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Performance Analysis of GARCH Family Models in Three Time-frames

(Analisis Prestasi Model Keluarga GARCH dalam Tiga Tempoh Jangka Masa)

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ABSTRACT

The proposed alternative p-value method can be used in finding the best performing models. The rank of the p-values namely t-test and z-test statistics can overcome the constraint imposed when using the Mean Absolute Percentage Error as the measurement error. It is crucial to select the right model in the right period so that the model can interpret volatility correctly. This study aimed to provide empirical analyses on the volatility of the Dhaka Stock Exchange market during the market crash in 2011. Three sub-samples were considered to represent pre-crisis, crisis, and post-crisis between November 16, 2009 to July 31, 2013 representing 889 observations. Various GARCH family models were fitted in order to capture the volatility and their performances were compared.

Keywords: GARCH models; error statistics; p-value; volatility; crisis
JEL codes: C01, C58, E37, G17

ABSTRAK

Kaedah alternatif nilai-p yang dicadangkan boleh digunakan dalam mencari model prestasi terbaik. Pangkat untuk nilai-p iaitu statistik ujian-t dan ujian-z dapat mengatasi kekangan yang dikenakan semasa menggunakan Ralat Peratusan Mutlak Min sebagai ralat pengukuran. Adalah penting untuk memilih model yang tepat dalam jangka masa yang tepat supaya model dapat menafsirkan kemeruapan dengan betul. Kajian ini bertujuan untuk menyediakan analisis empirik mengenai kemeruapan pasaran Bursa Saham Dhaka, semasa kejatuhan pasaran pada tahun 2011. Tiga sub-sampel telah dipertimbangkan untuk mewakili pra-krisis, krisis dan pasca krisis antara November 16, 2009 hingga Julai, 31, 2013 di mana diwakili sejumlah 889 cerapan. Pelbagai model keluarga GARCH disuaikan untuk merakam kemeruapan dan prestasi mereka dibandingkan.

Kata kunci: Model GARCH; statistik ralat; nilai-p; kemeruapan; krisis

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INTRODUCTION

Volatility is a common phenomenon in the modern financial market, especially the stock market index. Volatility in the stock market is a natural consequence because of variations in the activity level of a market. These activities, such as trading volume, new information, and market expectation, will cause shifts in the stock market variance of daily returns. In the stock market, volatility clustering is known as one of the stylized features, which indicates that large and small shifts in the return will also be followed by large and small shifts in the return. Robert Engle was the first to suggest the idea of volatility modeling in 1982 (Engle 1982). He proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model to capture nonconstant variances in time series data. Later, the ARCH model was further extended to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by Bollerslev (1986) and became popular among academics and practitioners. The GARCH framework is based on volatility dependence, of which to determine current volatility, the researcher needs to measure the impact of the last period forecast error and volatility. Eventually, various models of GARCH family models were further introduced, and among others are GARCH-Mean (Engle et al. 1987), Multivariate GARCH (Bollerslev et al. 1988), Integrated

GARCH (Nelson 1990), EGARCH (Nelson 1991), nonlinear GARCH (Higgins & Bera 1992), Glosten-Jagannathan-Runkle GARCH (Glosten et al. 1993), and Fractionally Integrated GARCH (Baillie et al. 1996).

The Bangladesh stock market started trading in 1956 and was renamed as Dhaka Stock Exchange (DSE) in 1964 (https://www.dsebd.org/ilf.php). Since established, the DSE had the first crash in 1996, but the most recent is in 2011 (Islam & Ahmed 2015). The 2011 crash was a massive fall of the stock price in the 55-years history of Bangladesh stock markets (BBC News 2011; Sarwar 2010). More than 3.5 million investors, where a large portion of the investors that comprised of small-scale individuals, lost their investment due to a sharp fall of stock prices (Banyan 2011). The reason behind the crash was the Bangladesh stock market scam in 2010-2011, which was due to an ongoing stock market chaos in two exchanges- Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE) (Bdnews24 2010). The market was started frenzy during 2009, and after a long bullish mood, it became grim. After the black days in 1996, it was a massive fall when the stock markets saw an extreme volatility within a short time. The stock analyzer claimed that perturbation began when Grameen Phone (GP) entered the stock market (The Financial Express 2010; Sarwar & Towhid Ahmed 2011). The market index climbed by 22 percent in one day on November 16, 2009 and a constant fluctuation of share prices stayed for a while, then hit the all-time highest index in 2010 (Bdnews24 2010). DSE index lifted to its all-time highest level on December 5, 2010, at 8,918 points. DSE index was 4568.40 on January 3, 2010 and surprisingly increased by 4,350 points, which was a 95.23 percent increase. Nevertheless, on January 10, 2011, DSE halted trade when it reached 660 points fall, which was a 9.25 percent decrease in less than one hour, which was a massive fall in the Bangladesh stock market history.

Until today, researchers are still interested in examining the 2011 Bangladesh stock market crash theoretically and empirically. Therefore, this study investigated the Dhaka Stock Exchange General Index (DSEGEN) further and considered the effect of Grameen Phone (GP) stock prices on the crash of the index in 2011 by using the GARCH family model. Furthermore, the model performance was compared and evaluated according to three sub-periods using the newly proposed alternative *p*-value method. This study found a significant effect of the GP stock prices on the DSEGEN index in every sub-samples. According to information criteria and log-likelihood (LL) values, EGARCH was identified as the best-performed model. Furthermore, according to the minimum error values (within the sample), GJR-GARCH performed well in the pre-crisis and GARCH-M in the crisis and post-crisis periods. According to the *p*-values (out-of-sample forecasting), GARCH-M, SAARCH, and EGARCH model selection are reported as the best performing models in pre-crisis, crisis, and post-crisis, respectively. Out-of-sample forecasting graphs also confirmed the findings. The next section is a brief literature about the drawback of this study. The section that follows discusses the methodology with data analysis, model representation, and model selection criteria. The subsequent section elaborates the results and followed by the discussion section. The final section is the section on concluding remarks.

LITERATURE REVIEW

The financial market, especially the stock market, plays an essential role in a country's economic growth. Moreover, capital markets are volatile due to the uncertainty of assets return, therefore, causing the complexity of risk management. High volatility produces high risk, and similarly, low volatility triggers lower risk. Much research has been done to capture the movement of volatility and forecasting (through analysing the daily logarithmic returns of bitcoin currency over the period of 2011-2017. Design/methodology/approach: In doing so, the symmetric informative analysis is estimated by applying the generalised auto-regressive conditional heteroscedasticity (GARCH Paolella et al. 2019; Ismail et al. 2015; Zivot 2009; Bera & Higgins 1993). Nevertheless, these studies are challenging because of the unpredictability of the stock price movement. Researchers developed various models to capture volatility in different aspects of different time-frames. Tai (2018) analyzed the dot.com crisis in 1999–2001 and the subprime crisis in 2007–2009 and provided experimental evidence of international diversification. Based on symmetric and asymmetric GARCH models, Othman et al. (2019) examined the price of Bitcoin and concluded that its price shows volatility persistence and has no leverage effect. Srinivasan and Ibrahim (2010) investigated volatility dynamics and model performance of the SENSEX stock Index of India and found that symmetric GARCH performs well and evidence of leverage effect.

Researchers also employed the GARCH family model to discover the effect of the COVID-19 crisis in agriculture commodity prices, such as Tanaka and Guo (2020) who explored the volatility of wheat price. On the other hand, the financial crisis (in 2008) of the MENA region was investigated by Ahmed (2018), and he found regime shift characteristics within three countries (Engle (2018) also took into account the similar crisis period in his study). Besides, he uncovered that volatility persistence during the crisis and post-crisis periods is more than that of the pre-crisis period. Bathia et al. (2020) applied the panel GARCH model and found that the financial crisis of emerging stock economics was affected by cross-border assets flows during the post-global financial crisis. Nevertheless, during the global financial crisis, Zekri and Razali (2019), Refai et al. (2017), Joseph et al. (2020), McIver and Kang (2020), Yamani (2019), and Belhassine (2020) also studied volatility dynamics using a different methodology.

Apart from that, Lim and Sek (2013) examined the Malaysian stock market volatility and model performance by applying different GARCH models. They found that oil price and exchange rates have significant effects on Malaysia stock index volatility, while in the normal and fluctuation periods, symmetric GARCH performs well. Meanwhile, volatility and model performance of the KSE 100 index of Pakistan was studied by Akhtar and Khan (2016) who concluded that volatility is highly persistent, the process is mean reverting, and GARCH (1, 1) is the best model. Recently, Broto and Lamas (2020) examined the relationship among returns, liquidity, and volatility of US Treasuries and found spillover effects and a lower persistence volatility after the crisis period. A study by Al-Rjoub and Azzam (2012) analyzed the Jordan's stock returns during the financial crisis and found an inverse relationship between volatility and stock returns. The Bangladesh stock market volatility investigated by Roni et al. (2017) considered three crisis periods from November 2001 to November 2016. They found volatility is persistence, and based on the model accuracy and error statistics, TGARCH and GARCH are the best models, respectively.

According to past literature as mentioned above, in studying the volatility model, some studies have found the models' significant dependence on time/periods of the index. Some studies considered two sub-periods of pre- and post-economic crisis (Akhtar & Khan 2016; Al-Rjoub & Azzam 2012), whereas others considered three sub-periods (see Ahmed 2018; Roni et al. 2017; Lim & Sek 2013; Refai et al. 2017; Zekri & Razali 2019) in evaluating the effects of certain events on the stock market volatility. Moreover, some studies also relied on the mean absolute percentage error (MAPE) to measure the model's performance. However, this study found that MAPE is not suitable for error measurement when taking the first difference in log-returns of original data, since the selection of time interval is wrong and exogenous variables are insignificant or not taken. This study uncovered a significant error in the model selection criteria using MAPE in Roni et al.'s (2017) and Lim and Sek's (2013) articles. Only Roni et al. (2017) analyzed the DSE index's volatility dynamics and model performance. However, as mentioned in their article, this study found that the selection of time intervals was wrong, and they did not include explanatory variable GP, which had a significant impact on the Bangladesh stock market crash in 2011. In this study, the selection of the time interval is clearly explained. Also, the importance of variable GP during the stock market crash in Bangladesh is explained with a proper reason.

It is known that all financial institutions from emerging and developed markets in the world faced a market crash locally or globally. Based on previous studies, it signifies the necessity and importance of the present study. Investors and government must have a depth knowledge during the crisis, before, and after the crisis in order to reduce loss and risk, and unwanted crash in the future. Therefore, this present study is essential and insightful. Different GARCH models, namely GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), GARCH-M (1,1), Simple Asymmetric ARCH or SAARCH (1,1), and Non-linear GARCH or NGARCH (1,1), were used to compare the performance in three periods. According to Ederington and Guan (2005), Awartani and Corradi (2005)we examine the relative out of sample predictive ability of different GARCH models, with particular emphasis on the predictive content of the asymmetric component. First, we perform pairwise comparisons of various models against the GARCH(1,1, Hansen and Lunde (2005), and Köksal (2009), only the first lag is taken for each model. Another reason is to avoid the complexity of lags squared return rates in all models. Different error measurement tools were used in the performance evaluation process, such as RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE, SMAPE (Symmetric Mean Absolute Percentage Error), and TIC (Theil Inequality Coefficient). AIC (Akaike Information Criteria), BIC (Bayesian Information Criteria), and LL (Log-Likelihood) were also used in the model's performance evaluation process. This study proposed a new technique of finding the best-performing model based on the *p*-value of t-test and z-test statistics. Moreover, this study attempted to investigate the influence of Grameen Phone (GP) in Bangladesh stock markets during the crash in 2011.

METHODOLOGY

DATA SOURCES

In this study, historical data of daily DSEGEN index and closing prices of GP stock from November 16, 2009 to July 31, 2013, were collected from www.dse.com. All the data were then firstly adjusted after considering the weekend and public holidays, where the stock transaction is closed. It was found that there are 98 public holidays besides the weekends between November 16, 2009 and July 31, 2013. The data involved a total of 889 observations. The period was chosen after considering that GP entered the DSE on November 16, 2009, and meanwhile, the DSEGEN index was terminated by the Bangladesh Securities and Exchange Commission on July 31, 2013. The total of 889 observations were divided into three sub-periods, namely the pre-crisis period (November 16, 2009 to December 15, 2010), with 263 observations, 198 observations represented the crisis period (December 19, 2010 to October 16, 2011), and the rest of 428 observations represented the post-crisis period (October 17, 2011 to July 31, 2013). For each period, there are two variables DSEGEN and GP, where DSEGEN1 and GP1, DSEGEN2 and GP2, and DSEGEN3 and GP3 each represent a pre-crisis, crisis, and post-crisis sub-sample, respectively. The crisis period in this study represented the market crash in early 2011. All analyses in this study were conducted using STATA 14. Table 1 shows the descriptive statistics for all the data.

From the descriptive analyses in Table 1, it shows that all the original series variance is very high, which indicates that the original data are spread further from the mean. Moreover, the skewness values show mixed results from relatively symmetric (-0.5 to 0.5) to moderately skewed (between -1.0 to -0.5 and between 0.5 to 1.0) and highly skewed (less than 1.0 and greater than 1.0). Meanwhile, the kurtosis values indicate the existence of a heavy-tail (when the value is greater than 3) and a light-tail (when the value is less than 3). In the return series, dlDSEG1 possesses the highest mean, and dlGP2 possesses the lowest mean. The crisis period is more volatile than the other two periods, which is expected. Only dlDSEG1 and dlGP3 are negatively skewed, and kurtosis that is > or < 3 confirm the presence of a tail disturbance.

According to the ADF test, Table 2 shows that all variables are stationary after taking the first difference of log-returns. Figures 1 to 3 show that the raw data are non-stationary, however, the returns are stationary for each sub-sample. Furthermore, the raw data histogram shows the right-tailed distribution, but they are almost symmetrical in their returns. The data also show the clustering characteristic for each sub-sample.

GARCH MODELS

In the GARCH process, conditional volatility recursively depends on the past lags and the function

TABLE 1. Descriptive statistics for each sub-sample.

Variables	Mean	Variance	Standard deviation	Skewness	Kurtosis	No. of Observations
DSEGEN1	6168.56	1377111.47	1173.50	0.42	2.62	263
dlDSEG1	0.0026	0.00012	0.010	-0.53	3.59	
GP1	262.26	2842.55	53.31	0.27	2.51	
dlGP1	0.0008	0.00075	0.027	0.40	4.46	
DSEGEN2	6299.73	501159.26	707.92	1.23	4.05	198
dlDSEG2	-0.0017	0.0009	0.029	0.32	6.38	
GP2	178.02	1036.76	32.19	1.10	3.40	
dlGP2	-0.002	0.0014	0.037	1.06	6.55	
DSEGEN3	4471.21	227856.51	477.34	0.40	2.40	428
dlDESG3	-0.00052	0.00039	0.019	0.10	4.75	
GP3	173.70	424.12	20.59	0.61	2.66	
dlGP3	0.00058	0.00059	0.024	-0.63	12.25	

TABLE 2. ADF test for the unit root of three periods.

Variables	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	p-value	Remarks
DSEGEN1	-0.443	-3.459	-2.880	-2.570	0.9027	Non-stationary
dlDSEG1	-15. 788	-3.459	-2.880	-2.570	0.0000	Stationary
GP1	-1.564	-3.459	-2.880	-2.570	0.5016	Non-stationary
dlGP1	-14.899	-3.459	-2.880	-2.570	0.0000	Stationary
DSEGEN2	-2.185	-3.478	-2.884	-2.574	0.2116	Non-stationary
dlDSEG2	-13. 659	-3.478	-2.884	-2.574	0.0000	Stationary
GP2	-1.645	-3.478	-2.884	-2.574	0.4595	Non-stationary
dlGP2	-15.250	-3.478	-2.884	-2.574	0.0000	Stationary
DSEGEN3	-2.461	-3.446	-2.873	-2.570	0.1254	Non-stationary
dlDSEG3	-21. 579	-3.446	-2.873	-2.570	0.0000	Stationary
GP3	-2.433	-3.446	-2.873	-2.570	0.1325	Non-stationary
dlGP3	-20.429	-3.446	-2.873	-2.570	0.0000	Stationary

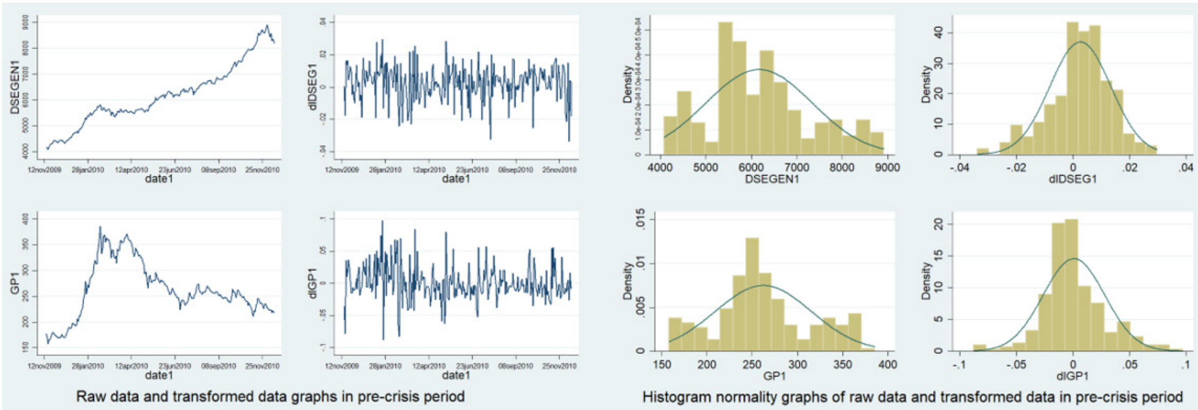

FIGURE 1. Graphs of raw data and its returns (first, second column) and histogram of raw data and its returns (last two columns) of DSEGEN1 and GP1 in the pre-crisis period.

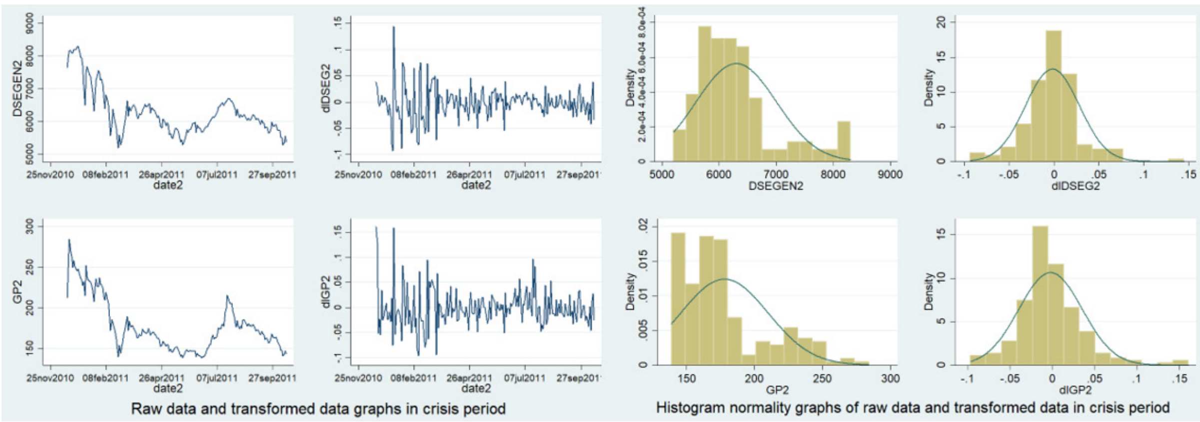

FIGURE 2. Graphs of raw data and its returns (first, second column) and normality histogram of raw data and its returns (last two columns) of DSEGEN2 and GP2 in the crisis period

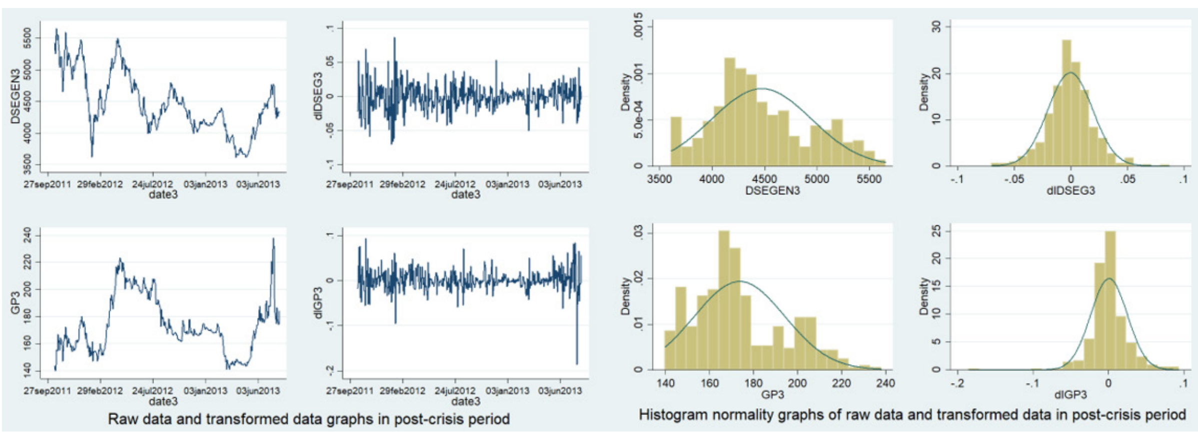

FIGURE 3. Graphs of raw data and its returns (first, second column) and normality histogram of raw data and its returns (last two columns) of DSEGEN3 and GP3 in the post-crisis period

of past innovation terms (Bollerslev 1986). Let ε_t be stochastic process at discrete time, and all information was set at time t is Ψ_t. Then the GARCH (1,1) process is as follows:

$$r_t = \mu + \varepsilon_t \tag{1}$$

$$\begin{gathered}\sigma_t^2 = \omega + a_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \\ \varepsilon_t \mid \Psi_{t-1} \sim N\left(0,\sigma_t\right)\end{gathered} \tag{2}$$

where asset return r_t, average return μ, residual return ε_t, variance return σ_t^2 and constant term, $\omega > 0$ ARCH term, $\alpha_1 \geq 0$, GARCH term, $\beta_1 \geq 0$. In the absence of the GARCH term, this process becomes ARCH (1). According to Bollerslev (1986) when $\alpha_1 + \beta_1 < 1$ the model becomes weakly stationary. Here, the short-run persistency of shocks represents by α_1, whereas the long-run persistency of shocks is represented by β_1. One of the weaknesses of this process is that it must be stationary in modeling volatility (Dyhrberg, Anne 2016).

Then, the Exponential GARCH or EGARCH model was proposed by Nelson (1991). Nelson and Cao (1992)q have argued that there is a restriction in nonnegativity constraints in the GARCH model, however, the restriction is not imposed in the EGARCH model parameters. The EGARCH (1,1) model can be written as:

$$\ln\sigma_t^2 = \omega + \sigma_1 z_{t-1} + \gamma\left(\left|z_{t-1}\right| - \sqrt{2/\pi}\right) + \beta_1 \ln\sigma_{t-1}^2 \tag{3}$$

where $z_t = \dfrac{\varepsilon_t}{\sigma_t}$ is distributed as N (0,1). Moreover, γ denoted as asymmetry term or leverage effect, and positive value of γ indicates the existence of leverage effects, and when $\gamma = 0$, the effects are symmetric. Glosten et al. (1993) have proposed the GJR-GARCH process, allowing the conditional variance to correspond differently to its past negative and positive innovations. The GJR-GARCH (1,1) model is written as:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma I\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{4}$$

where $\varepsilon_{t-1} < 0$ and I denotes as indicator function.

The GARCH-mean (GARCH-M), as proposed by Engle at al. (1987), has an integrating volatility effect on the mean. The GARCH-M (1,1) model is expressed as:

$$r_t = \mu + \lambda\sigma_t + \varepsilon_t \tag{5}$$

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{6}$$

One of the ARCH and GARCH process limitations is that it cannot capture asymmetric effects (Bollerslev et al. 1994). For that reason, Engle (1990) has introduced the Simple Asymmetric ARCH (SAARCH) model, which describes the ARCH and GARCH model's asymmetric effects. The SAARCH (1,1) model is written as:

$$r_t = \mu + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = \omega + a_1\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1} + \beta_1\sigma_{t-1}^2 \tag{8}$$

where γ representing asymmetry. Moreover, each Higgins and Bera (1992) and Engle and Bollerslev (1986) have introduced nonlinear GARCH or NGARCH model. The NGARCH (1,1) model is written as:

$$\sigma_t^2 = \omega + \alpha_1(\varepsilon_{t-1} - \gamma)^2 + \beta_1\sigma_{t-1}^2 \tag{9}$$

where $\gamma > 0$ represents asymmetry. A comprehensive discussion of the GARCH family model can be attained in the monograph by Francq and Zakoian (2019).

MODEL EVALUATION CRITERIA

In this study, different error measurement tools, such as RMSE, MAE, MAPE, SMAPE and TIC were used to compare the performance of various GARCH family models. The mathematical formulations are given below.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2} \tag{10}$$

$$\text{MAE} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|e_i\right| \tag{11}$$

$$\text{MAPE} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\left|\frac{e_i}{y_i}\right| \tag{12}$$

$$S\text{MAPE} = \frac{1}{N}\sum\nolimits_{i=1}^{N}\frac{\left|e_i\right|}{\left(\left|y_i\right| + \left|\hat{y}_i\right|\right)/2} \tag{13}$$

Here N is the number of observations, $e_i = y_i - \hat{y}_i$, where y_i is the actual value and $\hat{y}_i$ is the fitted value at time t. The Generalized Entropy, GE (1) to represent Theil's T index (TIC) is written as:

$$\text{GE}(1) = \frac{1}{N}\sum_{i=1}^{N}\frac{y_i}{\hat{y}}\, ln\left(\frac{y_i}{\hat{y}}\right) \tag{14}$$

where $\hat{y}$ denotes the fitted value at time t (see Cowell and Jenkins (1995), Cowell (1998) and Murphy 1985)).

P-VALUE OF TWO TEST STATISTICS

In statistics, p-value or probability value is a very well-known concept in hypothesis testing. Usually, to test the hypotheses of two samples, t-test and z-test are used. For each test, the results come with its p-values. According to statistical concepts, failure in rejecting the null hypothesis means no difference between two mean sample data (actual and forecast values). On the other hand, when the difference of two means decreases, the *p*-value also increases, and in the case of identical means, the *p*-value is one. The same principle was adopted in this study, but only that, as the *p*-value increases, it implies that the forecast values tend to approach the actual values- whereby, the *p*-value is one implying that the forecast values and actual values are identical. Therefore, it can be concluded that the increased *p*-value indicates the increased accuracy of the model estimation.

Let d be the differences between the actual and forecast values, m represents mean, s is the standard deviation of d, and n is the sample size of d. Then, the *t*-test statistics value is calculated as

$$t = \frac{m}{s/\sqrt{n}} \tag{15}$$

Next, the *t*-value is compared with the critical value of Student's *t* distribution, which can be found from the statistical table, according to the specified significance level of alpha (usually alpha is 5 %) with $n-1$ degrees of freedom (df). Now, let $\hat{x}_1$ and $\hat{x}_2$ be the means of two samples, Δ represent the hypothesized difference of sample mean (for the equal mean Δ is 0) for the null hypothesis, σ_1 and σ_2 represent standard deviations of two samples, and n_1 and n_2 represent two sample sizes. Then z-test statistics can be evaluated as

$$z = \frac{\hat{x}_1 - \hat{x}_2 - \Delta}{\sqrt{\frac{\sigma_1^{\ 2}}{n_1} + \frac{\sigma_2^{\ 2}}{n_2}}} \tag{16}$$

Based on the z-value, one or two-tailed test can be applied by comparing the statistical table's statistics value.

RESULTS AND DISCUSSION

In the pre-crisis period, according to the two tests, (namely Breusch-Pagan and IM-test), the *p*-value is 0.0047, and the value 0.0461 leads to the null hypothesis of constant variance being rejected, i.e., there exists heteroskedasticity. Meanwhile, the ARCH test shows that the p-value is 0.0508; the null hypothesis was rejected at the 10 % level, which suggests the presence of the ARCH effects. In the crisis period, according to the two tests, the p-value is 0.0000, and 0.0000 implies the existence of heteroskedasticity, and the ARCH test shows that the p-value is 0.0022 indicating the presence of the ARCH disturbance. In the post-crisis period, according to the two tests, the p-value is 0.0030, and 0.0000 indicates the presence of heteroskedasticity, and the ARCH test shows that the p-value is 0.0000 implying the ARCH disturbance. Thus, based on all these results, it is recommended to use the GARCH family model. The GARCH family models for pre-crisis, crisis, and post-crisis periods are given in Tables 3, 4, and 5.

In each sub-sample, it was found that the dlGP (dlGP1, dlGP2, and dlGP3) has positive shocks on dlDSEG, which implies its significant impact on DSE volatility. Also, in the crisis period, the dlGP2 value was recorded higher compared to other periods, indicating its significant influence on the fluctuation of DSE. This finding confirms the study's assumption that the GP did affect the DSE stock market crash in 2011. On the

TABLE 3. Summary results of GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), GARCH-M (1,1), SAARCH (1,1) and NGARCH (1,1) models in pre-crisis period.

Parameters	GARCH	EGARCH	GJR-GARCH	GARCH-M	SAARCH	NGARCH
dlGP1	0.23*** (-0.0216)	0.242*** (-0.0191)	0.23*** (-0.0215)	0.231*** (-0.0216)	0.23*** (-0.0216)	0.23*** (-0.0216)
μ (const.)	0.00252*** (-0.000577)	0.0024*** (-0.00056)	0.0025*** (-0.000577)	0.00329 (-0.00239)	0.00249*** (-0.000586)	0.00249*** (-0.000586)
α_1	0.171** (-0.0712)	0.0398 (-0.0358)	0.232** (-0.0932)	0.229** (-0.105)	0.158** (-0.0756)	0.159** (-0.0758)
β_1	0.48** (-0.208)	0.975*** (-0.0304)	0.443** (-0.188)	0.458** (-0.186)	0.494** (-0.201)	0.493** (-0.2)
γ		0.136** (-0.0589)	-0.162 (-0.137)	-0.172 (-0.132)	-0.000571 (-0.000816)	0.00188 (-0.00295)
sigma2 (λ)				-11.26 (-33.44)		
ω (const.)	0.00003** (-0.00001)	-0.238 (-0.289)	0.00003*** (-0.00001)	0.00003*** -0.00001	0.0000264** (-0.00001)	0.00003** (-0.00001)
$\alpha_1 + \beta_1$	0.651	0.975	0.675	0.687	0.652	0.652
No. of observations		262				

Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

contrary, in the pre-crisis period (Table 3), it shows that the sum of ARCH and GARCH terms is less than one, giving evidence on the existence of volatility persistence. Moreover, in the crisis and post-crisis periods, the sum of the ARCH and GARCH terms are close to one (Tables 4 and 5). However, the variance process is not integrated, indicating that volatility remains in a prolonged period, giving evidence of the possibility of long-term memory persistency in a conditional volatility. For the GJR-GARCH model, the sum of ARCH and GARCH terms is one in both the crisis and post-crisis periods, whereby in the GARCH-M model, the sum is one in the post-crisis period, implying the integrated variance.

Furthermore, there are evidence of a larger GARCH term (β_1) compared to the ARCH term (α_1) in all the six GARCH family models for each sub-samples, implying that the shocks on conditional variance have reduced after a certain period, and in the same time, the volatility on returns is high due to its own lagged returns and persistence in each period. In the crisis period

TABLE 4. Summary results of GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), GARCH-M (1,1), SAARCH (1,1) and NGARCH (1,1) models in crisis period.

Parameters	GARCH	EGARCH	GJR-GARCH	GARCH-M	SAARCH	NGARCH
dlGP2	0.7*** (-0.0276)	0.715*** (-0.0281)	0.722*** (-0.0265)	0.715*** (-0.0257)	0.718*** (-0.0295)	0.716*** (-0.0288)
μ (const.)	0.000342 (-0.000939)	0.0000331 (-0.00091)	0.0000573 (-0.000922)	-0.00108 (-0.00141)	-0.000111 (-0.000949)	-0.0000942 (-0.00095)
α_1	0.0722** (-0.0299)	-0.15*** (-0.0575)	0.139** (-0.0605)	0.129** (-0.0586)	0.0598** (-0.0296)	0.0595** (-0.0293)
β_1	0.875*** (-0.0356)	0.945*** (-0.0204)	0.863*** (-0.0379)	0.855*** (-0.0443)	0.869*** (-0.038)	0.871*** (-0.0379)
γ		0.177*** (-0.0653)	-0.163** (-0.0653)	-0.159** (-0.0628)	-0.00206** (-0.000823)	0.016* (-0.00966)
sigma2 (λ)				6.372 (-5.939)		
ω (const.)	0.0000074* (-0.000004)	-0.475*** (-0.169)	0.000013*** (-0.0000046)	0.00002*** (-0.000006)	0.0000121** (-0.0000051)	-0.0000039 (-0.000013)
$\alpha_1 + \beta_1$	0.9472	0.795	1.002	0.984	0.9288	0.9305
No. of observations				197		

Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

TABLE 5. Summary results of GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1), GARCH-M (1,1), SAARCH (1,1) and NGARCH (1,1) models in post-crisis period.

Parameters	GARCH	EGARCH	GJR-GARCH	GARCH-M	SAARCH	NGARCH
dlGP3	0.594*** (-0.0259)	0.562*** (-0.0247)	0.588*** (-0.026)	0.587*** (-0.0261)	0.581*** (-0.0257)	0.581*** (-0.0256)
μ (const.)	-0.000265 (-0.000479)	-0.000557 (-0.00058)	-0.000601 (-0.000566)	-0.000606 (-0.00086)	-0.000618 (-0.000576)	-0.000608 (-0.000575)
α_1	0.195*** (-0.0454)	-0.0537* (-0.0313)	0.241*** (-0.0635)	0.24*** (-0.064)	0.189*** (-0.0458)	0.187*** (-0.0452)
β_1	0.794*** (-0.0438)	0.942*** (-0.0215)	0.798*** (-0.0432)	0.798*** (-0.0434)	0.788*** (-0.0466)	0.789*** (-0.0461)
γ		0.338*** (-0.0679)	-0.108* (-0.0558)	-0.108* (-0.0575)	-0.000921* (-0.000524)	0.00239* (-0.00127)
sigma2 (λ)				0.0378 (-5.134)		
ω (const.)	0.000006** (-0.000003)	-0.49*** (-0.188)	0.0000068** (-0.0000029)	0.000007** (-0.000003)	0.0000078** (-0.0000032)	0.000007** (-0.000003)
$\alpha_1 + \beta_1$	0.989	0.8883	1.039	1.038	0.977	0.976
No. of observations		427				

Standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

(Table 4), the larger GARCH term (β_1) suggests that the stock market has a long memory, and the volatility is prone to its previous lag value than to the present value. Meanwhile, the negative values of ARCH term in the EGARCH model during the crisis and post-crisis periods show the impact of a negative shock compared to the positive shock.

Regarding each model's asymmetry, the values ($\alpha + \beta + \gamma / 2 < 1$) imply that the shock is volatility persistence. The significant asymmetric term or leverage effect (γ), with the values in the interval $-1 < \gamma < 1$, suggest that a negative shock (or bad news) increases the debt-equity ratio. This result portrays a high-risk market to the investors and consequently increase volatility. On the other hand, a positive shock (or good news) also increases volatility, however, the volatility increase is more due to adverse shocks of bad news, which leads to the asymmetry volatility (as shown in Akhtar and Khan (2016), Al Refai et al. (2017)). Also, the negative values on the asymmetric term or leverage effect (γ) suggest a negative correlation between past and future returns. Inversely, the insignificant γ represents no asymmetric effect on the stock market. The findings suggest there is no influence of the sub-sample effect on returns, as shown as the insignificant value of sigma2 (λ) in each period, which is similar to the findings reported in Othman et al. (2019).

Next, from Table 6, according to the smallest AIC and BIC values, and the largest likelihood values (LL), the results indicate that overall, the EGARCH is performing well compared to other GARCH family models for each sub-sample. Meanwhile, the second-best model is GARCH during the pre-crisis period and GJR-GARCH models in the crisis and post-crisis periods. Next, Table 7 and Table 8 present the in-sample forecasting performance analysis of three time periods. For out-of-sample forecasting, we generated 12 observations using the one-step-ahead prediction. Table 9 and Table 10 display the performance analysis of out-of-sample forecasting using the newly proposed method based on the *p*-value. The models' performance evaluation process was ranked based on the smallest to the largest error for Table 7 and Table 9. Similarly, Table 8 and Table 10 were ranked based on the highest to the lowest *p*-value. The lowest value of total rank represents the best model.

The results in Table 7 report five error measurement tools to indicate the best performing model among the six GARCH family models, and each result is in a different model. According to RMSE, the GARCH-M and GARCH (picked twice) models were chosen as the best performing model in each sub-sample, respectively. Meanwhile, the NGARCH, GARCH-M, and EGARCH are the best picks by MAPE values for each pre, crisis,

TABLE 6. Different types of GARCH model performance based on information criteria and log-likelihood.

Model	Based on information criteria and log-likelihood (LL)						
	AIC	Rank	BIC	Rank	LL	Rank	Total Rank
	Pre-crisis Period						
GARCH	-1747.129	2	-1729.287	1	878.5644	6	9
EGARCH	-1749.458	1	-1728.048	2	880.7292	1	**4**
GJR-GARCH	-1746.386	3	-1724.976	3	879.1932	3	9
GARCH-M	-1744.579	6	-1719.601	6	879.2897	2	14
SAARCH	-1745.696	5	-1724.286	5	878.8481	5	15
NGARCH	-1745.817	4	-1724.407	4	878.9086	4	12
	Crisis Period						
GARCH	-1067.706	6	-1051.29	3	538.8528	6	15
EGARCH	-1076.414	1	-1056.715	1	544.2071	1	**3**
GJR-GARCH	-1073.368	2	-1053.669	2	542.684	3	7
GARCH-M	-1072.235	3	-1049.253	6	543.1175	2	11
SAARCH	-1070.212	4	-1050.513	4	541.106	4	12
NGARCH	-1069.332	5	-1049.633	5	540.666	5	15
	Post-crisis Period						
GARCH	-2476.104	5	-2455.82	2	1243.052	6	13
EGARCH	-2481.084	1	-2456.743	1	1246.542	1	**3**
GJR-GARCH	-2477.703	2	-2453.362	3	1244.852	2	7
GARCH-M	-2475.703	6	-2447.305	6	1244.851	3	15
SAARCH	-2477.391	3	-2453.05	4	1244.695	4	11
NGARCH	-2476.945	4	-2452.605	5	1244.473	5	14

TABLE 7. Different types of GARCH model performance based on error statistics (in sample).

Model	Error Statistics										
	RMSE	Rank	MAE	Rank	MAPE	Rank	SMAPE	Rank	TIC	Rank	Total Rank
	Pre-crisis Period										
GARCH	.0086187	6	.0066199	1	18.6936	4	1.20107	1	.38192	1	13
EGARCH	.0086169	2	.0066411	6	19.1037	6	1.20231	3	.40087	6	23
GJR-GARCH	.0086185	3	.0066221	2	18.6359	3	1.20228	2	.38571	2	**12**
GARCH-M	.0086168	1	.0066291	5	18.7545	5	1.20235	4	.39604	5	20
SAARCH	.0086185	4	.006623	4	18.6022	2	1.2029	6	.38723	4	20
NGARCH	.0086186	5	.0066228	3	18.6020	1	1.20289	5	.38677	3	17
	Crisis Period										
GARCH	.0194081	1	.0125196	6	3.01591	2	0.80489	5	.4729	3	17
EGARCH	.019498	3	.0124769	4	3.15092	3	0.80122	2	.47677	5	17
GJR-GARCH	.019547	6	.012464	2	3.17058	4	0.79936	1	.47553	4	17
GARCH-M	.0194233	2	.0124075	1	2.92968	1	0.81974	6	.49057	6	**16**
SAARCH	.0195169	5	.012475	3	3.20134	6	0.80297	3	.47191	2	19
NGARCH	.0195023	4	.0124784	5	3.18881	5	0.80323	4	.47108	1	19
	Post-crisis Period										
GARCH	.0147235	1	.0106103	6	3.19236	6	1.06768	5	.43089	6	24
EGARCH	.0146736	6	.0106076	5	3.03809	1	1.07162	6	.41705	1	19
GJR-GARCH	.014702	5	.0105802	1	3.15023	5	1.05914	1	.41881	3	15
GARCH-M	.0147002	4	.0105807	2	3.14844	4	1.05946	2	.41877	2	**14**
SAARCH	.0146911	2	.0105844	3	3.11875	2	1.06153	3	.42116	5	15
NGARCH	.0146918	3	.0105849	4	3.12072	3	1.06167	4	.4201	4	18

TABLE 8. Different types of GARCH model performance based on the p-value of t-test and z-test statistics (in sample).

Model	t-test and z-test (one-tail test)				t-test and z-test (two-tail test)				
	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	Total Rank
	Pre-crisis Period								
GARCH	0.42268	6	0.44621	6	0.84536	6	0.89243	6	24
EGARCH	0.49537	1	0.49683	1	0.99073	1	0.99366	1	**4**
GJR-GARCH	0.44078	5	0.45886	5	0.88157	5	0.91772	5	20
GARCH-M	0.48297	2	0.48819	2	0.96593	2	0.97638	2	8
SAARCH	0.44918	3	0.46471	3	0.89836	3	0.92941	3	12
NGARCH	0.44777	4	0.46372	4	0.89555	4	0.92745	4	16
	Crisis Period								
GARCH	0.29994	5	0.39852	5	0.59988	5	0.79705	5	20
EGARCH	0.39011	3	0.44584	3	0.78023	3	0.89168	3	9
GJR-GARCH	0.38737	4	0.44455	4	0.77473	4	0.88909	4	16
GARCH-M	0.20729	6	0.34597	6	0.41457	6	0.69195	6	24
SAARCH	0.43204	1	0.46673	1	0.86408	1	0.93347	1	**4**
NGARCH	0.42605	2	0.46376	2	0.85210	2	0.92752	2	8
	Post-crisis Period								
GARCH	0.19983	6	0.30578	6	0.39967	6	0.61157	6	24
EGARCH	0.34144	5	0.40121	5	0.68288	5	0.80242	5	20
GJR-GARCH	0.35696	3	0.41229	3	0.71392	3	0.82459	3	12
GARCH-M	0.35520	4	0.41116	4	0.71040	4	0.82233	4	16
SAARCH	0.36797	1	0.41895	1	0.73594	1	0.83791	1	**4**
NGARCH	0.36233	2	0.41541	2	0.72466	2	0.83083	2	8

TABLE 9. Different types of GARCH models performance based on error statistics (out-of-sample).

Model	Error Statistics										
	RMSE	Rank	MAE	Rank	MAPE	Rank	SMAPE	Rank	TIC	Rank	Total Rank
	Pre-crisis Period										
GARCH	.01999232	6	.01064605	4	5.33324	1	1.21337	6	.42755	2	19
EGARCH	.01996925	2	.01100825	5	5.82286	5	1.20951	2	.44335	6	20
GJR-GARCH	.01998661	5	.01064453	3	5.35237	2	1.21281	5	.42905	3	18
GARCH-M	.01996771	1	.01112979	6	5.91183	6	1.19989	1	.35748	1	**15**
SAARCH	.01998414	3	.01063983	2	5.35684	4	1.21258	3	.42964	5	17
NGARCH	.0199847	4	.01063738	1	5.35255	3	1.21263	4	.42946	4	16
	Crisis Period										
GARCH	.02270786	1	.01878084	4	1.05704	1	0.95533	4	.28269	2	**12**
EGARCH	.02279456	4	.01877898	3	1.06196	4	0.95404	2	.29183	4	17
GJR-GARCH	.02291465	5	.01883153	5	1.0677	5	0.95133	1	.29112	3	19
GARCH-M	.02335076	6	.01919295	6	1.09427	6	0.96343	6	.27610	1	25
SAARCH	.02277297	3	.01875072	2	1.06105	3	0.9553	3	.29623	6	17
NGARCH	.02274786	2	.01874263	1	1.05982	2	0.95574	5	.29571	5	15
	Post-crisis Period										
GARCH	.03176745	6	.01817676	6	3.91306	6	1.35527	6	.28777	4	28
EGARCH	.03149634	1	.01762472	1	3.64901	1	1.34408	1	.30840	6	**10**
GJR-GARCH	.03161791	5	.01797283	5	3.79697	5	1.35096	5	.15590	1	21
GARCH-M	.03161339	4	.0179629	4	3.79521	4	1.35108	4	.30801	5	21
SAARCH	.0315741	2	.01786862	2	3.75021	2	1.34656	2	.15641	3	11
NGARCH	.03157953	3	.01787738	3	3.75489	3	1.34779	3	.15618	2	14

TABLE 10. Different types of GARCH models performance based on t-test and z-test statistics (out-of-sample).

Model	t-test and z-test (one-tail test)				t-test and z-test (two-tail test)				
	p-value	Rank	p-value	Rank	p-value	Rank	p-value	Rank	Total Rank
	Pre-crisis Period								
GARCH	0.21938	6	0.43875	6	0.28907	6	0.57814	6	24
EGARCH	0.21978	5	0.43957	5	0.29237	2	0.58474	2	14
GJR-GARCH	0.22056	4	0.44112	4	0.29007	5	0.58014	5	18
GARCH-M	0.31300	1	0.62601	1	0.35655	1	0.71311	1	**4**
SAARCH	0.22117	2	0.44233	2	0.29055	3	0.58109	3	10
NGARCH	0.22111	3	0.44222	3	0.29048	4	0.58095	4	14
	Crisis Period								
GARCH	0.04382	5	0.08764	5	0.15448	5	0.30896	5	20
EGARCH	0.04682	3	0.09365	3	0.15993	3	0.31987	3	12
GJR-GARCH	0.04612	4	0.09225	4	0.15884	4	0.31768	4	16
GARCH-M	0.03783	6	0.07565	6	0.14091	6	0.28182	6	24
SAARCH	0.04856	1	0.09711	1	0.16285	1	0.3257	1	**4**
NGARCH	0.04846	2	0.09691	2	0.16266	2	0.32531	2	8
	Post-crisis Period								
GARCH	0.12715	6	0.25430	6	0.14029	6	0.28059	6	24
EGARCH	0.14204	1	0.28408	1	0.15454	1	0.30909	1	**4**
GJR-GARCH	0.13596	4	0.27193	4	0.14941	4	0.29882	4	16
GARCH-M	0.13518	5	0.27036	5	0.14861	5	0.29722	5	20
SAARCH	0.13822	2	0.27645	2	0.15146	2	0.30292	2	8
NGARCH	0.13789	3	0.27578	3	0.15113	3	0.30225	3	12

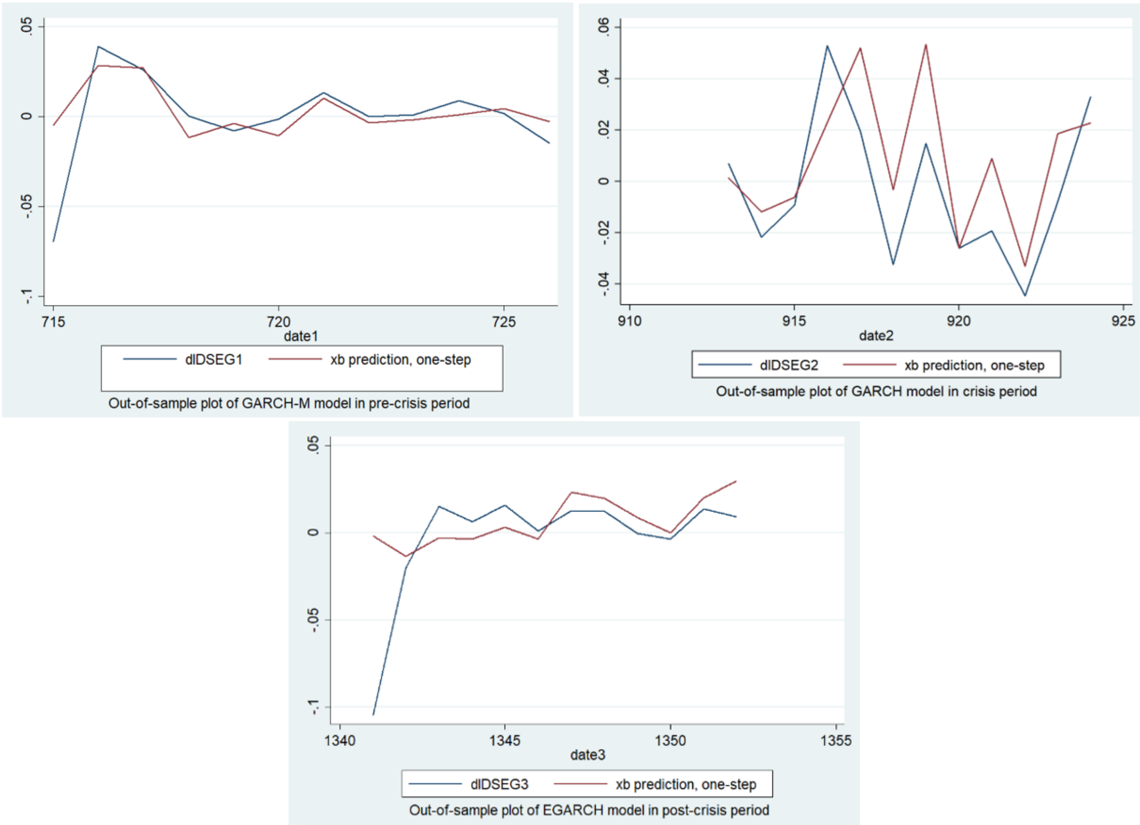

FIGURE 4. Out-of-sample forecast graph of GARCH-M model in the pre-crisis period (upper left), GARCH model in crisis period (upper right) and EGARCH model in the post-crisis period (bottom).

and post periods. Next, the *p*-values of the t-statistics and z-statistics are reported in Table 8. The one-tailed and two-tailed tests were considered in this study. The idea was to choose the model with the highest values of *p*-value. The results suggest that the EGARCH performs better in the pre-crisis period, whereby the SAARCH performs well in both crisis and post-crisis periods. Also, during the pre-crisis period, GARCH-M is the second-best model, and the NGARCH is the second-best model for each the crisis and post-crisis periods.

Table 9 presents the model performance evaluation according to their error statistics values, and the smallest value indicates the best performing model. The analyses show that the best performing models are GARCH-M, GARCH, and EGARCH for the pre-crisis, crisis, and the post-crisis period. Besides, the *p*-values of the out-of-sample forecasting results are reported in Table 10, which results are in the selection of GARCH-M, SAARCH, and EGARCH model, as the best performing model, each for pre-crisis, crisis, and post-crisis, respectively. As shown in Figure 4, the out-of-sample forecasting graphs confirm the similar pattern of the chosen models to their original data (dlDSEG), emphasizing that the models are well-fitted.

Previous studies by Srinivasan and Ibrahim (2010), Lim and Sek (2013), Roni et al. (2017) analyzed the performance of the GARCH types of model based on the ranking of error statistics. However, the usage of MAPE as the comparison tools had flawed, as shown in this study, when considering the first difference of log returns. The values become too small, and there is a possibility to be less than one. In their studies, the computation of MAPE involved dividing the difference between the actual and forecast values with actual values. When the actual values become very small (less than one), it will produce a larger MAPE. There will be a time when the value is much larger, it will produce an unexpected error. For example, in this study, one of the actual values is 0.00000191, and the predicted value is 0.0081875, then computing the MAPE (| (0.00000191-0.0081875)/0.00000191|=4258.65) produces a higher value. Thus, this will violate the consistency of the calculated MAPE for all observations. Alternatively, this study is proposing the technique by ranking the *p*-values instead of searching for the best model. As the *p*-values increases, the accuracy increases, and at the same time, the error of estimation will decrease.

CONCLUSION

It is crucial to select the right model in the right period so that the model can interpret volatility correctly. In addition, alternative techniques based on the rank of the *p*-values (t-test and z-test statistics) can overcome the constraint imposed when using the Mean Absolute Percentage Error as the measurement error. The paper proposed an alternative in evaluating model performance, and the Grameen Phone stock prices were considered to investigate its effect on the crash of the DSEGEN market. It is shown that the Grameen Phone does has a significant effect on the crashed event as validated in the studied GARCH family models. The larger and positive values in dlGP2 during the crisis period compared to other sub-sample periods confirms the positive effect of the stock. As for the within sample data, the best model was identified as EGARCH in three periods according to information criteria and LL, but GJR-GARCH in the pre-crisis and GARCH-M in the crisis and post-crisis period depend on the minimum error. On the other hand, the EGARCH in the pre-crisis and SAARCH in the other two crisis periods were based on the *p*-value. For out-of-sample data, GARCH-M, GARCH, and EGARCH were identified as the best model depending on the minimum rank of error; GARCH-M, SAARCH, and EGARCH are the best models depending on the *p*-value. These findings are partially similar to the results shown by other studies, such as Roni et al. (2017) and Lim and Sek (2013).

When we introduced Grameen Phone as the explanatory variable and corrected the time interval, our results differed from the original results of Roni et al. (2017). Therefore, our findings are the evidence that the previous results are wrong and misleading. Although the Dhaka Stock Exchange General Index market crashed almost ten years ago, hopefully, the findings reported in this article would be a reference for improving the policies and stock market regulations by authorities. These findings will also give investors and fund managers insights in identifying the crisis indicator in determining a portfolio diversification and avoiding or reducing capital loss.

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