Econometrics*, 52, 5-59.

[3] Box, G. E. P. and Jenkins, G. M. (1970). Time Series Analysis Forecasting and Control, *San Francisco*: Holden-Day.

[4] Chong, C.W., Ahmad, M. I. and Abdullah, M. Y. (1999). Performance of GARCH Models in Forecasting Stock Market Volatility, *Journal of Forecasting*, 18, 333-343.

[5] Chowdhury, A. (1994). Statistical properties of daily returns from Dhaka stock exchange, *Bangladesh Development Studies*, 26, 61-76.

[6] Engle, F. R. and Ng, K. V. (1993). Measuring and testing the impact of news on volatility, *The Journal of Finance*, XLVIII (5): 17, 49-78.

[7] Engle, R. and Bollerselv, T. (1986). Modeling the persistence of conditional variances. *Econometric Reviews*, 5: 81-87.

[8] Fabozzi, F. J., Tunaru R. and Wu, T. (2004). Modeling Volatility of Chinese Equity Markets, *Annals of Economics and Finance*, 5: 79-92. Peking University Press, USA.

[9] Goldstein, M. (1998). The Asian Financial Crisis: Causes, Curses and Systematic implications, *Policy Analyses in International Economics No. 55*, Washington, DC: Institute for International Economics.

[10] Glosten, L., Jagannathan, R. and Runkle, D. (1992). On the relation between the expected value and the volatility nominal excess return on stocks, *Journal of Finance*, 46:1779- 801.

[11] Gokcan, S. (2000). Forecasting Volatility of Emerging Stock Markets: Linear versus Non-linear GARCH Models, *Journal of Forecasting*, 19: 499-504.

[12] Hasan, M. K., Basher, S. A. and Islam, M. A. (2004). Time Varying Volatility and Equity Returns in Bangladesh Stock Market, *Finance 0310015*, Economics working paper Achieved at WUSTL

[13] Longmore, R. and Robinson, W. (2004). Modeling and Forecasting Exchange Rate Dynamics in Jamaica: An Application of Asymmetric Volatility Models, *Working Paper WP2004/03*, Research Services Department Bank of Jamaica,

[14] Mark, N. C. (1995). Exchange Rates and Fundamentals: Evidence of Long-Horizon Predictability, *The American Economic Review*, 85(1): 201-218.

[15] McMillan, D.G. and Speight, A. H. (2004). Daily Volatility Forecasts: Reassessing the Performance of GARCH Models, *Journal of Forecasting*, 23: 449-460

[16] Meese, R. and Rogoff, K. (1983). Empirical Exchange Rate Models of the Seventies: Do They Fit the Out of Sample? *Journal of International Economics*, 14(1/2): 3-24.

[17] Morgan, J. P. (1995). RiskMetrics-technical document, 3rd ed. New York: Morgan Trust Company Global Research, 1995.

[18] Palm, F. C. (1996). GARCH Models of Volatility in Maddala, G. S. and C.R. Rao (eds.), it Handbook of Statistics, Vol.14, Amsterdam, Elsevier Science B.V., pp. 209-40.

[19] Samuelson, P. A. (1965), Proof that properly anticipated prices fluctuate randomly, *Industrial Management Review*, 6:41-50.

[20] Tabak, B. M., Chang, E. J. and Andrade, B. S. C. (2002). Forecasting Foreign Exchange Volatility, *University of Berkeley*, Haas Business School, Brazil.

[21] Vlaar, P. and Palm, F. (1993). The Message in Weekly Exchange Rates in the European Monetary System: Mean Reversion, Conditional Heteroskedasticity, and Jumps, *Journal of Business and Economic Statistics* 11: 351-60.