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Forecasting Volatility of Selected Banks of Dhaka Stock Exchange (DSE), Bangladesh with GARCH (p, q) Type Models

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ABSTRACT

Stock price volatility is an indication of unreasonable market performance in Bangladesh although stock prices produce valuable information to safeguarding the competence of capital markets. The objective of this paper is to study the volatility and forecasting volatility of selected Banks of the Dhaka Stock Exchange (DSE) by using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. The volatility of DSE returns of selected banks Brac bank, City Bank, Pubali bank, and Eastern bank have been modelled from 2008 to 2018 based on a daily scale. The asymmetric volatility model E-GARCH and GJR-GARCH perform better in modelling the volatility of selected banks of DSE. There is a significant impact of positive shocks on volatility for Brac and Eastern banks whereas for City bank negative shocks tend to produce higher volatility. Volatility is persistent for City, Pubali, and Eastern banks meaning that in upcoming days they could be affected by volatility. The fitted models for Brac, City, and Eastern banks performed well in backtesting while Pubali bank does not perform well. In the upcoming days all bank's volatility will have a chance to be increasing where Brac bank is less volatile and Pubali bank is the most volatile bank of DSE.

ملخص

يُعد تقلب أسعار الأسهم مؤشرا على أداء السوق غير عقلاني في بنغلاديش على الرغم من أن أسعار الأسهم تُنتج معلومات قيمة لحماية كفاءة أسواق رأس المال. ويتمثل الهدف من هذا المقال في دراسة التقلبات والتنبؤ بتقلبات البنوك المختارة في بورصة دكا (DSE) باستخدام نماذج التباين الذاتي

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الشرطي المعمم (GARCH). وقد تم نمذجة تقلبات عائدات بورصة دكا بالنسبة لبنوك مختارة تشمل بنك براك وبنك سيتي وبنك بوبالي والبنك الشرقي من عام 2008 إلى عام 2018 بناء على مقياس يومي. ويعمل نموذجي التقلبات غير المتماثلة، التباين الذاتي الشرطي المعمم المتسارع (E-GARCH) والتباين الذاتي الشرطي المعمم-جلوستن، جاغاناثان، رانكل (GJR-GARCH) بشكل أفضل في نمذجة تقلبات البنوك المختارة التابعة لبورصة دكا. وإن هناك تأثير كبير للصدمات الإيجابية على التقلبات في مصرف براك والبنك الشرقي، بينما تميل الصدمات السلبية إلى زيادة التقلبات فيما يتعلق ببنك سيتي. وتستمر التقلبات في الاستمرار بالنسبة لكل من بنوك سيتي وبوبالي والشرق الأمر الذي يعني أنها قد تتأثر بالتقلبات في الأيام القادمة. وكان أداء النماذج المتوائمة لبنوك براك وسيتي والشرق جيدا في التنبؤ العكسي بينما أداء بنك بوبالي لم يكن كذلك. وفي الأيام المقبلة، ستكون هناك فرصة لتزايد تقلبات البنوك حيث يكون بنك براك أقل تقلبا وبنك بوبالي هو البنك الأكثر تقلبا في بورصة دكا.

ABSTRAITE

La volatilité des prix des actions est une indication de la performance déraisonnable du marché au Bangladesh bien que les prix des actions produisent des informations précieuses pour sauvegarder la compétence des marchés de capitaux. L'objectif de cet article est d'étudier la volatilité et la prévision de la volatilité de certaines banques de la Dhaka Stock Exchange (DSE) en utilisant des modèles GARCH (Generalized Autoregressive Conditional Heteroscedasticity). La volatilité des rendements du DSE de certaines banques - Brac bank, City Bank, Pubali bank et Eastern bank - a été modélisée de 2008 à 2018 sur la base d'une échelle quotidienne. Les modèles de volatilité asymétrique E-GARCH et GJR-GARCH sont plus performants pour modéliser la volatilité des banques sélectionnées du DSE. Il y a un impact significatif des chocs positifs sur la volatilité pour les banques de Brac et de l'Est, tandis que pour la banque de la ville, les chocs négatifs ont tendance à produire une volatilité plus élevée. La volatilité est persistante pour les banques City, Pubali et Eastern, ce qui signifie qu'elles pourraient être affectées par la volatilité dans les jours à venir. Les modèles ajustés pour les banques Brac, City et Eastern ont donné de bons résultats dans le backtesting, tandis que la banque Pubali n'a pas donné de bons résultats. Dans les prochains jours, la volatilité de toutes les banques aura une chance d'augmenter, la banque Brac étant moins volatile et la banque Pubali étant la plus volatile du DSE.

Keywords: Volatility, Forecast, GARCH, Selected Banks, Dhaka Stock Exchange

JEL Classification: O16, N2, G11, G17, G21

1. Introduction

The stock market is the powerhouse of the world economy and plays an important role in mobilizing savings and investments for organizing the production of goods and services, creating employment opportunities, and enhancing economic development (Ahmed et al., 2014). There are two stock exchanges namely the Dhaka stock exchange (DSE) and Chittagong stock exchange (CSE) (Sarbabidya & Saha, 2018). Dhaka stock exchange (DSE) functions as a strong mechanism in the industrialization and economic growth of Bangladesh.

Volatility is mainly related to investment markets and it is referring to fluctuation or movement in the price of a particular stock or index major over some period of time (Roni, et al., 2017; Mala & Reddy, 2007). The collapse of the stock market always tends to trigger a financial crisis and push the economy into recession. Most of the major stock markets in the world were greatly affected by this global financial crisis (Oseni & Nwosa , 2015). Over the past two decades, the Bangladesh stock market has to face two big bubbles the first time in 1996 and the second time in 2011. Reasons of recent catastrophe in stock market involving the lack of government awareness/control over the stock market, political instability, uncontrollable macroeconomic factors, syndication or manipulation in the stock market, scarcity of information or reliable information, trade & budget deficits, lack of proper knowledge/ skill of investors (Hossain & Islam, 2012; Saha, 2012).

Despite of all these factors that increase volatility, to make the stock market efficient and reduce uncertainty, volatility modeling and forecasting is necessary for the policymakers, researchers, and practitioners. Some of them have given an effort to find the volatility persistency property of the stock return, some tried to model the risk return relationship while some others tried to forecast the volatility only. But there lies in contradiction and lack of knowledge among the researchers about the robustness of the volatility model. As it is not possible to control volatility or cannot completely eradicate this financial hazard; it is possible to know the future situation of the volatility. A timely accurate forecast with early warnings with sufficient lead time is one of the best way to reduce the loss of stocks which may enhance the sustainability of the economic growth of Bangladesh. Therefore, the main objective is to study the volatility and forecasting volatility of selected

Banks of Dhaka Stock Exchange by using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) type models. Motivated by the limited research in this sector and the drawback of methods used in previous studies will develop this study to reach into the defined goal. Moreover, the current study tries to address the questions: What is the current situation of volatility in the commercial Banks of DSE? What are the impacts of the leverage effect (rumors, bad news) on volatility? And what could be the future scenario of volatility in the selected Banks of DSE?

Due to strong economic growth in the region, South Asian capital markets have become more attractive investment opportunities for foreign and domestic investors. Compared to any other country in South Asia, Bangladesh has made significant progress in economic development in the last two or three years and the Bangladeshi stock market especially the commercial banks have played an important role in this economic progress (The Financial Express, 2019). The Dhaka Stock Exchange (DSE) is one of the most vibrant, well-functioning and efficient stock market in South Asia with a favorable outlook for investors (Islam & Alam, 2019). This could be a growing concern for many national and international traders, especially for South Asian traders as well as Chinese and Japanese.

The remaining sections of this paper are organized as follows: A review of related literature presents the most relevant domestic and international studies on the stock market, volatility and volatility forecasting was carried out in section two. The focus of section three is the research methodology, estimation techniques, analytical tools, data collection and data requirements for modeling and forecasting volatility of DSE. Section four is concerned with data analysis as well as the various data presentation techniques used and estimated results of the analysis. The summary and conclusion from the study, recommendation and policy implications in this field covered in section five.

2. Literature Review

The necessity of modelling and forecasting of stock market volatility has been extensively explored in developing and developed countries in last few years. For accurate modelling of stock market volatility some researchers used Support Vector Machines (SVM), ARIMA model, VAR model, ANN model, GARCH model (Adebiyi, et al., 2014; Pai & Lin, 2004). For example, Wang (2010) investigates the time-series relationship between stock market volatility and macroeconomic variable volatility for China using exponential generalized autoregressive conditional heteroscedasticity (EGARCH) and lag-augmented VAR (LA-VAR) models and found that there is a bilateral relationship between inflation and stock prices. Oseni & Nwosa, (2015) employed EGARCH (p, q) technique to examine the volatility in stock market and macroeconomic variables. Abdalla (2017) employed a bi-variate vector autoregressive-generalized autoregressive conditional heteroscedasticity model to investigate the stock market fluctuation. Ashraf & Noor (2010) investigated the impact of financial intermediary factors on stock market bubbles by using two techniques: first a simulation based technique and second an ordinary least square regression technique. According to a study by Liu and Hung (2010), GJR-GARCH has achieved better volatility forecasts where E-GARCH is slightly behind. In contrast, Mukherjee and Mishra (2010) found that E-GARCH is better compared to the T-GARCH (also referred to as GJR-GARCH) model for the SENSEX returns. Lee, et al. (2008) found that Bayesian Chiao's (BC) was selected the best model for short-term forecasting while SARIMA model was considered as the best model for mid-term and long-term forecasting. McMillan et al. (2000) revealed that GARCH, moving average and smoothing models produced marginally better daily volatility forecasts whereas the random walk model gives immensely better monthly volatility forecasts. Ederington & Guan (2005) reported that in emerging stock markets, GARCH (1,1) model outperforms for volatility forecasting. Al-Zeaud (2011) conducted a study on modeling and forecasting volatility using ARIMA model and found that ARIMA (2,0,2) is the best model in the banking sector.

Sharif & Hasan, (2019) found that for predicting stock prices Holt’s Method performs better for short time than a long time interval. Abdullah, et al., (2018) applied various GARCH models to forecast future volatility and examined that GARCH (2,1) and EGARCH (1,3) is the best model to capture volatility. Roni, et al., (2017) suggested that (TGARCH) model is more accurate for the model accuracy and statistic error measurements and also indicates that the GARCH model is more efficient than others and it has also more forecasting ability. Khan & Hossain, (2016) examined the GARCH type models for capturing the stylized factors of the stock index return’s volatility. The appropriateness of the GARCH (1,

1) model has been endorsed by Miah & Rahman, (2016) who conducted their study on Dhaka Stock Exchange (DSE) returns of four selected companies, namely BEICL, BPL, PBL and ABBL for the period January 2000 to November 2014. Hossain, et al., (2015) found that for projecting volatility of DSE, Vector Autoregressive (VAR) model performs better than the ARIMA model and they give further direction to use the GARCH model.

In economic and financial data, time-varying volatility is more common than constant volatility and by reviewing the literature, for accurate modeling of time-varying volatility or variance dynamics, GARCH models perform better than other models and some suggested to use GARCH model (Hossain, et al.,2015; Malik, 2017). As such, GARCH models differ from homoscedastic models which assume a constant volatility. That's why in this study GARCH models will be used to predict or forecast volatility. Many researchers have examined the volatility of stock market by considering different models for different time period and sample size and found contradictory results in some cases. Very limited numbers of scholar tried to modelling and forecasting volatility but there exists plenty research gaps in their works. For example, many researchers used traditional techniques such as regression analysis technique, ARIMA, SARIMA etc. to model and predict volatility but these methods are completely failed to capture the "stylized facts" of financial returns such as volatility clustering, fat tails, leverage effect etc. (Cont, 2001) and most importantly it's quite impossible to find out any seasonal pattern in the time-varying volatility. To capture the asymmetry effect of stock returns, asymmetric volatility model E-GARCH and GJR-GARCH can perform better but most of the studies didn't consider this issue and just used simple GARCH i.e. GARCH (1,1) model. A few articles have been studied in Bangladesh to predict volatility and most of them just fitted several models and made comparisons among them (Islam, et al., 2012; Alam, et al., 2013; Kamruzzaman, et al., 2017). Most of the researchers in Bangladesh used the DSEX index (general index) for modeling volatility, none of them focused on the specific Companies volatility modeling except Miah & Rahman, (2016). And as a methodological-based study obviously the novelty of this paper lies in the detailed procedure of the applied models (GARCH type models) with historical Backtesting procedure.

3. Data and Methodology

3.1. Data Description and Variables

Time series data are used for modeling volatility on the daily closing prices of Banks in DS30 (leading 30 Companies on 10^{th} January 2019) named as BRAC BANK, CITY BANK, EBL (Eastern Bank Limited), and PUBALI BANK for the period from March 2008 to December 2018 based on daily scale. Among the five banks of DS30, due to the unavailability of data NBL (National Bank Limited) could not be considered in this study. The data are collected from DSE library, 9F Motijhil Commercial Area, Dhaka, Bangladesh; Stock Bangladesh, 99 Kazi Nazrul Islam Road, Towfiq Hossain Ave, Dhaka; Unique Trade Centre, Panthapath, Dhaka; Bangladesh Securities and Exchange Commission (BSEC), Agargaon, Dhaka and Bangladesh Bank.

In this data set, among 11 variables (DATE, TRADING CODE, LTP, HIGH, LOW, CLOSEP, YCP, CHANGE, TRADE, VALUE (mn), and VOLUME) only the most important variables including DATE, TRADING CODE, CLOSEP (closing price) are used for this study. Daily returns (r_t) are calculated from equation (1) as the continuously compounded returns which are the first difference in logarithm of closing prices of each selective Companies of successive days:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \tag{1}$$

Where p_t and p_{t-1} are the closing price of each selective Companies at the current day and the previous day respectively and log is Natural Logarithm.

3.2. Empirical Methods

The perfect modeling of the conditional mean can be considered as a prerequisite of correct model specification of the conditional variance of the stock market return. Along with independent variables researchers of volatility modeling usually augment the conditional mean model either with Autoregressive (AR) or with Moving Average (MA) or even with a mixture of these two (Autoregressive Moving Average, ARMA) process. In this study ARMA specification is used as a conditional mean model in the following way:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \ \dots + \emptyset_p y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ \dots + \theta_q \varepsilon_{t-q} + e_t \qquad (2)$$

Where, y_t is the differenced series, c is a constant term, $\emptyset_1, \emptyset_2 \dots \emptyset_p$ are the coefficients of autoregressive part, $\theta_1, \theta_2 \dots \theta_q$ are the coefficients of the moving average part and e_t is the error term.

Considering the following general specification of the variance model: $\epsilon_t = \sigma_t v_t$ where $v_t \sim IID(0, 1)$ and specification of σ_t determines different varieties of GARCH family models; the following models have been used to analyze the different feature of stock market return with volatility.

3.2.1. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

For accurate modelling of time-varying volatility or variance dynamics, Tim, (1986) extended the Engle, (1982) ARCH model into the generalized ARCH (GARCH) model. The general form of GARCH (p, q) model is defined as follows:

$$z_t = \mu_t + \varepsilon_t, \text{ where } \varepsilon_t \sim N(0, \sigma_t^2) \qquad (3)$$

$$\varepsilon_t = \sigma_t v_t, \text{ where } v_t \sim IID(0, 1)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 = \omega + \sum_{\mathrm{i}=1}^{\mathrm{q}} \alpha_i \varepsilon_{t-i}^2 + \sum_{\mathrm{j}=1}^{\mathrm{p}} \beta_j \sigma_{t-j}^2$$

Where μ_t is the conditional mean of GARCH (p, q) model along with ARMA specification which is showed above by equation (1), σ_t^2 is conditional variance, ε_{t-i}^2 is squared residual return, σ_{t-j}^2 is the past conditional variance and p and q denotes the lag order of GARCH and ARCH terms respectively. The most commonly used GARCH model is GARCH (1, 1) that meets

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \ \omega > 0, \ \alpha, \beta \geq 0 \qquad (4)$$

Where ω, β and α are the parameters, which are assumed to be non-negative to guarantee that volatility is always positive. This model is able to capture the volatility clustering. $\beta + \alpha < 1$, implies that the volatility is stationary and the speed for which the shock to volatility decays becomes slower as $\beta + \alpha$ approaches to one.

3.2.2. Exponential GARCH (EGARCH) Model

The exponential GARCH (EGARCH) model developed by (Nelson, 1991) can demonstrate the existence of asymmetry in volatility with respect to the direction of real growth. The EGARCH (p, q) model is given by

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{k=1}^{p} \gamma_k \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \quad (5)$$

The left side of the equation is logarithmic conditional variance, which means that the leverage effect is exponential, not quadratic. The existence of leverage effect (γ) is tested through the hypothesis. Further, the variance of the right side of the equation coefficients can be positive or negative.

3.2.3. Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) Model

The GJR-GARCH model is proposed by Glosten, Jagannathan and Runkle (1993) to capture the asymmetry of data. The GJR-GARCH (p, q) model is as follows:

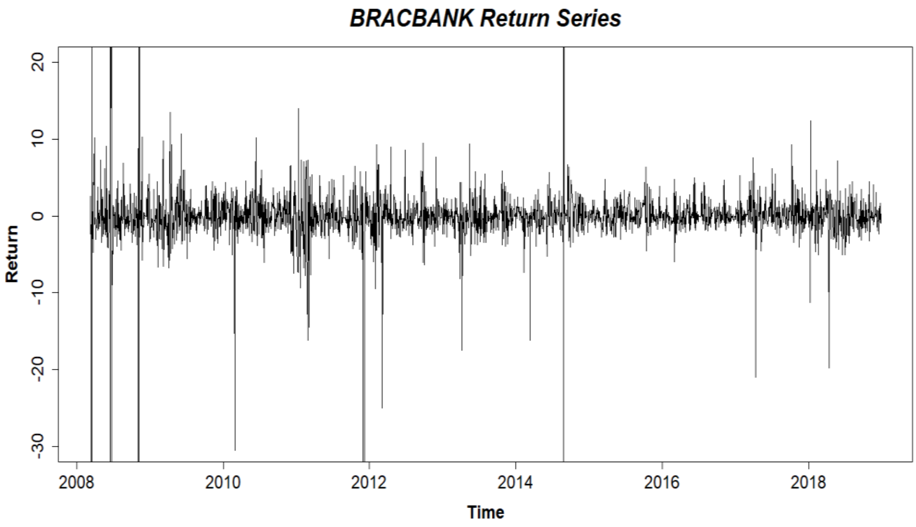
$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{p} \gamma_k \sigma_{t-k}^2 d_{t-k} \quad (6)$$

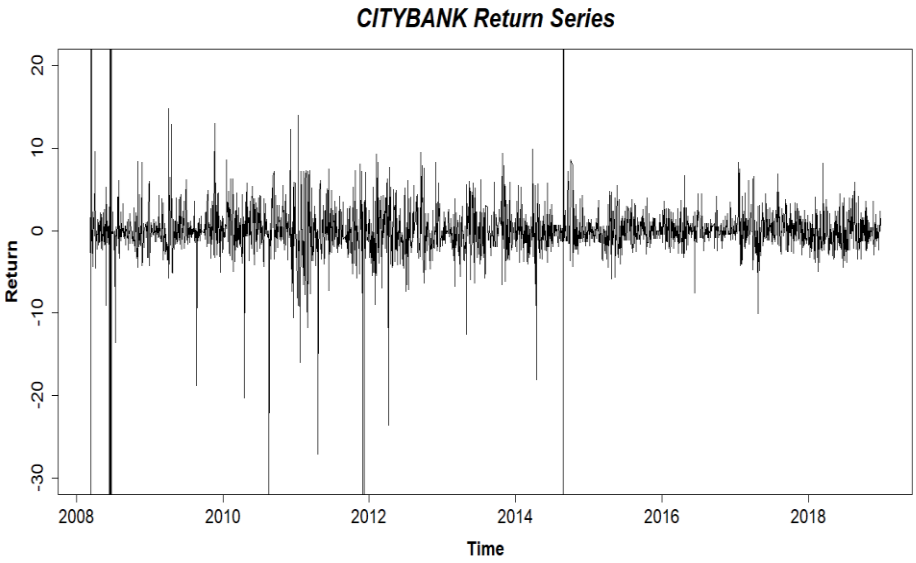
Where d_t is a dummy variable, defined by the time $\varepsilon_t < 0$, d_t=1; then as long as $\gamma_k \neq 0$, the asymmetric effect exists. In the above equation, the term asymmetric effect of items, good information d_t= 0 will have an impact time, and bad information will have another impact. The equation demonstrates the asymmetric effect and the good rumor have a low impact on the volatility returns in the stock market which is associated with leverage effect.

4. Empirical Results

4.1. Basic Statistical Analysis

From Figure 1 it is observed that the return series appears to be stable with an average return of approximately zero: however the volatility or variability of the data changes over time. In fact, the data shows volatility clustering, which is highly volatile periods tend to be clustered together means there is no visual evidence of serial correlation in the return but there is evidence of serial correlation in the amplitude of the returns.





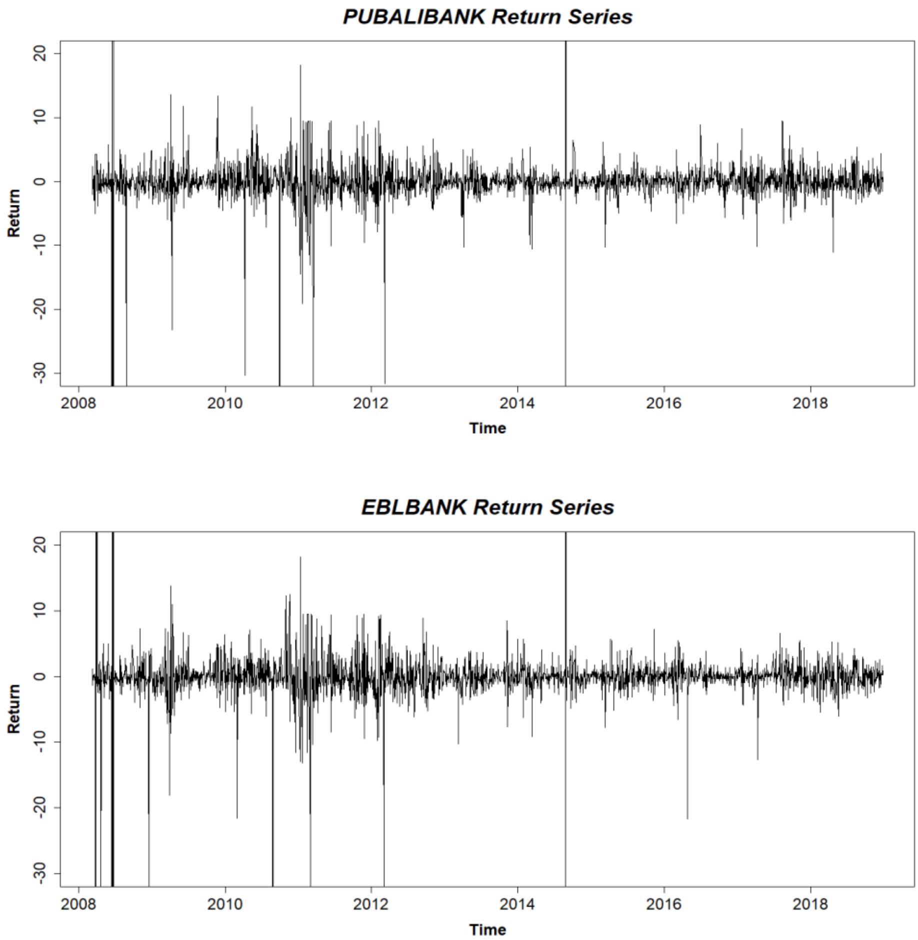


Figure 1: Distribution of Daily Return Series Data of selected Banks

From Table 1, it is observed that the average daily returns of all the banks lie between (-0.11 to -0.14) where the standard deviations are in (28.51 to 39.72) that reflects high level of dispersion from the average return in the share market. The mounting gap between maximum and minimum returns for the selected banks gives high volatility of price changes in the DSE which showed the shape of distribution too. Here the positive or negative value of skewness indicates asymmetry of the series and the large value of kurtosis around (500) suggests shocks of either are more likely to be present the return series are clearly leptokurtic which support the works of Khan & Hossain, (2016); Miah & Rahman, (2016) and Panait & Slăvescu, (2012).

Table 1: Descriptive Statistics of Daily Return Series

	Name of the Banks			
Descriptive Statistics	Brac Bank	City Bank	Pubali Bank	Eastern Bank
No. of observation	2595	2595	2595	2595
Mean	-0.11	-0.12	-0.14	-0.13
Standard deviation	39.72	36.91	28.51	39.48
Minimum	-701.75	-643.49	-676.65	-693.34
Maximum	698.66	643.49	676.94	691.55
Skew ness	-0.21	-0.11	-0.16	-0.08
Kurtosis	281.74	283.22	497.14	279.63

Source: Author's computation

Since from Figure 1 the mean reversion would possibly be quite frequent in the stock return series of four banks, it might contain the stationary condition of time series. To check the stationary of the return series Augmented Dickey-Fuller Test is applied.

Table 2: Result of Augmented Dickey-Fuller Test

	Brac Bank	City Bank	Pubali Bank	Eastern Bank
Augmented Dickey-Fuller (P-value)	-18.925 (0.01)	-18.53(0.01)	-18.41(0.01)	-20.29(0.01)

Source: Author's computation

From above Table 2 it is concluded that all the return series hold the stationary condition as P-value is less than 0.05 and gives an indication of fitting mean model.

4.2. Selection of the Conditional Mean model for Volatility

To identify the conditional mean model appropriately for modeling the volatility in the concerned variable and the way the selection of the estimation method of a conditional mean model for stock return series is of vital importance. Fitting an ARMA in the mean equation of the GARCH model, helps to correct the problem of serial correlation in the residuals, once the absence of serial correlation is confirmed by adding the required ARMA terms, the conditional volatility can be modeled using GARCH. To eliminate non-stationary, the price time series has been transformed into a return time series by taking logarithmic because logarithmic returns are analytically more tractable. To find out the best fitted ARMA model with the appropriate order of lags “p” and “q”, Akaike Information Criterion (AIC) is used. By considering some tentative ARMA models, it is observed from Table 3 that ARMA (4, 4) for Brac bank, ARMA (3,4) for City bank, ARMA (4, 3) for Pubali bank and ARMA (4, 4) for Eastern bank are achieved by using the minimum value of AIC.

Table 3: Selecting the Mean Model using AIC

	Brac Bank AIC	**City Bank AIC**	**Pubali Bank AIC**	**Eastern Bank AIC**
ARMA (3, 2)	25149	25409	23975	25593
ARMA (3, 3)	25061	25349	23819	25347
ARMA (3, 4)	24989	**25240**	23802	25349
ARMA (4, 2)	24775	25362	23701	25595
ARMA (4, 3)	24752	25358	**23627**	25345
ARMA (4, 4)	**24750**	25249	23723	**25324**

Source: Author’s computation

4.3. Results of the Volatility Test

4.3.1. Box-Ljung Test

After fitting the ARMA (4, 4) for Brac bank, ARMA (3,4) for City bank, ARMA (4, 3) for Pubali bank and ARMA (4, 4) for Eastern bank, the square of the residuals are calculated. To check whether there exists any autocorrelation in the mean model or not, Ljung & Box, (1978) test is applied. The null hypothesis for Box-Ljung test is stated as the squared residuals are uncorrelated hence follows a white noise process. From Table 4, the Ljung-Box test gives the result that autocorrelation is present in the mean model of each selected bank.

Table 4: Results on the Test of Presence of Autocorrelation and ARCH Effect

	Brac Bank	**City Bank**	**Pubali Bank**	**Eastern Bank**
Q statistic (P-value)	1104.1 (0.0001)	3276.3 (0.0001)	2416.8 (0.0001)	2109.3 (0.0001)
ARCH LM (P-value)	4.560 (0.0327)	140.57 (0.0001)	21.254 (0.0001)	113.13 (0.0001)

Source: Author’s computation

4.3.2. Engle's ARCH LM Test

From the Box-Ljung test results where autocorrelation is present in the series. To make sure of the presence of a significant ARCH effect, Engle's ARCH LM test is applied. The null hypothesis of the test is no ARCH effect is present in the mean model of each selected bank. Table 4 ARCH LM test indicates that there is a significant ARCH effect present in the mean model of selected banks. Thus DSE stock price return for different banks is conditional heteroscedastic. So the modeling of volatility clustering is necessary.

4.4. Selection of the Conditional Variance Model for Volatility

For each selected bank three types of GARCH model are fitted, one is the symmetric GARCH model i.e. GARCH (1,1) and other asymmetric models are E-GARCH and GJR-GARCH model which is explored in Table 5.

Table 5: Results on Selecting the Best Model using AIC and BIC

	Selection criteria	**Brac Bank** ARMA (4, 4)	**City Bank** ARMA (3,4)	**Pubali Bank** ARMA (4, 3)	**Eastern Bank** ARMA (4, 4)
GARCH (1,1)	AIC	5.16	5.30	4.74	5.65
	BIC	5.18	5.33	4.76	5.68
E-GARCH (1,1)	AIC	**5.02**	5.34	5.97	**4.99**
	BIC	**5.05**	5.37	6.00	**5.02**
GJR-GARCH (1,1)	AIC	5.15	**5.30**	**4.73**	5.53
	BIC	5.18	**5.32**	**4.75**	5.56

Source: Author's computation

From these various combinations, the best model is being selected according to the lowest Akaike information criterion (AIC) and Bayesian information criterion (BIC). E-GARCH (1, 1) is found to be the least model for volatility measurement based on the lowest AIC and BIC for both Brac bank and Eastern bank while GJR-GARCH (1,1) considered the best model for City bank and Pubali bank.

4.5. Conditional Mean-Variance Model Estimation

Table 6 presents the estimates of EGARCH and GJR-GARCH asymmetric volatility models. These estimates are used to examine the existence of asymmetry in stock returns volatility of the selected banks of DSE.

Table 6: Results of the EGARCH and GJR-GARCH Models

	Brac Bank	**City Bank**	**Pubali Bank**	**Eastern Bank**
Parameter	ARMA(4, 4)-EGARCH (1,1)	ARMA(3, 4)-GJRGARCH (1,1)	ARMA(4, 3)-GJRGARCH (1,1)	ARMA(4, 4)-EGARCH (1,1)
μ	-0.18298	-0.051779	-0.024372	0.257802***
AR (1)	-1.08813 ***	-0.040750	-0.529640***	0.770912***
AR (2)	0.58216 ***	-0.377694 ***	-1.062443***	0.157290***
AR (3)	0.81752 ***	-0.370868	-0.079233***	0.190486***
AR (4)	0.13691 ***		-0.093533***	-0.339972***
MA (1)	1.10840 ***	0.196436	0.547086 ***	-0.749015***
MA (2)	-0.57023 ***	0.376110 ***	0.964030***	-0.073334***
MA (3)	-0.84246 ***	0.392487	0.043336***	-0.221249***
MA (4)	-0.15396***	2.290019 ***		0.273433***
ω	1.16952***	0.332646***	0.730333***	0.201921***
α	-0.18092***	0.073023***	0.396251***	0.194334***
β	0.41049***	0.607160 ***	0.555310***	0.924450***
$\boldsymbol{\gamma}$	0.46853***	0.079086***	0.094878	0.251598***

*** indicates significant at 5% level

Source: Author's computation

The estimated E-GARCH and GJR-GARCH models for the selected banks are fitted as follows:

The estimated ARMA(4,4)-E-GARCH (1,1) model for Brac bank is:

$$\widehat{y_t} = -0.18298 - 1.08813\ y_{t-1} + 0.58216\ y_{t-2} + 0.81752\ y_{t-3} + 0.13691\ y_{t-4} + 1.1084\ \varepsilon_{t-1} - 0.57023\ \varepsilon_{t-2} - 0.84246\ \varepsilon_{t-3} - 0.15396\ \varepsilon_{t-4}$$

$$ln\widehat{\sigma_t^2} = 1.169 - 0.18092\ \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.41049\ ln\ \sigma_{t-1}^2 + 0.46853\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \qquad (7)$$

The estimated ARMA(3,4)- GJRGARCH (1,1) model for City bank is:

$$\widehat{y_t} = -\ 0.051779 - 0.04075 y_{t-1} - 0.377694\ y_{t-2} - 0.370868\ y_{t-3} + 0.196436\varepsilon_{t-1} + 0.376110\varepsilon_{t-2} + 0.392487\varepsilon_{t-3} + 2.290019\ \varepsilon_{t-4}$$

$$\widehat{\sigma_t^2} = 0.332646 + 0.073023\ \sigma_{t-1}^2 + 0.607160\ \sigma_{t-1}^2 - 0.079086\ \sigma_{t-1}^2 d_{t-1} \qquad (8)$$

The estimated ARMA(4, 3)-GJRGARCH (1,1)model for Pubali bank is:

$$\widehat{y_t} = -0.024372 - 0.52964\ y_{t-1} - 1.062443 y_{t-2} - 0.079233\ y_{t-3} - 0.093533 y_{t-4} + 0.547086\ \varepsilon_{t-1} + 0.964030\varepsilon_{t-2} + 0.043336\varepsilon_{t-3}$$

$$\widehat{\sigma_t^2} = 0.730333 + 0.396251\ \sigma_{t-1}^2 + 0.555310\ \sigma_{t-1}^2 + 0.094878\ \sigma_{t-1}^2 d_{t-1} \qquad (9)$$

The estimated ARMA(4,4)-EGARCH (1,1) model for EBL bank is:

$$\widehat{y_t} = 0.257802 - 0.770912\ y_{t-1} + 0.15729\ y_{t-2} + 0.190486\ y_{t-3} - 0.339972\ y_{t-4} - 0.749015\ \varepsilon_{t-1} - 0.073334\ \varepsilon_{t-2} - 0.221249\ \varepsilon_{t-3} + 0.273433\ \varepsilon_{t-4}$$

$$ln\widehat{\sigma_t^2} = 0.201921 + 0.194334\ \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + 0.92445\ ln\ \sigma_{t-1}^2 + 0.251598\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \qquad (10)$$

For Brac bank, table 6 shows the significance of ARCH parameter α, GARCH parameter β and leverage effect γ. The significance of ARCH parameter $\alpha =$ -0.18092 indicates that the news about volatility from the previous day has less explanatory power on current volatility. The GARCH parameter $\beta =$ 0.41049 indicate explanatory power on current volatility but also suggests volatility clustering in the daily returns of the DSE. Volatility persistence is measured by $\alpha + \beta$ = 0.229 which indicates that volatility is not persistent for Brac bank. The asymmetric volatility model E-GARCH with their estimates are used to examine the existence of asymmetry in stock returns volatility of Brac Bank of DSE. For E-GARCH(1,1) the leverage effect γ = 0.46853 which shows a negative correlation between the past return and future volatility of the return. The γ coefficient is positive and significant suggesting that positive shock (good news) tends to produce higher volatility in the immediate future than the negative shocks (bad news).

For City bank, the ARCH parameter $\alpha = 0.073023$ is found to be significant as the news about volatility from the previous day has less effect on current volatility. The GARCH parameter $\beta = 0.60716$ is positive and significant which does not indicate explanatory power on current volatility but also suggests volatility clustering in the daily price returns of City bank of DSE. Volatility persistence is measured by $\alpha + \beta + \gamma/2 = 0.719726$ which indicates that volatility is persistent for City Bank. The statistically significant γ coefficient indicates that the null hypothesis of no asymmetric effects in the volatility of the city bank of DSE is false. In other words, there is an asymmetric effect in the volatility of stock returns of city bank in the Dhaka Stock Market. The $\gamma = 0.079086$ is positive indicating that negative shocks (bad news) tend to produce higher volatility in the immediate future than the positive shocks (good news).

For Pubali bank, the significance of ARCH parameter $\alpha = 0.396251$ indicates that the news about volatility from the previous day has less effect on current volatility. The GARCH parameter $\beta = 0.55531$ indicate explanatory power on current volatility but also suggests volatility clustering in the daily returns of the DSE. The asymmetric volatility model GJR-GARCH with their estimates are used to examine the existence of asymmetry in stock returns volatility of Pubali bank of DSE. For GJR-GARCH (1,1), the $\gamma = 0.094878$ is positive but insignificant. For the GJR-GARCH model volatility persistence of Pubali bank is measured by the sum of α, β and γ coefficient with $\alpha + \beta + \gamma/2 < 1$. For pubali bank the sum of three coefficient is $\alpha + \beta + \gamma/2 = 0.998$ which indicates that volatility is persistent for Pubali bank. It means that today's volatility tells something not only about volatility tomorrow, but also about volatility many days ahead of Pubali bank of DSE. High persistence implies that average variance will remain high since increases in conditional variance due to shocks will decay slowly (Rachev et al., 2007) and the persistence in volatility shocks supports with (Emenike, 2010; Roni, et al., 2017; Abdullah, et al., 2018).

For Eastern bank, the significance of the ARCH parameter $\alpha = 0.194334$ indicates that the news about volatility from the previous day has less effect on current volatility. The GARCH parameter $\beta = 0.92445$ indicate explanatory power on current volatility but also suggests volatility clustering in the daily returns of the DSE. Volatility persistence is measured by $\alpha + \beta = 1.118784$ which indicates that volatility is persistent for Eastern Bank. For E-GARCH (1,1), the $\gamma = 0.251598$ is significant suggesting that positive shock increases volatility more than the negative shocks of the same magnitude.

4.6. Model Diagnosis

One of the most important assumptions of GARCH model that standardized residuals are independent and identically distributed. From Table 7 Ljung-Box test gives the large p-value for the selected banks which suggests that autocorrelation is not present i.e. the residuals are independent and follows white noise.

Table 7: Test of Presence of Autocorrelation and ARCH Effect

	Brac Bank ARMA(4,4)-EGARCH (1,1)	**City Bank** ARMA(3, 4)-GJRGARCH (1,1)	**Pubali Bank** ARMA(4, 3)-GJRGARCH (1,1)	**Eastern Bank** ARMA(4, 4)-EGARCH (1,1)
Q Statistic (P-value)	0.3549 (0.6155)	0.6776 (0.4104)	0.0602 (0.8008)	0.1376 (0.7107)
ARCH LM (P-value)	0.0036 (0.9614)	0.0009 (0.976)	0.00164(0.9680)	0.0026 (0.9589)

Source: Author’s computation

From the ARCH LM test, the greater p-value indicates that not the rejection of the null hypothesis i.e. there is no existing ARCH effect present in all the series which indicates that the models are fitted better for each selected bank.

4.7. Backtesting

A backtest shows how reliable a model is by reconstructing scenarios with historical data. The procedure is conducted by comparing the confidence level and actual returns that fall outside this VaR estimate (Blanco and Oks, 2004). The backtest is a part of the model validation which verifies to what extent actual losses match expected losses. It is a tool that risk managers apply to check how well their forecasts on VaR are attuned (Jorion, 2007). After fitting the GARCH type model, the performance of the model is checked by performing historical backtest.

Table 8: Back Testing Report of the Fitted Model

	Brac Bank ARMA(4,4)-EGARCH (1,1)	**City Bank** ARMA(3, 4)-GJRGARCH(1,1)	**Pubali Bank** ARMA(4, 3)-GJRGARCH (1,1)	**EasternBank** ARMA(4, 4)-EGARCH (1,1)
Backtest Length	1095	1095	1095	1095
Expected Exceed	11	11	11	11
Actual VaR Exceed	8	4	15	9
Kupiec Test (p-value)	0.347[a]	0.015[a]	0.244[a]	0.541[a]

[a] means significant at 1%

Source: Author's computation

Here, in Table 8 the returns of the data of Brac, City, Pubali and Eastern bank hits the 1% VaR limits 8, 4, 15 and 9 times compared to 11 times expected. So the above fitted models for Brac, City and Eastern banks perform well in modelling changing volatility but the GJR-GARCH model for Pubali bank with normally distributed errors does not perform well at least in this case. We don't reject the null hypothesis of Kupiec's unconditional coverage at 1% Var limits and concluded that the exceedances are correct and independent. These results are not surprising since the data exhibits some excess kurtosis that cannot be captured by the normal GARCH model. Thus, the results obtained from backtesting that almost all models are found to be able to sufficiently cope with the changing volatility.

4.8. Volatility Forecasting

This study compared the forecasting performance of selected banks using the GARCH-type models. This study indicated that the EGARCH (1,1) and GJRGARCH(1,1) model outperforms in the volatility of DSE returns. The inclusion of leverage effects or asymmetric components is thus important for forecasting short-run volatility. Table 9 shows the short-term forecasted volatility of different banks by using previously fitted GARCH type models.

Table 9: Seven days forecasted volatility of different banks

Time	Forecasted Volatility			
	Brac Bank	City Bank	Pubali Bank	Eastern Bank
Day 1	2.37	2.48	1.70	1.94
Day 2	2.56	2.59	1.91	2.04
Day 3	2.64	2.67	2.09	2.14
Day 4	2.67	2.72	2.25	2.23
Day 5	2.68	2.76	2.41	2.32
Day 6	2.69	2.79	2.55	2.41
Day 7	2.69	2.81	2.69	2.50

Source: Author's computation

From Table 9 it is observed that in the next seven days all banks will be more volatile as their volatility increasing continuously. But among them Brac bank shows a slightly increasing pattern and it has the lowest volatility changes comparing other banks. Among the four selected banks, Pubali bank shows a very increasing pattern and it has a very high increasing pattern in the next seven days comparing all other banks.

5. Conclusion

The volatility of Dhaka Stock Exchange (DSE) returns of four selected banks Brac Bank, City Bank, Pubali Bank and Eastern Bank have been modeled from March 2008 to December 2018 using different GARCH(p,q) models; GARCH(1,1), E-GARCH(1,1), GJR-GARCH(1,1). From the empirical results, it is concluded that the asymmetric volatility models E-GARCH and GJR-GARCH perform better for the selected banks of DSE which are supported by Roni, et al. (2017), Abdullah, et al. (2018) and Khan & Hossain (2016) and contradicted with the study of Miah & Rahman (2016). Another similar study was also conducted by Abdalla (2017) where he reported satisfactory results of VAR-GARCH model in modeling volaitily of Sudanese stock market. The existence of asymmetry in stock returns volatility, asymmetric GARCH models (E-GARCH, GJR-GARCH, PGARCH etc.) performs better in modeling volatility which was absent Miah & Rahman, (2016) as the distribution of daily returns are non-normal with negative skewness and pronounced excess kurtosis. The coefficient of γ (leverage effect) under E-GARCH (1,1) and the GJR-

GARCH (1,1) model is recorded significant for the selected banks except for Pubali bank. For Brac and Eastern bank, positive shock (good news) tend to produce higher volatility in the immediate future than the negative shocks (bad news) and the impact of the positive shock on volatility is much higher for Eastern bank than the other banks. There is a significant impact of negative shocks on City bank. Volatility is persistent for City, Pubali and Eastern bank which means that today's volatility tells something not only about volatility tomorrow, but also about volatility many days ahead that means they could be affected by volatility in upcoming days which also similar to the findings of Abdalla (2017) where he indicated volatility of Sudanese stock returns as an explosive process especially after the secession of South Sudan.

Backtestng was conducted to check the performance of GARCH type models. The fitted models for Brac, City and Eastern banks performed quite well in this case while for Pubali bank the GJR-GARCH model does not perform well. Though all bank's volatility is continuously increasing day by day, in the next seven days Brac bank will be the lowest volatile bank comparing all other selected banks and on the contrary Pubali bank may be the most volatile bank in the leading 30 companies (DS30) of DSE.

The findings of this study would help investors and traders to buy and sell share or multiple shares in the future domestically or internationally to their chosen financial institution with a minimum risk and the government and the regulators would get an idea about the future condition of the volatility of the selected financial institution to formulate policies.

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