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Modelling & Forecasting Volatility of Daily Stock Returns Using GARCH Models: Evidence from Dhaka Stock Exchange

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Abstract

Modelling volatility has become increasingly important in recent times for its diverse implications. The main purpose of this paper is to examine the performance of volatility modelling using different models and their forecasting accuracy for the returns of Dhaka Stock Exchange (DSE) under different error distribution assumptions. Using the daily closing price of DSE from the period 27 January 2013 to 06 November 2017, this analysis has been done using Generalized Autoregressive Conditional Heteroscedastic (GARCH), Asymmetric Power Autoregressive Conditional Heteroscedastic (APARCH), Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH), Threshold Generalized Autoregressive Conditional Heteroscedastic (TGARCH) and Integrated Generalized Autoregressive Conditional Heteroscedastic (IGARCH) models under both normal and student's t error distribution. The study finds that ARMA (1,1)- TGARCH (1,1) is the most appropriate model for in-sample estimation accuracy under student's t error distribution. The asymmetric effect captured by the parameter of ARMA (1,1) with TGARCH (1,1), APARCH (1,1) and EGARCH (1,1) models shows that negative shocks or bad news create more volatility than positive shocks or good news. The study also provides evidence that student's t distribution for errors improves forecasting accuracy. With such an error distribution assumption, ARMA (1,1)-IGARCH (1,1) is considered the best for out-of-sample volatility forecasting.

Keywords: ARCH, GARCH, Volatility, Forecasting, DSE

1. Introduction

Over the past decades, modelling and forecasting volatility of financial time series has become a fertile area for research (Zakaria & Winker, 2012). Many models in the field of academic finance use variance (or standard deviation) as a measure of uncertainty (Niyitegeka & Tewari, 2013). "In most of these models' variance is assumed to be constant through time; this is known as homoscedasticity" (Brooks, 2002, p. 386). Financial time series such as stock prices often exhibit volatility clustering. The time series are found to depend on their own past values and

exhibit non-constant variance or heteroscedasticity. A time series with some periods of low volatility and some periods of high volatility is said to be “volatility clustering” (Banumathy & Azhagaiah, 2013). It has been found that the stock market volatility changes with time and exhibits “volatility clustering.”

The knowledge of volatility is of crucial importance for many economic and financial applications like portfolio management, risk management, asset pricing and investment in general (Floros, 2008; Niyitegeka & Tewari, 2013; Zakaria & Winker, 2012; Parvaresh & Bavaghar, 2012). Volatility is the most important variable in evaluating derivative instruments. Volatility is closely related to risk. Investors in the stock market are obviously interested in analysing and learning about the nature of the stock market volatility of stock prices, for high volatility could mean huge losses or gains and hence greater uncertainty (Parvaresh & Bavaghar, 2012).

Several models have been developed since the 1980s that are especially suited to estimate the conditional volatility of financial assets (Zakaria & Winker, 2012). Frequently applied models of this type are the generalized conditional heteroscedastic models (Zakaria & Winker, 2012). Engle (1982) introduced Autoregressive Conditional Heteroscedasticity (ARCH) to the world to model financial time series that exhibit time-varying conditional variance. A generalized ARCH model (GARCH) was extended by Bollerslev (1986). These are popular models for estimating stochastic volatility. These models are widely used in time series econometrics, especially in financial time series analysis. With the introduction of models of ARCH and GARCH, there have been wide empirical applications of modelling volatility of financial time series. However, the GARCH cannot account for leverage and to account for that effect, APARCH, E-GARCH and T-GARCH models have been developed over time.

However, it is widely recognized among researchers that for excess kurtosis along with an increase in data frequency, the rate of return in financial variables might have a levy distribution or a fat-tailed (Mandelbrot, 1963). Under normality assumption for errors, the volatility modelling and forecasting based on such modes will be misleading. The main objective of this paper is to model stock returns volatility in Dhaka Stock Exchange (DSE) by employing different GARCH family type models for daily observations on the index returns series over the period of 27 January 2013 to 06 November 2017. The volatility models employed in this paper include both symmetric and asymmetric GARCH models. Moreover, student's t distribution is used to correctly model and forecast the volatility of stock return and normal distribution for errors is used to compare with student's t distribution for errors. The rest of the paper organized as follows: Section 2 provides the relevant literature review. Section 3 describes data and potential methodology. Section 4 provides estimation results and their discussion respectively. Section 5 provides the results of volatility forecasting both in-sample estimation and out-of-sample forecasting accuracy. Finally, the paper concludes and suggests some policy implications.

2. Literature Review

GARCH family models have been used in scholarships by authors from different corners of the world for the modelling and forecasting of daily stock returns (Floros, 2008; Niyitegeka & Tewari, 2013; Peters, 2001; Karmakar, 2005; Banumathy & Azhagaiah, 2013; Zakaria & Winker, 2002; Abd El Aal, 2011; Parvaresh & Bavaghar, 2012; Qamruzzaman, 2015; Huq, Rahman, Rahman, Shahin, & Ali, 2013). The most used models are GARCH(1,1), GARCH-M(1,1), exponential GARCH(1,1), threshold GARCH(1,1) and power GARCH(1,1). The first two models imply the symmetric effect of past shocks whereas the second group of models allows capturing asymmetric effects. Stock market volatility is widely studied both in developed markets like Israel (Floros 2008), South Africa (Niyitegeka & Tewari, 2013), Europe (Peters, 2001) and emerging markets like India (Karmakar, 2005; Banumathy and Azhagaiah, 2013), Egypt (Zakaria & Winker, 2002; Floros, 2008; Abd El Aal 2011), Iran (Parvaresh & Bavaghar, 2012), Sudan (Zakaria & Winker, 2002). However, studies in the context of Bangladesh are almost non-existent since two scholarships are found only regarding the analysis of Dhaka and Chittagong stock market (Qamruzzaman, 2015; Huq et al., 2013).

In the middle eastern stock markets, EGARCH models are seen to be dominant in determining the leverage effect of daily stock prices (Floros, 2008; Parvaresh & Bavaghar, 2012). Floros (2008) examined the volatility in

Egyptian and Israeli stock indices and found coefficients of the EGARCH model showed a negative and significant value for both indices, indicating the existence of the leverage effect. Parvaresh and Bavaghar (2012) have examined GARCH models in forecasting volatility for Tehran Stock Market and the study suggested that GARCH models used in this paper have the same forecasting power while evaluating forecasting with MSE criteria, while CGARCH has the best forecasting power given the log-likelihood is evaluation criteria. Abd El Aal (2011) examined five models for forecasting volatility of the Egyptian stock market index and employed different statistical metrics. After using usual statistical metrics, they found that the EGARCH model beat the other volatility forecasting models for the Egyptian stock market. However, after using DM statistics they found no significant differences between the forecasting volatility models performance.

However, the scholarships relating to African stock markets employed symmetric and asymmetric GARCH models to model volatility that capture the most common stylized facts about index returns such as volatility clustering and leverage effects (Zakaria & Winker, 2002; Niyitegeka & Tewari 2013; Abd El Aal 2011). Zakaria and Winker (2002) examined the return volatility using daily prices of Khartoum Stock Exchange (KSE) and Cairo and Alexandria Stock Exchange (CASE) where the results showed significant evidence for the existence of the leverage effects in the two markets, based on asymmetrical EGARCH (1,1) and TGARCH (1,1) estimation. However, the result of EGARCH and GJR-GARCH (1,1) failed to indicate the existence of leverage effects in South African stock returns (Niyitegeka & Tewari, 2013). In terms of volatility in African stock markets, results indicate the mixed outcome. GARCH-M (1,1) described statistically significant conditional variance for Egyptian and Sudanese stock markets with a positive sign (Zakaria & Winker, 2002). On the other hand, the results from the GARCH (1,1) model show that volatility of stock returns is persistent in South Africa (Niyitegeka & Tewari, 2013). However, some studies are limited as they did not test to what extent volatility forecasts based on the present models are useful in the context of risk management for the stock markets considered (Zakaria & Winker 2002).

Meanwhile, the only western stock markets literature reviewed in this paper, studied two major European stock exchanges using daily data over a 15-years period (Peters, 2001). Study results revealed that overall estimation is improved when fat-tailed densities are considered in the conditional variance and when asymmetric GARCH is used. In addition to that, GJR and APARCH models are found to be giving better forecasts than symmetric GARCH.

South Asian stock markets studied the heteroscedasticity behaviour of the stock markets making use of several GARCH models (Karmakar, 2005; Banumathy & Azhagaiah 2013; Qamruzzaman, 2015). Banumathy and Azhagaiah (2013) showed that bad news or negative shocks create more volatility than positive shocks or good news by giving negative and positive significant coefficients for EGARCH (1,1) and TGARCH (1,1) models respectively. Karmakar (2005) showed the suitability of the GARCH (1,1) model that gave remarkably good forecasts of market volatility. The scholarships again produced mixed results in the South Asian stock market in terms of capturing symmetric and asymmetric volatility. Some studies examined whether there is asymmetric volatility by using the E-GARCH models and observed that volatility is an asymmetric function of past innovation that increases at a higher rate during market decline (Karmakar, 2005). However, GARCH (1,1) and TGARCH (1,1) estimators are found to be the most suitable models to capture the symmetric and asymmetric volatility respectively in some other studies (Banumathy & Azhagaiah, 2013). Qamruzzaman (2015) examined a wide variety of popular volatility models for Chittagong Stock Exchange (CSE) and the results indicated that GARCH-z, EGARCH-z, IGARCH-z, GJR-GARCH-z and EGARCH-t are suitable for that specific stock exchange with the volatility of the return being significantly higher after 2009. An important limitation of some studies being their suffering from the constraint of non-calculation of intraday volatility and only used a short period of time-series data (Banumathy & Azhagaiah, 2013).

In a different study, Abdullah, Siddiqua, Siddiquee, and Hossain (2017) tried to model and forecast exchange rate volatility by addressing the issue of error distributional assumption between the Bangladeshi taka and the US dollar. This study attempted to model the dynamics by using five different models from January 1, 2008, to April 30, 2015, under both normal and student's t distribution. The models' findings were compared under the regular normal distribution assumption for the residuals against Student's t-distribution and it was later found that the

application of student's t distribution improved forecasting accuracy more than the normal distribution. Moreover, the findings also indicated that for modelling in-sample volatility dynamics, AR (2)-IGARCH (1, 1) was found to be the most accurate, while AR (2)-GARCH (1,1) gave the best performance under error distribution for the out-of-sample volatility forecasting.

However, there are relatively fewer studies on the stock return volatility of DSE. In one current example, Huq et al. (2013) modelled the stock return volatility using daily closing price data from December 06, 2010, to March 12, 2013. According to them, ARMA (1,1) with GARCH (1,1) and GARCH (2,1) are more appropriate models for the general index of the Dhaka Stock Exchange (DSE). But this study has some limitations. They addressed the lag specification of the mean equation properly, but they did not consider the excess kurtosis and skewness. Hence, their results may be misleading. Besides, the I-GARCH model was not used even though the sum of the persistence parameter exceeds the unitary value of almost all the papers. We were appreciative of the work of Abdullah et al. (2017) on exchange rate volatility and therefore attempted to apply the I-GARCH model in the field of stock return volatility of DSE. However, there is a need to identify the true nature of stock market volatility in an emerging market like Bangladesh. Moreover, selecting proper mean equations, addressing excess kurtosis by using student's t distribution and selecting appropriate models may contribute to the field of stock return volatility of DSE. This paper, therefore, analyses the presence and pattern of the volatility clustering in the Dhaka stock index return series using the GARCH family of models. Additionally, the study examines the presence of leverage effect or asymmetric information effect in the DSE index and thus contributes to the existing literature.

3. Data and Methodology

3.1 Data Sources and Variable Formation

The study is based on the secondary data that was collected from Dhaka Stock Exchange Indices. The daily closing price of the DSE general index namely DSEX over five years from 27 January 2013 to 06 November 2017 were considered for the analysis. The study used 1153 daily observations excluding holidays. Since the daily closing price is normally nonstationary, it is inappropriate for the analysis. However, several studies (Karmakar 2005, Abdullah et al., 2017) suggest estimating the volatility of the return series. The DSE daily stock return series is, therefore, calculated using the following log transformation:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$$

$$\text{Or } r_t = \ln(p_t) - \ln(p_{t-1})$$

Where r_t is the logarithmic return on DSE indices for time t , p_t is the closing price at time t , and p_{t-1} is the corresponding price in the period at time $t-1$. The statistical software EViews 7 was used for the quantitative analysis.

3.2 Methodology

3.2.1 Unit Root Test

In a time series, the stationary check is a must. Unit root test is usually used to test whether the data are stationarity. In this regard, the study performed Augmented Dickey-Fuller Test (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test.

3.2.2 The ARCH Model

It is well known that volatility is commonly modelled by GARCH family models. Usually, one can use the mean equation for the level of the series and then the ARCH model is used for modelling the variance. When data are serially correlated, the misspecification of the mean equation could fail to address the autocorrelation problem that

could arise in the volatility model. Hence, the accurate specification of the mean equation is very important. We, therefore, estimated all the GARCH family models for the following appropriate mean equation:

Mean Equation: ARMA (1,1)

$$r_t = \mu + \rho_1 r_{t-1} + \rho_2 \varepsilon_{t-1} + \varepsilon_t$$

We used five different GARCH family models to specify the variance equation to model volatility for different purposes. The sensitivity of the estimation results of the models was checked by changing distributional assumptions. The distributional assumption is changed from normal to student's t distribution. The reason is that in many pieces of literature on financial asset returns, it is established that the return variable is more likely to follow a "levy distribution" with "fat tails" and kurtosis is likely to increase with data frequency (Andersen & Bollerslev, 1998). The useful variance equation is assumed as:

Variance equation:

$$\varepsilon_t = v_t \sqrt{h_t}$$

Where, $v_t \sim \text{i.i.d}(0,1)$ and

$$h_t = v_t \sqrt{\alpha_0 + \alpha \varepsilon_{t-1}^2}$$

3.2.3 The Generalized ARCH (GARCH) Model

The Pioneer of modelling volatility, Engle (1982) used Autoregressive Conditional Heteroscedasticity (ARCH) model to model volatility. But the main problem with the ARCH model is that in practice, a long lag is often required to capture the time-varying volatility. The GARCH model proposed by Bollerslev (1986) allows conditional variance to depend upon its lag which typically reduces the number of ARCH lags required. So, the conditional variance equation should follow as:

$$\text{GARCH (1,1): } h_t = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

Here, the GARCH (1,1) model has one ARCH term denoted as ε_{t-1}^2 and one GARCH term denoted as h_{t-1} . For the variance to remain well behaved (finite and positive), some restrictions are needed: $\alpha \geq 0$, $\alpha_0 > 0$, $\beta \geq 0$. The sum of the ARCH and GARCH coefficients leads to the persistency of volatility shocks. To ensure that series ε_t is stationary and the variance is well behaved, it is necessary to assume that $\alpha + \beta < 1$.

3.2.4 The Symmetric Power ARCH or (APARCH) model

Ding, Granger, and Engle (1993) introduced the asymmetric power ARCH or (APARCH) model. The APARCH (1,1) can be expressed as:

$$\text{APARCH (1,1): } h_t^d = \alpha_0 + \alpha (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^d + \beta h_{t-1}^d$$

This model is developed to allow for possible non-linearity in the parameters of the variance equation. Here d donates the power parameter that requires that $d > 0$ and γ is the parameter capturing any asymmetric or leverage effect which requires the condition $|\gamma| < 1$.

3.2.5 The Exponential GARCH (EGARCH) model

The main drawback of the standard GARCH (1,1) model is that the conditional variance is unable to respond asymmetrically to the rise and fall in the stock returns. This model suggests that the shock in ε_{t-1} has the same effect irrespectively of whether $\varepsilon_{t-1} > 0$ or $\varepsilon_{t-1} < 0$. A typical feature of financial data is that negative shocks or bad news create more volatility than positive shocks or good news. To test the presence of leverage effect in financial data, Nelson (1991) proposed the Exponential Autoregressive Conditional Heteroscedasticity (EGARCH) model. The EGARCH model is given by:

$$\text{EGARCH (1,1): } \ln(h_t) = \alpha_0 + \alpha \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \gamma \left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right| + \beta \ln h_{t-1}$$

Where α is the size parameter measuring the magnitude of shocks, γ is the asymmetric parameter measuring leverage effect, β measures the persistence in conditional volatility irrespectively of shocks to the market. An important feature of the EGARCH model is that there is no need for any non-negativity restrictions.

3.2.6 The Threshold GARCH (TGARCH) model

The threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) model was introduced by Zakoian (1994) and Glosten, Jagannathan, and Runkle (1993). The threshold GARCH (1,1) model specification follows as

$$\text{TGARCH (1,1): } h_t = \alpha_0 + \alpha \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} \quad d_{t-1} = \begin{cases} (1; \text{if } \varepsilon_{t-1} < 0 \\ 0; \text{if } \varepsilon_{t-1} \geq 0 \end{cases}$$

Where, $\varepsilon_{t-1} > 0$ (good news) and $\varepsilon_{t-1} < 0$ (bad news) produces a differential effect on conditional variance. Good news has an impact on α while bad news has the impact of $(\alpha + \gamma)$. When γ is significant and positive, negative shocks have a larger effect on volatility than positive shocks. Here non-negativity restrictions also need for α , α_0 , γ and β like that of standard GARCH (1,1).

3.2.7 The Integrated GARCH (IGARCH) Model

GARCH model with unit root (non-stationary GARCH model) can be regarded as an integrated GARCH or IGARCH model. This model was originally developed by Engel (1982) and Bollerslev (1986). In practice, when the parameters of the GARCH model are restricted to a sum equal to one and ignore the constant term, a standard GARCH model is transformed into an IGARCH model.

$$\text{IGARCH (1,1): } h_t = \alpha \varepsilon_{t-1}^2 + (1 - \alpha) h_{t-1}$$

Where the additional constraints are $\{\alpha + (1 - \alpha)\} = 1$ and $0 < \alpha < 1$

4. Results and Discussion

The daily closing price of the DSE index is non-stationary. This non-stationary behaviour can be seen from the graph of the daily price which is presented in Figure 1 (Appendix). To make the series stationary, the daily closing price of the DSE index is converted into daily logarithmic return series. This return series is now stationary, which is shown in Figure 2. (Appendix). Descriptive statistics on DSE stock return are summarized in Table 1.

Table 1: Descriptive statistics of the DSE return series

Statistics	Values
Mean	0.000355
Median	0.000215
Maximum	0.036847
Minimum	-0.053585

Standard Deviation	0.008394
Skewness	-0.161429
Kurtosis	6.588151
Jarque – Bera	623.5359
Probability	0.00000
Observations	1153

The mean of the returns is positive, indicating that the price has increased over the period. Statistically, the risk or volatility is the dispersion of the returns. Daily performance (average probability) for the period is 0.000355 and the risk (standard deviation) per day is 0.008394 which reflects the high volatility of the Dhaka Stock Index. The descriptive statistics show that the returns are negatively skewed, indicating that there is a high probability of earning returns that is greater than the mean. The kurtosis of the series is greater than 3 which implies that the return series is fat-tailed and does not follow a normal distribution. The histogram of the return series shown in Figure 3 (Appendix) remains centred at the zero with a slight negative bias (-0.161429) and a kurtosis value of (6.588151) which shows excess kurtosis regarding the standard normal and is further confirmed by the Jarque-Bera test statistics which is significant of 1% level and hence the null hypothesis of normality is rejected.

To detect if the DSE return series is stationary, a unit root test is carried out with the statistical Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

Table 2: Stationarity test for the DSE return series

Augmented Dickey-Fuller (ADF) test		
Ho: Return Series has a unit root		
	Intercept	Trend & Intercept
Test Statistic	-30.50930	-30.51298
Probability	0.0000	0.0000
Kwiatkowsk-Phillips-Schmidt-Shin (KPSS) test		
Ho: Return Series is stationary		
	Intercept	Trend & Intercept
Test statistic	0.078875	0.047207
1% critical values	0.739000	0.216000

Table 2 shows the presence of unit root in the series tested using ADF and KPSS tests. The p-values of ADF with both “intercept” & “trend and intercept” are less than 0.01 which leads to conclude that the data of the time series for the entire period is stationary. The p-value of the KPSS test with both “intercept” & “trend and intercept” is greater than 0.01 which leads us to conclude that the null hypothesis of “return series is stationary” is accepted at a 1% level. Both the ADF and KPSS test reported in Table 2 confirms that the return series is stationary.

Table 3: Estimation of conditional mean model and testing for ARCH effect

Variables	Coefficients
(Dependent Variable, r_t)	
μ	0.000323 (0.000339)
r_{t-1}	0.772003*** (0.097197)
ϵ_{t-1}	-0.685053*** (0.111587)
ARCH Effect (Dependent variable, ϵ_t)	
Constant	4.55E-05*** (5.00E-06)

ϵ_{t-1}	0.339794*** (0.339794)
Ho: No ARCH Effect	
F statistic	149.9683***
Probability	0.0000

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

The estimation result of the conditional mean model for the logarithmic stock return using the Ordinary Least Squares (OLS) method is presented in Table 3. Since the series was observed to be mean reverting, OLS was applied to estimate the regression. The model was not augmented with further AR and MA terms because they were not significant.

The Heteroscedasticity test is applied to find out the presence of ARCH effect in the residuals of the return series. From Table 3, it is concluded that the F-statistics is highly significant. Since the p-value is less than 0.01, the null hypothesis of “no ARCH effect” is rejected at a 1% level which confirms the presence of ARCH effects in the residuals of time series models in the returns.

The volatility clustering of return series for the study period from 27 January 2013 to 06 November 2017 is also been observed (Figure 4 (Appendix)). It shows that the period of low volatility tends to be followed by a period of low volatility for a prolonged period and the period of high volatility is followed by a period of high volatility for a prolonged period, which means the volatility is clustering and the return series vary around the constant mean, but the variance is changing with time. Hence, these results suggest the estimation of GARCH family models.

Since the ARCH effect is detected in the model, GARCH family model is therefore used for modelling the volatility of return series in the Dhaka Stock Exchange Market.

Table 4: Estimation results of GARCH (1,1) model with normal and student-t distribution

Coefficients	GARCH (1,1) with normal distribution	GARCH (1,1) with student's t distribution
μ	0.000562** (0.000221)	0.000525** (0.000230)
p_1	0.624279*** (0.109187)	0.641317*** (0.104261)
p_2	-0.488288*** (0.130069)	-0.500652*** (0.123571)
α_0	7.04E-07** (3.09E-07)	7.24E-07*** (3.30E-07)
α	0.153107*** (0.020740)	0.152057*** (0.022947)
β	0.844343*** (0.019438)	0.844678*** (0.021246)
$\alpha + \beta$	0.99745	0.996736
Log-likelihood	4101.584	4102.530
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.0540	0.0586
Prob, chi-square (1)	0.0540	0.0585

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

The GARCH (1,1), model is applied for the purpose of capturing variance dynamics. Table 4 shows the estimation results. Here, it is evident that the autoregressive coefficients of this lagged dependent variable for the mean equation p_1 and MA (1) coefficient p_2 for the mean equation are statistically significant at 1% level.

The coefficients of the GARCH components (α and β) are positive and statistically significant at a 1% level (Table 4). In the conditional variance equation, the estimated β coefficient shows that the volatility is persistent. The sum of these parameters (α and β) is 0.99745, which is close to unity indicating that the stock will persist to many future periods. Further, ARCH-LM test is employed to check ARCH effect in residuals and from the result, it is inferred that the $p > 0.05$, which led to conclude that the null hypothesis of “no ARCH effect” is accepted. In other words, the test statistics do not support any additional ARCH effect remaining in the residuals of the models, which implies that the variance equation is well specified for the market.

Table 5: Estimation results of the APARCH (1,1) model with normal and student t distribution

Coefficients	APARCH (1,1) with normal distribution	APARCH (1,1) with student's t distribution
μ	0.000311 (0.000238)	0.000299 (0.000242)
ρ_1	0.688410*** (0.093600)	0.692550*** (0.091479)
ρ_2	-0.553730*** (0.113572)	-0.555000*** (0.111034)
α_0	2.71E-06 (5.94E-06)	2.96E-06 (6.79E-06)
α	0.147482*** (0.020624)	0.148116*** (0.021964)
γ	0.179302*** (0.063007)	0.178892*** (0.066680)
d	1.743423*** (0.425484)	1.732061*** (0.445515)
β	0.855087*** (0.425484)	0.854436*** (0.022750)
$\alpha + \beta$	1.002569	1.002552
Log-likelihood	4107.561	4107.990
ARCH-LM test for Heteroscedasticity		
ARCH-LM test statistics	0.0430	0.0425
Prob.chi-square (1)	0.0430	0.0425

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

The results from the APARCH model is presented in Table 5, and it is evident that the autoregressive coefficient of the lagged dependent variable ρ_1 for the mean equation and MA (1) coefficient ρ_2 are statistically significant at the 1% level. The coefficients α and β are again found to be positive and statistically significant at 1% level, having a sum greater than 1 for both distributions. The coefficient d is positive and significant and not equal to 2 which implies that it is not a standard GARCH model (Ding et al., 1993). The significance and sign of the coefficient γ determine the leverage effect.

The positive significant value of γ indicates the existence of a leverage effect where negative past values of ε_t increase volatility more than positive past values of the same magnitude. Table 5 also shows, the leverage effect is positive and significant. Thus, an asymmetric volatility effect exists for stock returns. The coefficients of the ARCH & GARCH sum to more than 1 and the constant term in the variance equation of the APARCH model using both normal and student t distribution are not statistically different from 0. Thus, as the necessary non-negativity restrictions have not been satisfied, so the variance equation is not well behaved.

To capture the asymmetric effect in the return series and eliminate the problem of non-negativity restrictions, we estimate an EGARCH model. Table 6 shows the estimation result of the EGARCH (1,1) model using both normal and student t distribution.

Table 6: Estimation results of EGARCH model with normal and student's t distribution

Coefficients	EGARCH with Normal distribution	EGARCH with student's T distribution
μ	0.000232 (0.000229)	0.000225 (0.000233)
p_1	0.701056*** (0.91658)	0.696559*** (0.091011)
p_2	-0.574259*** (0.111412)	0.564811*** (0.110250)
α_0	-0.422221*** (0.079043)	-0.432761*** (0.086100)
α	0.274410*** (0.031330)	0.276309*** (0.034090)
γ	-0.053319*** (0.017888)	-0.053416*** (0.019448)
β	0.979282*** (0.006898)	0.978365*** (0.007527)
$\alpha + \beta$	1.253692	1.254674
Log-likelihood	4106.421	4107.027
ARCH-LM test for Heteroscedasticity		
ARCH-LM test statistics	0.0766	0.0740
Prob. Chi-square (1)	0.0765	0.0739

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

The sum of ARCH(α) & GARCH (β) is greater than one (Table 6), reporting that the conditional variance is explosive. Here in the variance equation γ is popularly known as the “asymmetry parameter” and α represents the “size parameter”. The estimated coefficients are statistically significant at a 1% level. The leverage coefficient, γ is negative and statistically significant at 1% level, exhibiting the leverage effect in return during the study period. The analysis reveals that there is a negative correlation between past return and future return. Hence, EGARCH (1,1) model supports the presence of leverage effect on the DSE return series. Finally, the ARCH-LM test statistics reveals that the null hypothesis of no heteroscedasticity in the residuals is accepted.

An alternative model to test for asymmetric volatility in the DSE return is TGARCH. Table 7 shows the estimation results of TGARCH using both normal and student's t distribution.

Table 7: Estimation results of TGARCH model with normal and student's t distribution

Coefficients	TGARCH with normal distribution	TGARCH with student's t distribution
μ	0.000332 (0.000237)	0.000321 (0.000241)
p_1	0.680906*** (0.093303)	0.686704*** (0.091275)
p_2	-0.544337*** (0.113327)	-0.547455*** (0.110726)
α_0	7.21E-07** (2.86E-07)	7.41E-07** (3.04E-07)
α	0.099293*** (0.023211)	0.099744*** (0.024485)
γ	0.1000258*** (0.031708)	0.100312*** (0.33991)
β	0.848170*** (0.019109)	0.847306*** (0.02081)

$\alpha + \beta$	0.947463	0.947048
Log-likelihood	4107.347	4107.768
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.1072	0.1065
Prob. chi-square (1)	0.1072	0.1065

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

Table 7 shows that the coefficient of leverage effect is positive and significant at a 1% level, which implies that a negative shock or bad news has greater volatility on the condition variance than the positive shocks or good news. The diagnostic test is performed to test whether there is an ARCH effect. The ARCH-LM test statistics for TARCH (1,1) model show that there are no additional ARCH effects in the residuals of the model.

Since it has been found that the sum of the persistence parameters exceeds 1 for some models, it can be deduced that the variance might not be well behaved in such models. Therefore, it would be interesting to model volatility clustering with such models while imposing restrictions on the persistence parameters. Our popular restriction on the “persistent parameters sum up to unit”. Thus, the estimation of GARCH models with this restriction leads to the IGARCH model. Table 8 shows the estimation result of IGARCH (1,1) using both normal and student t distribution.

Table 8: Estimation results of IGARCH (1,1) model with normal and student's t distribution

Coefficients	IGARCH with normal distribution	IGARCH with student's t distribution
μ	0.000540*** (0.000166)	0.000512*** (0.000181)
p_1	0.634229*** (0.095513)	0.652534*** (0.090678)
p_2	-0.502716*** (0.113702)	-0.513506*** (0.107578)
α	0.115773*** (0.010529)	0.114814*** (0.011925)
$1-\alpha$	0.884227*** (0.010529)	0.885186*** (0.011925)
Log-likelihood	4092.622	4094.235
ARCH-LM test for heteroscedasticity		
ARCH-LM test statistics	0.1362	0.1495
Prob. chi square (1)	0.1360	0.1492

Standard Errors are in parenthesis. ***, **, * indicates significant at 1%, 5% and 10% level respectively.

The IGARCH (1,1) model successfully overcomes all of the diagnostic tests for both normal and student's t distribution, is used as the error distribution (Table 8). There is no additional ARCH effect and no autocorrelation detected in the regular and squared residuals. Finally, the evidence indicates that all of the models (GARCH, EGARCH, TGARCH & IGARCH without APARCH) satisfy the required diagnostic standard under both normal distributions as well as student's t distribution as the assumption for the residuals.

5. Volatility Forecasting

5.1 In-sample estimation performance

To find out whether the accuracy of volatility forecasting among the five models (GARCH, APARCH, EGARCH, TGARCH & IGARCH) varied with distributional assumptions, we compared the log-likelihood, Schwarz Bayesian Information Criterion (BIC), and Akaike Information Criterion (AIC) for all those models, estimating for the whole sample observations under normal and student's t distribution. Table 9 shows the results. The

performance of each model improved under the student's t distribution. The reason behind that log-likelihood increased while both AIC and BIC decreased compared to the normal distributional assumptions applied for the residuals. Considering the student's t distribution for the residuals, a comparison of log-likelihood indicates that among all the models used for in-sample estimation, ARMA (1,1)-APARCH (1,1) is the best since it has maximum likelihood and a comparison of BIC and AIC indicators that among all the models used for in-sample estimation, ARMA (1,1)-TGARCH (1,1) is the best since it has lowered BIC and AIC. However, the ARMA (1,1)-APARCH (1,1) model is more problematic since it can't overcome any of the diagnostic tests, that is, there exist additional ARCH effects and autocorrelation problem in the residuals. Without APARCH (1,1), the other models successfully overcome all the diagnostic tests. Without APARCH (1,1), a comparison of all 3 indicators indicates that ARMA (1,1)-TGARCH (1,1) is the best since it has maximum likelihood and minimum BIC and AIC.

Table 9: Comparisons of models in within-sample estimation performance

Normal Distribution			
Models	Log-likelihood	SBC	AIC
ARMA (1,1)-GARCH (1,1)	4101.584	-7.084090	-7.110389
ARMA (1,1)-APARCH (1,1)	4107.561	-7.082229	-7.117293
ARMA (1,1)-EGARCH (1,1)	4106.421	-7.086368	-7.117050
ARMA (1,1)-TGARCH (1,1)	4107.347	-7.087977	-7.118659
ARMA (1,1)-IGARCH (1,1)	4092.622	-7.080771	-7.098303
Student's t distribution			
ARMA (1,1)-GARCH (1,1)	4102.530	-7.079614	-7.110295
ARMA (1,1)-APARCH (1,1)	4107.990	-7.076855	-7.116303
ARMA (1,1)-EGARCH (1,1)	4107.027	-7.081301	-7.116366
ARMA (1,1)-TGARCH (1,1)	4107.768	-7.082589	-7.117653
ARMA (1,1)-IGARCH (1,1)	4094.235	-7.077451	-7.099367

5.2 Out of sample forecasting performance

The accuracy of a forecasting model is its out-of-sample performance, which measures its performance in "real-time." Out-of-sample forecasting is a stepwise method for stimulating real-time performance. To find the out-of-sample forecasting accuracy of the models, we created a pseudo sample using the period from January 27, 2013, to December 31, 2016. Then we estimated the variance in stock returns for the period January 01, 2017, to November 6, 2017. The forecasting performance of the model was compared based on four different indicators under normal and student t distribution. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE), and Theil inequality (TI).

Table 10: Comparisons of models in out-of-sample forecasting performance

Normal Distribution				
Models	RMSE	MAE	MAPE	TI
ARMA (1,1) GARCH (1,1)	0.005847	0.004473	133.5426	0.806878
ARMA (1,1)- APARCH (1,1)	0.005855	0.004495	137.4733	0.804234
ARMA (1,1)- EGARCH (1,1)	0.005871	0.004509	135.5386	0.817928

ARMA (1,1)-TGARCH (1,1)	0.005855	0.004495	137.5431	0.804392
ARMA (1,1)-IGARCH (1,1)	0.005847	0.004473	133.5818	0.807652
Student's t Distribution				
ARMA (1,1)-GARCH (1,1)	0.005844	0.004474	132.6207	0.802523
ARMA (1,1)-APARCH (1,1)	0.005855	0.004496	139.4704	0.802119
ARMA (1,1)-EGARCH (1,1)	0.005869	0.004508	137.0148	0.814867
ARMA (1,1)-TGARCH (1,1)	0.005855	0.004497	139.5167	0.802257
ARMA (1,1)-IGARCH (1,1)	0.005843	0.004473	133.1608	0.800971

Table 10 shows the comparative forecasting accuracy of the different models. For ARMA (1,1)-GARCH (1,1) model, RMSE, MAPE, and TI decreased while when changing the distributional assumption. Thus, this model's forecasting accuracy was improved under the student's t distribution. Likewise, the forecasting accuracy of ARMA (1,1)-IGARCH (1,1) was improved under student's t distribution since all the four indicators decreased. For ARMA (1,1)-APARCH (1,1) model, MAPE and TI decreased while RMSE remained constant, and MAE increased under student's t distribution. Thus, this model's forecasting accuracy was improved under the student's t distribution.

For the ARMA (1,1)-EGARCH (1,1) model, RMSE, MAE, and TI decreased while MAPE increased when changing distribution assumption. Thus, this model's forecasting accuracy was improved under the student's t distribution. For ARMA (1,1)-TGARCH (1,1) model which had the best in-sample estimation accuracy under student's t distribution showed lower accuracy when such distribution was used for out of sample forecasting since two of the four indicators increased, one (RMSE) constant and another TI decreased. Without ARMA (1,1)-TGARCH (1,1) model, the rest of the model's forecasting accuracy was improved under the student's t distribution assumption. Considering the student's t distribution for residuals, a comparison of RMSE, MAE, MAPE, and TI indicate that ARMA (1,1)-IGARCH (1,1) is the best for out-of-sample forecasting.

6. Conclusion

It is well known that the capital market is the engine of growth for an economy since it contributes to a country's economic growth through the creation of wealth. Since the stock market attracts investment, stock return volatility will have a significant effect on investment and consequently on the whole economy. For this reason, it is very important to properly model and forecast stock return volatility. In this study, the volatility of the Dhaka Stock Exchange (DSE) return is tested using the symmetric and asymmetric GARCH models. The Dhaka Stock Exchange (DSE) is the country's leading stock exchange. The daily closing prices of DSE for five years are collected and modelled using five different GARCH models that capture the volatility clustering and leverage effect for the study period i.e., from 27 January 2013 to 06 November 2017. To estimate volatility models, the leptokurtic fat-tailed nature of the stock return series usually provides a reason for using skewed distribution such as student's t distribution. The main objective was on whether the same result exists in the stock return and whether the results were improved with student's t distribution. In particular, the volatility dynamics of the daily stock return of DSE are modelled using GARCH models such as GARCH, APARCH, EGARCH, TGARCH, and IGARCH. The findings from the models under the normal distribution assumption for residuals were compared to the student's t distribution. All models successfully passed the diagnostic tests under both distribution assumptions for residuals only except APARCH (1,1) model.

In the sample, estimation accuracy was improved when the student's t distribution was used. For modelling in-sample volatility dynamics, ARMA (1,1)-T-GARCH (1,1) was found to be the most accurate model. We further tried to find the appropriate model for out-of-sample forecasting. In the case of out-of-sample forecasting accuracy, ARMA (1,1)-I-GARCH (1,1) is considered the best compared to the other three models since MRSE, MAE, and

TI were lower than the other models under student's t distribution. Since an investor is always interested in making easy and riskless money, he or she should take into consideration all other factors before investing in the stock market. Therefore, valuations in such markets should be dealt with carefully by considering conditional variance. The limitation of the study is that the study used only 5 years' data of DSE. Future researchers might study to what extent volatility forecasts based on the present models are useful in the context of structural break, the causes of it and how it can be considered in the volatility equations.

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Appendix



Figure 1: Daily closing price of DSE

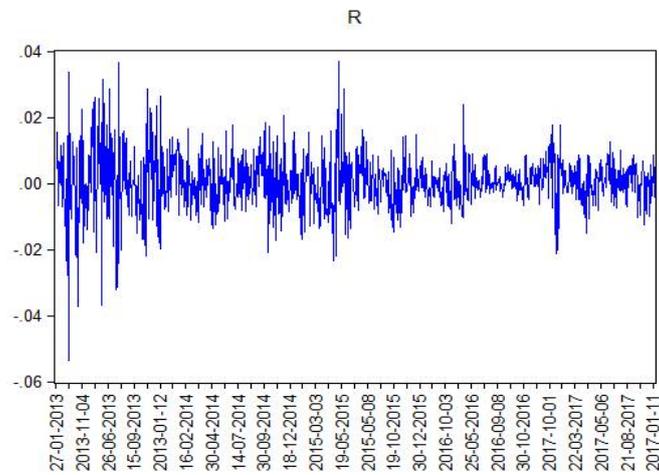


Figure 2: Return series

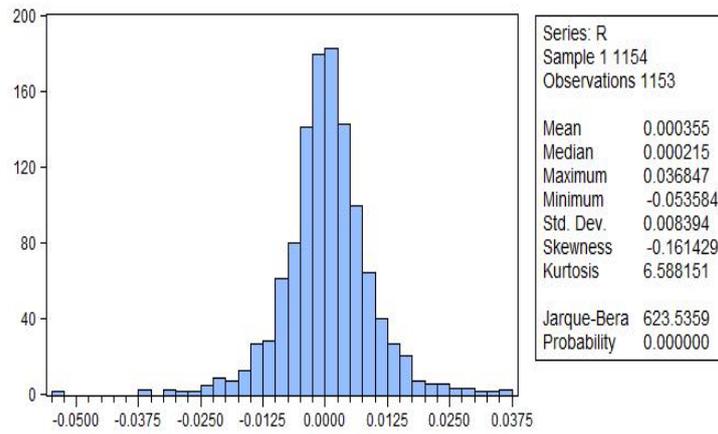


Figure 3: Histogram of return series

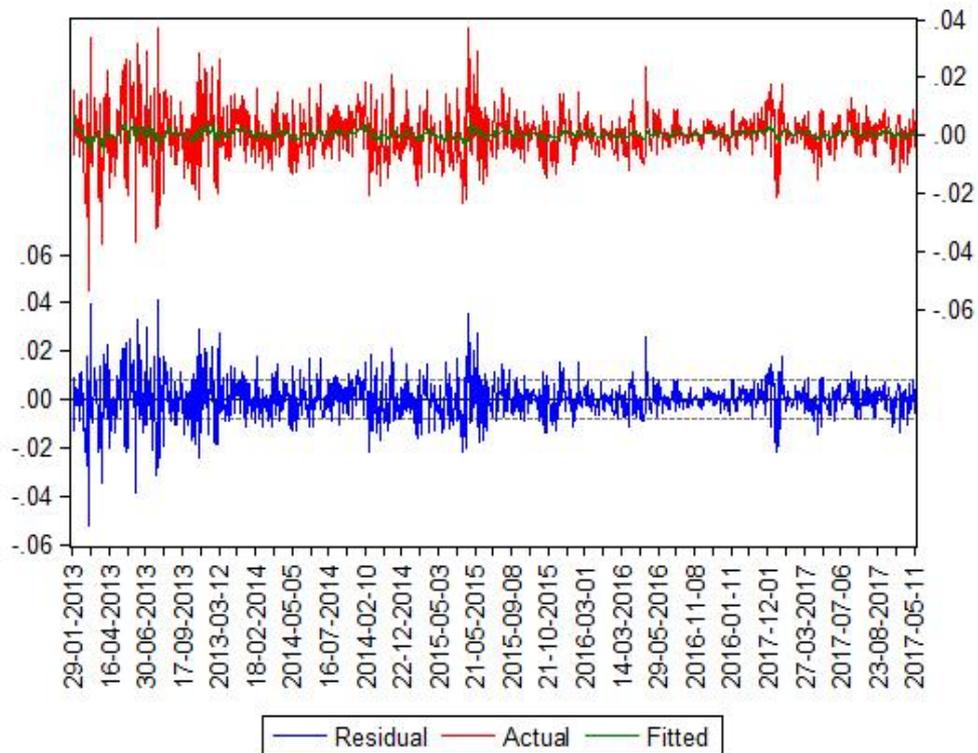


Figure 4: Volatility of return series