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# VOLATILITY OF STOCK PRICES IN TANZANIA: APPLICATION OF GARCH MODELS TO DAR ES SALAAM STOCK EXCHANGE

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## ABSTRACT

We use Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models to examine volatility of stock prices for firms listed in the Dar es Salaam Stock Exchange (DSE). In doing so, both symmetric and asymmetric GARCH models are used in this study. The descriptive analysis of the data shows that standard deviation of the series returns is high, indicating a high level of daily fluctuations, and the log value of the mean is close to zero. Our empirical results clearly exhibit evidence of volatility and volatility clustering, a typical feature of financial time series. Moreover, our results indicate that the series are highly leptokurtic, flat tailed and asymmetric consistent with characteristics of financial time series data. Out of all models examined, EGARCH (1,1) and GARCH (1,1) seem to perform plausibly better than others.

**Contribution/ Originality:** This study contributes to the existing literature through the application of both GARCH and the EGARCH models in order to capture both symmetry and asymmetry effects, and determines key characteristics of stock returns at Dar es salaam Stock Exchange.

## 1. INTRODUCTION

This paper attempts to model volatility of stock prices in Dar es salaam Stock Exchange (DSE) in Tanzania for the period between January 2014 and November 2019. The motivation for undertaking this exercise is two folds. First, although much has been documented on the volatility of stock prices elsewhere in the world, relatively little is known in the context of Tanzania (see for example, (Achal, Girish, Ranjit, & Bishal, 2015; Ajaya & Swagatika, 2018; Akhtar & Khan, 2016; Mathur, Chotia, & Rao, 2016)). Existing studies that have attempted to examine volatility within the context of GARCH models in Tanzania have mainly focused on other macroeconomic variables such as inflation (Edward, Eliab, & Estomih, 2004) exchange rate (Carolyn, Betuel, & Pitos, 2018; Epaphra, 2016) tax revenues (Chimilila, 2017). Secondly, while there exists a paucity of research in this area, it remains indisputable that traders in the stock exchange need reasonable understanding of stock volatility and forecasts on future values of stock prices. Since volatility of stock price may hike transaction costs and reduce the gains to traders in the financial markets, it suffices to argue that knowledge of stock price volatility estimation and forecasting is extremely imperative for asset pricing and risk management (Srinivasan & Ibrahim, 2010).

Over the last three decades or so, volatility modeling has been a subject of rigorous empirical investigation, pioneered by Eagle (1982); Domowitz and Hakkio (1985) and Bollerslev (1986). The Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle takes into consideration differences between conditional and unconditional variance, and in doing so, it allows for unconditional variance to change overtime as a function of past disturbance terms. GARCH, on the other hand, allows for a more flexible of lag structure that permits a more parsimonious description in many economic situation. The GARCH models are oftentimes preferred by researchers in financial modelling because they provide a more real-world context than other forms when trying to predict stock prices. In short, GARCH model involves three steps. The first step is to estimate a best-fitting autoregressive model. The second step is to compute and plot the autocorrelations of the disturbance term. Third, is to test for significance whereby the null hypothesis states that there are no ARCH or GARCH errors. Numerous extensions of the GARCH model have been developed in the literature, and it is the major preoccupation of this paper to examine them in our analysis.

Our estimated results show that a null hypothesis of no ARCH effect is strongly rejected since the p-value is less that 5 percent level of significance, suggesting the presence of ARCH effect in the data series. We also find that our data series have heteroscedastic characteristics and therefore support use of GARCH models. The weighted average of Akaike Information Criterion (AIC) and Schwarz Information criterion (SIC) of the selected GARCH shows that EGARCH (1, 1) has the lowest values of AIC and SIC followed by the GARCH (1, 1) model respectively. A correlogram of Standardized Residuals Squared shows that the null hypothesis of no serial correlation is accepted for both models. The *Jarque Bera* test of normality in the residuals is accepted at five percent level of significance showing that residuals are normally distributed. And lastly, the forecast of the two models show an evidence of volatility in returns, and a low value of Root Mean Square Error (0.0093) for both GARCH (1,1) and EGARCH indicates the two models are reasonably accurate.

We contribute to the literature in two major dimensions. First, unlike the relatively few previous studies done in Tanzania (see for example, Mutaju and Dickson (2019)), we apply both GARCH and the EGARCH models to capture both symmetry and asymmetry effects, and determine key characteristics of DSE stock returns. Secondly, unlike Mutaju and Dickson (2019) we divide our data set into three periods, namely; the period between 2014 and 2019, the period before "General Election" (2014-2015) and after "General Election" of 2015 (2016-2019). We believe this categorization of period is important because change of power by those in government may influence investor's participation in the stock market through the adoption of "wait and see" attitude (Nancy, 2016) and this might have remarkable consequences on the behavior of stock prices. Our results, nevertheless, are not susceptible to the effects of "General Election" of 2015.

The remainder of this study is organized as follows. Section 2 reviews briefly empirical literature. Section 3 spells out model specification. Section 4 reports and discusses the empirical results. Section 5 concludes.

## 2. LITERATURE REVIEW

On the empirical front, numerous studies have empirically applied the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) developed by Bollerslev (1986). Aktan, Korsakienė, and Smaliukienė (2010) examine Baltic Stock Markets comprising of Estonia, Latvia and Lithuania using a broad range of GARCH volatility models. The study tested GARCH models that include basic GARCH model, GARCH-in-mean model, asymmetric exponential GARCH, GJR GARCH, power GARCH and component GARCH model in Baltic Stock Markets comprising of Estonia, Latvia and Lithuania; and found a strong evidence that daily returns are better-modelled using GARCH-type models, though did not specify a best-fit model.

Srinivasan and Ibrahim (2010) attempted to forecast conditional variance of the SENSEX Index returns of Indian Stock Market using daily data from January 1996 to January 2010 and found that symmetric GARCH models perform better in forecasting conditional variance rather than the asymmetric GARCH models, despite the presence of leverage effect. Though the paper provides substantial empirical evidence of the characteristics of BSE-30 index, it did not undertake rigorous discussion of the literature cited.

Ahmed and Suliman (2011) on the other hand, used the symmetric and asymmetric GARCH model to estimate volatility in the daily returns of Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. The study found that conditional variance process is highly persistent and provide evidence of the existence of risk premium for the KSE index return series; which supported the positive correlation hypothesis between volatility and the expected stock returns. Although this study successfully compared symmetric and asymmetric GARCH models in the context of KSE, did not specify the best-fit model for the KSE return series. On the other hand, Prateek (2015) undertook a robust comparison of the daily conditional variance forecasts of seven GARCH-family models using daily price observations of 21 stock indices of the world for the period 1 January 2000 to 30 November 2013. The study found that standard GARCH model outperforms the more advanced GARCH models and provides the best one-step-ahead forecasts of the daily conditional variance. The study did not undertake model-fitting tests to confirm the models.

Ajaya and Swagatika (2018) measured return volatility and dynamic conditional correlation between the stock markets of North America region using weekly stock market returns data from January 1995 to June 2016. Using univariate ARCH and GARCH approaches, the study found an evidence of return volatility and its persistence within the region. Further, as expected, emerging markets are less linked to the developed market in terms of return and there exists weak linkage between the stock markets; and there is no evidence of market integration throughout the sample period. Though the study provides substantial empirical work to benchmark stock markets of the North American region, the study could go further to capture characteristics of the stock markets with reference to any asymmetric model such as EGARCH.

In the context of Tanzania, Mutaju and Dickson (2019) attempted to model volatility of stock returns at Dar es Salaam Stock Exchange (DSE) using daily closing stock price indices from 2nd January 2012 to 22nd November 2018. Both symmetrical and asymmetrical Generalized Autoregressive Heteroskedastic Models, namely, GARCH (1,1), E-GARCH (1,1) and P-GARCH (1,1), were employed. The findings revealed that all three models were statistically significant to forecast stock returns volatility. Our paper differs from Mutaju and Dickson (2019) in that it examines the characteristics of the stock returns on three sub-periods, as has been mentioned above, namely, from January 2014-November 2019; January 2014-December 2015 (election period) and from January 2016-November, 2019. Secondly, we compare the best model based on AIC, SIC and log likelihood estimators as opposed to Mutaju and Dickson (2019) which compared the forecasting accuracy of the models. Third, unlike Mutaju and Dickson (2019) this paper performs a battery of diagnostic tests to check for serial correlation, normality and presence of ARCH effect in the selected models. Fourth, our work is based on recent data and therefore reveals more accurate returns conditions to stock investors.

## 3. MODEL SPECIFICATION

### *3.1. ARCH and GARCH Models Notation*

The ARCH model developed by Eagle (1982) is used to model conditional variance. Let $\delta_t^2$ denote the variance conditional on information at time t-1, the ARCH (p) model can be expressed as follows:

$$\delta_t^2=\alpha_0+\alpha_1\varphi_{t-1}^2+\alpha_2\varphi_{t-2}^2+\alpha_3\varphi_{t-3}^2+\alpha_4\varphi_{t-5}^2+\alpha_5\varphi_{t-6}^2+\ldots\ldots\ldots\ldots\alpha_q\varphi_{t-q}^2 \quad (1)$$

In which the mean Equation 1 is expressed as a function of exogenous variables with an error term. $\delta_t^2$ is a conditional variance, a one period ahead variance based on the past information; $\varphi_{t-1}^2$, …..$\varphi_{t-q}^2$ are lagged squared residuals estimated from the mean equation and $\alpha_0$>0, $\alpha_i$≥0, $i = 1, 2, 3, \ldots\ldots.. q$. Based on this information, the conditional variance equation in which the explanatory variables are incorporated can be written as:

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varphi_{t-i}^2 + \pi_t^{'}\theta \quad (2)$$

Where $\pi_t = (\pi_{1t}, \pi_{2t}, \pi_{3t}, \pi_{4t})'$ is a vector of explanatory variables at time t, $\theta = (\theta_1, \theta_2, \theta_3, \theta_4)'$ is a vector of regression coefficients that shows the effect of explanatory variables on the returns of DSE all share index.

GARCH model (Bollerslev, 1986) is an extension of ARCH model developed by Eagle (1982). In the GARCH model, previous days variances are used to forecast future variance given by the following conditional variance equation:

$$\delta_t^2 = \alpha_0 + \alpha_1 \varphi_{t-1}^2 + \beta \delta_{t-1}^2 \quad (3)$$

Where $\alpha_0$ is a constant; $\varphi_{t-1}^2$ is the ARCH term, measured as the lag of squared residuals from the mean equation; and $\delta_{t-1}^2$ is the GARCH term, last period's forecast variance. Extending from this basic model, the higher order GARCH (*q, m)* can be expressed compactly by the following equation:

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varphi_{t-i}^2 + \sum_{j=1}^{m} \beta_j \delta_{t-j}^2 + \pi_t^{'}\theta \quad (4)$$

Where $\alpha_0$ represents long term volatility; $\alpha_{1;}\alpha_2 \ldots\ldots\ldots\ldots \alpha_n$ indicate the severity of past shocks; $\beta_1$, $\beta_2$, $\beta_3 \ldots\ldots \beta_n$ indicate the impact of past volatility on the current volatility of time series under consideration, and $\theta = (\theta_{1,} \theta_{2,} \theta_{3,}, \theta_{4,} \ldots\ldots)'$ is a vector of regression coefficients that show the effect of the explanatory variables on the volatility of the price return series under consideration, as defined in equation 2 above.

### *3.2. The Exponential GARCH Model (EGARCH)*

The EGARCH model captures response of time-varying variance to shock, and at the same time ensures the variance is positive (Ayele, Gabreyohannes, & Tesfay, 2017). An EGARCH with order (*p, q)* is given by the following equation:

$$\text{In}\, \delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \left\{ \left| \frac{\varphi_{t-i}}{\delta_{t-i}} \right| + \eta_i \frac{\varphi_{t-i}}{\delta_{t-i}} \right\} + \sum_{j=1}^{m} \beta_j In \delta_{t-j}^2 + \pi_t^{'}\theta \quad (5)$$

The left-hand side is the log of the conditional variance, the leverage effect is exponential and conditional variance is non-negative. The parameter $\eta_i$ indicate the leverage effect of $\varphi_{t-i}$; we expect $\eta_i$ to be negative as bad news in corporate finance leads to uncertain future in making decisions. Empirically, it has been demonstrated that bad news has a greater impact on volatility than good news of the same magnitude.

### *3.4. Threshold GARCH (TGARCH) Model*

We develop the variance equation based on the model defined by Ayele *et al* 2017 as follows:

$$\delta_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varphi_{t-i}^2 + \sum_{i=1}^{q} \eta_i ¥_{t-i} \varphi_{t-i}^2 + \sum_{j=1}^{m} \beta_j \varphi_{t-j}^2 + \pi_t^{'}\theta \quad (6)$$

Where $¥_{t-i}$ is a dummy variable defined as follows:

$$¥_{t-i} = \begin{vmatrix} 1\ if \varphi_{t-i}^2 < 0, \text{bad news} \\ 0\ if \varphi_{t-i}^2 \geq 0, \text{good new} \end{vmatrix}$$

$\alpha_1, \eta_i and \beta_j$ are parameters that satisfy the conditions of non-negativity of the parameter $\delta_t^2$; that is $\alpha_{0,} \alpha_1$ >0; and $\alpha_1 + \eta_i \geq 0$.

### *3.5. Stock Prices: All Share Price Index Return*

In this paper, daily returns were calculated as the continuously compounded returns, which are first difference in logarithm of closing all share prices, using the following formula:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) = logP_t - logP_{t-1} \quad = \Delta logP_t \qquad (7)$$

Where $r_t$ is the return of all share index at the current day; and $P_t$ and $P_{t-1}$ are closing all share price index for the current and previous days, respectively. The index is a weighted index based on market capitalization where the weight of any company is taken as the number of ordinary shares listed in the market. The index allows the price movements of larger companies to have a greater impact on the index.

## 4. EMPIRICAL RESULTS AND DISCUSSION

### *4.1. Descriptive Analysis of the Data*

The first step before applying GARCH models is to test for the presence of ARCH effect. Both Figure 1 (a) of the series trend and Figure 1 (b) of plotted residuals show that periods of high volatility are followed by periods of low volatility.

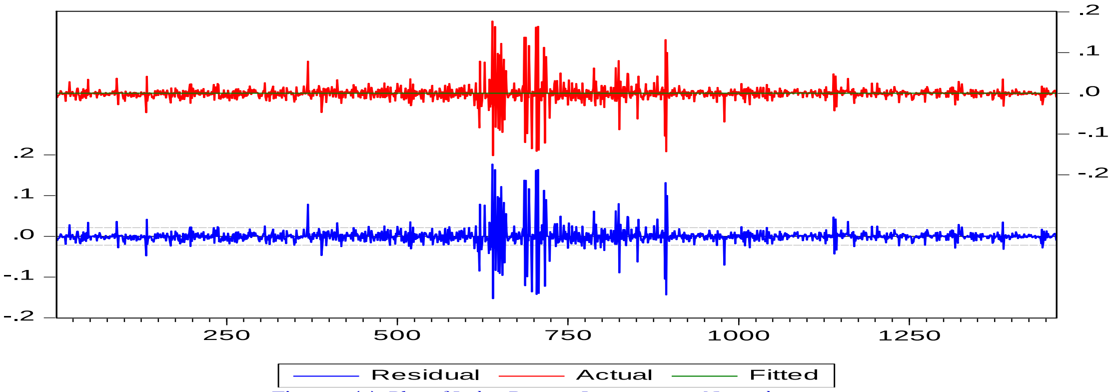


**Figure-1(a).** Plot of Index Return: January 2014-November 2019.

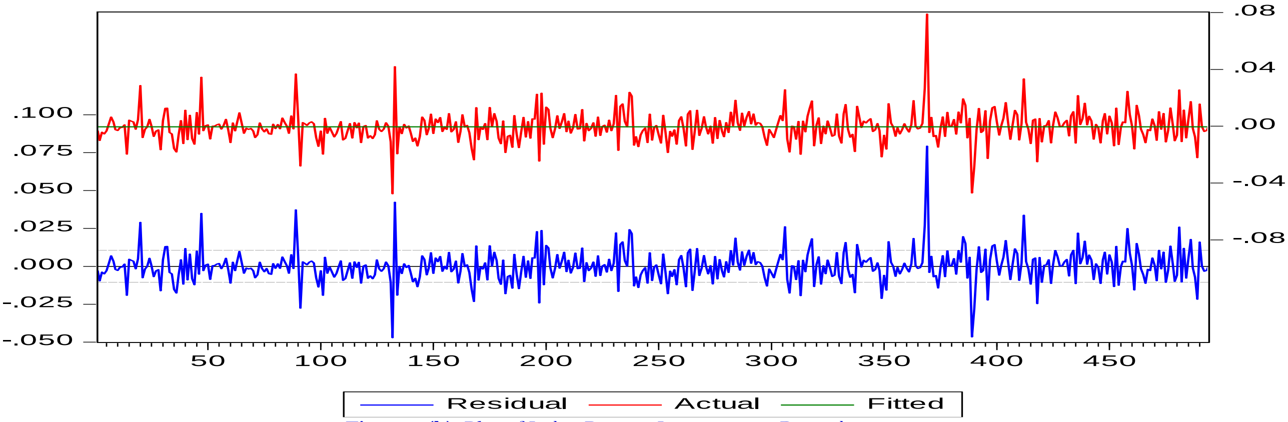


**Figure-1(b).** Plot of Index Return: January 2014-December 2015.

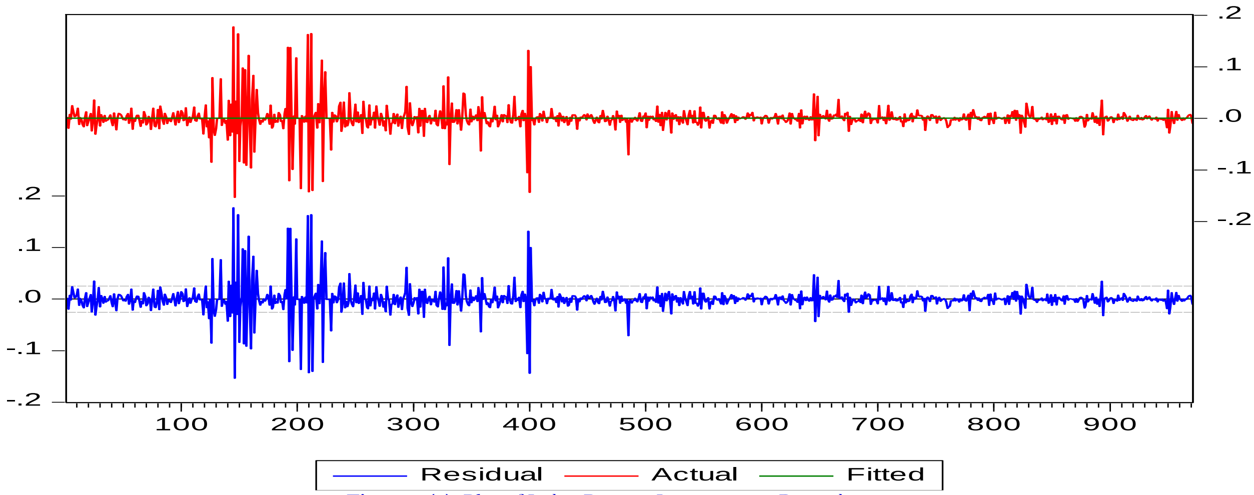


**Figure-1(c).** Plot of Index Return: January 2016-December 2015.

**Table-1.** Descriptive Analysis of the Data

| | January 2014-November 2019 (A) | January 2014-December 2015 (B) | January 2016-November 2019 (C) |
|---|---|---|---|
| Mean | -0.0000209 | -0.000202 | 0.0000713 |
| Median | 0.0000 | -0.000326 | 0.0000 |
| Maximum | 0.070817 | 0.033080 | 0.070817 |
| Minimum | -0.072202 | -0.021125 | -0.072202 |
| Std. Dev. | 0.009280 | 0.004544 | 0.010931 |
| Variance | 0.000086 | 0.0000206 | 0.000121 |
| Skewness | 0.008730 | 0.778077 | -0.041303 |
| Kurtosis | 27.43288 | 10.82 | 21.3592 |
| Jarque-Bera | 36,414.9 | 1308.86 | 13623.18 |
| Probability | 0.0000 | 0.00000 | 0.0000 |
| Sum | -0.030610 | -0.099780 | 0.069170 |
| Sum Sq. Dev. | 0.125985 | 0.010179 | 0.115782 |
| Observations | 1464 | 494 | 970 |

The descriptive analysis shows series A and C have small positive mean; whereas series B has a positive mean. The daily variance and volatility intensity for Series A, B and C are 0.000086, 0.0000206 and 0.000121with series A showing highest volatility followed by series A and B. The high kurtosis values of 27.4, 10.8 and 21.4 indicate that the returns are leptokurtic, flat tailed; asymmetric and do not follow normal distribution. Series A and B are positively skewed, and Series C is negatively skewed. The standard deviation is found to be high, indicating a high level of daily fluctuation of DSE returns. The mean return is close to zero as expected for return series (Srinivasan & Ibrahim, 2010). The mean log return is negative for series A and B, and is positive for series C during post-election period.

### *4.2. Unit Root Test*

As shown in Table 2, the Augmented Dickey Fuller (ADF) Unit Root test rejects a null hypothesis of presence of unit root for the time series, suggesting that the series are stationary at level and hence mean reverting. This is important in order to ensure model stability.

**Table-2.** Augmented dickey fuller unit root Test (ADF).

| | | | Critical Values | | |
|---|---|---|---|---|---|
| | ADF Statistics | Probability | 1% | 5% | 10% |
| Index return (Series A) | -39.680 | 0.000 | -3.435 | -2.863 | -2.568 |
| Index return (Series B) | -13.687 | 0.000 | -3.443 | -2.867 | -2.569 |
| Index return (Series C) | -25.542 | 0.000 | -3.437 | -2.864 | -2.568 |

### *4.3. Heteroscedasticity Test*

As shown in Table 3, the null hypothesis of no ARCH effect is rejected since the p-value is less that 5 percent level of significance, implying presence of ARCH effect in the data series. The time series have heteroscedastic characteristics and therefore support use of GARCH models.

**Table-3.** Heteroscedasticity Test.

| Series Name | F-Statistic | Observed R-squared | Probability Chi-Square |
|---|---|---|---|
| Index return (Series A) | 190.044 | 302.239 (0.000) | 0.000 |
| Index return (Series B) | 10.780 | 10.59168 (0.001) | 0.001 |
| Index return (Series C) | 241.2237 | 193.5018 (0.000) | 0.000 |

### *4.4. Model Results*

The weighted average of AIC, SIC of the selected GARCH shows that EGARCH (1, 1) has the lowest values of AIC and SIC followed by the GARCH (1, 1) model respectively. The log likelihood values of the two models are highest, as shown in Table 4:

**Table-4.** The AIC, SIC and log likelihood results.

| January 2014-December 2019 (A) | | | | January 2014-December 2015 (B) | | | January 2016-November 2019 (C) | | |
|---|---|---|---|---|---|---|---|---|---|
| | AIC | SIC | LL* | AIC | SIC | LL* | AIC | SIC | LL* |
| EGARCH | -7.439 | -7.421 | 5450.3 | -8.039 | -7.997 | 1990.8 | -7.225 | -7.195 | 3510.3 |
| GARCH (1,1) | -7.441 | -7.426 | 5450.3 | -8.027 | -7.993 | 1986.7 | -7.202 | -7.177 | 3498.2 |
| TARCH (GJR-GARCH) | -7.444 | -7.426 | 5454.1 | -8.026 | -7.983 | 1987.4 | -7.204 | -7.173 | 3499.7 |
| PARCH | -7.443 | -7.422 | 5454.8 | -8.026 | -7.975 | 1988.4 | -7.209 | -7.179 | 3502.8 |
| IGARCH | -7.357 | -7.349 | 5387.2 | -7.859 | -7.842 | 1943.1 | -7.124 | -7.109 | 3458.2 |

**Note:**
**1. LL*:** Log Likelihood.
**2.** By definition AIC = 2 log (likelihood)+2T and BIC = 2 log (likelihood)+log (Tk), where T denotes the number of observations used for the estimation of parameters, and k is the number of (free) parameters in the model. Given a set of candidate models, the model with the minimum AIC and BIC value is taken as the best-fit model.

The weighted average results for these models show that DSE is successfully modeled using EGARCH and GARCH (1,1) since they have slightly lowest aggregated values of AIC and SIC, and highest log likelihood. Interestingly, all models analyzed have slightly small difference in terms of the AIC, SIC and Log Likelihood and all of them were statistically significant. Of these two models, EGARCH is superior followed by the GARCH (1, 1). To understand the key characteristics of these models, we closely examine them to show their applicability to DSE return series.

### *4.3. EGARCH (1, 1) and GARCH (1, 1)*

#### *4.3.1. GARCH (1,1) Model*

In this section, we determine the significance of coefficients of the mean and variance equation for GARCH (1, 1) for all the three periods. The results are indicated in Table 5.

**Table-5(a).** Mean and Variance Equation (January 2014 – November 2019).

| Mean Equation | | | Variance Equation | | | |
|---|---|---|---|---|---|---|
| | Coefficient | z-statistic | | Coefficient | z-statistic | Probability |
| Constant | -0.000184 | -0.52869 | α | 0.00000261 (0.000000214) | 12.18812 | 0.000 |
| | | | $\alpha_1$ | 0.243241 (0.0014048) | 17.3151 | 0.000 |
| | | | $\beta$ | 0.745101 (0.012016) | 62.00722 | 0.000 |

**Table-5(b).** Mean and variance equation (January 2014 – December 2015).

| Mean Equation | | | Variance Equation | | | |
|---|---|---|---|---|---|---|
| | Coefficient | z-statistic | | **Coefficient** | **z-statistic** | **Probability** |
| Constant | -0.000326 (0.000188) | -1.737587 | α | 7.89E-05 (8.64E-06) | 9.124816 | 0.000 |
| | | | $\alpha_1$ | 0.269757(0.034662) | 7.782584 | 0.000 |
| | | | $\beta$ | 0.015152(0.076123) | 0.199044 | 0.000 |

**Table-5(c).** Mean and Variance Equation (January 2016 – November 2019).

| Mean Equation | | | Variance Equation | | | |
|---|---|---|---|---|---|---|
| | Coefficient | z-statistic | | **Coefficient** | **z-statistic** | **Probability** |
| Constant | -8.71E-06 (0.000359) | -0.024290 | α | 0.000000654 (6.90E-08) | 9.4806 | 0.000 |
| | | | $\alpha_1$ | 0.139710 (0.008344) | 16.74303 | 0.000 |
| | | | $\beta$ | 0.875796 (0.003532) | 247.9364 | 0.000 |

Table 5(a)-(c) show that the coefficients of variance equations are statistically significant. All coefficients of the variance equation meet the conditions of the GARCH (1,1) model, their sum being less than 1. Table 5 (a) for Series A indicate that the volatility of returns is quite persistent, with the sum of α and β being 0.99; implying a volatility half-life of about 173 days. In other words, this indicates that lagged conditional variance and squared disturbance have an impact on the conditional variance: news about volatility from the previous periods has an explanatory power on current volatility. On the other hand, Series B has less persistency of 0.27, which shows a high decay to long run variance, and half-life of a half day. We therefore conclude that the returns volatility of these two series are mean reverting as the sum of α and β is significantly less than one. Series C has a persistence greater than one and thus indicates that the shocks to the conditional variance are highly persistent, i.e. the conditional variance process is explosive.

### *4.3.2. The EGARCH Model*

The coefficients of EGARCH model defined in equation 6 shows the values of the coefficients as follows: $\alpha_0 = -0.54$; $\alpha_1 = 0.36$ (the ARCH term); $\eta_1 = 0.25$ (the leverage term); and $\beta_1$=0.96 (the GARCH term). The coefficient $\alpha_i$ is positive which indicates there is a positive relationship between the past variance and the current variance. The positive value of $\eta_i$ indicates that good news increases the future volatility more than the bad news. The coefficient $\beta_j$ is significantly different from zero implying that the EGARCH model is asymmetric and the positive leverage effects are present. The positive value indicates that good news increases the future volatility more than the bad news, which is consistent with the findings of Joldes (2019).

**Table-6(a).** The Mean and Variance Coefficients of EGARCH Model (Series A).

| Variable | Coefficient | Std. Error | z-Statistic | Probability |
|---|---|---|---|---|
| C | 0.000373 | 0.000268 | 1.390717 | 0.000 |
| **Variance Equation** | | | | |
| $\alpha_0$ | -0.542044 | 0.025326 | -21.40252 | 0.0000 |
| $\alpha_1$ | 0.355020 | 0.013950 | 25.44983 | 0.0000 |
| $\eta_i$ | 0.025447 | 0.009759 | 2.607449 | 0.0091 |
| $\beta_j$ | 0.963298 | 0.002548 | 378.0911 | 0.0000 |

**Table-6(b).** The Mean and Variance Coefficients of EGARCH Model (Series B).

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.0000429 | 0.000228 | 1.882400 | 0.0598 |
| Variance Equation | | | | |
| $\alpha_0$ | -0.674113 | 0.035257 | -19.12012 | 0.0000 |
| $\alpha_1$ | 0.368690 | 0.015049 | 24.49887 | 0.0000 |
| $\eta_i$ | 0.037905 | 0.010149 | 3.735031 | 0.0002 |
| $\beta_j$ | 0.957325 | 0.003035 | 315.4411 | 0.0000 |

**Table-6(c).** The Mean and Variance Coefficients of EGARCH Model (Series C).

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| C | 04.75E-05 | 0.000386 | 0.123260 | 0.9019 |
| Variance Equation | | | | |
| $\alpha_0$ | 7.28E-07 | 7.45E-08 | 9.771344 | 0.0000 |
| $\alpha_1$ | 0.173547 | 0.015167 | 11.44266 | 0.0000 |
| $\eta_i$ | -0.066541 | 0.021353 | -3.116305 | 0.0018 |
| $\beta_j$ | 0.873867 | 0.003746 | 233.2594 | 0.0000 |

### *4.3.3. Model Diagnostics*

In order to investigate whether the two models fulfill the best fit conditions, a correlogram of Standardized Residuals Squared test is used to find out whether the two models are serially correlated or not. The null hypothesis of no serial correlation is accepted for both models since the p-values are greater than five percent, which is a desirable condition (see Appendix 1 (a)-(b)). Then, the models are tested to check whether they have ARCH effect: the null hypothesis of no ARCH effect is accepted at five percent level of significance since both p-values are greater than five percent Table 7. Lastly, as required, the *Jarque Bera* test of normality in the residuals is accepted at five percent level of significance showing that residuals are normally distributed [see Appendix 2 (a)-(f)]. Therefore, we empirically show that both GARCH (1, 1) and EGARCH models have fulfilled all conditions of best-fit models, and can be used to describe and model DSE ASI returns. As shown in appendix 3, the forecast of the two models shows an evidence of volatility in returns, and a low value of Root Mean Square Error (0.0093) for both GARCH (1,1) and EGARCH indicates the two models have forecasting power and are accurate.

**Table-7.** Heteroscedasticity Test: ARCH.

| | F-Statistic | Probability | Obs*R-squared | Prob. Chi-Square(36 |
|---|---|---|---|---|
| Series A | 0.472349 | Prob. F(36,1391) (0.9968) | 17.24605 | 0.9965 |
| Series B | 0.890099 | Prob. F(36,421) (0.6541) | 32.39411 | 0.6408 |
| Series C | 0.506892 | Prob. F(36,897) (0.9934) | 0.9934 | 0.9926 |

## 5. CONCLUDING REMARKS

This study has attempted to undertake empirical investigation of DSE all-share price returns and using (GARCH (1,1), EGARCH, TGARCH, PGARCH and component GARCH; using a sample size of 1465 observations from 02 January 2014 to 28 November, 2019. We can safely conclude the following: firstly, the ASI returns are volatile and demonstrate volatility clustering, which is a key characteristic underlying financial time series. Secondly, the series demonstrate ARCH effect supporting use of GARCH models. Third, the ASI returns are stationary at level, which is a desirable condition for our analysis. Fourth, the ASI return is normally distributed and is highly leptokurtosis as seen from the high kurtosis values discussed above. Fifth, the EGARCH model for Series A and B has positive leverage effect, unlike Series C which has negative leverage effect meaning bad news has an impact on volatility more than good news. Of all models, GARCH (1,1) and EGARCH models are superior with the lowest AIC and SIC and largest log likelihood values followed by the PARCH model. We empirically show presence of return volatility and persistence in the return series analyzed; and that lagged conditional variance and squared residuals have an impact on the conditional variance. The two models passed a battery of diagnostic test in order to check the best-fit.

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**Appendix-1(a).** Correlogram of Standardized Residuals Squared for GARCH models.

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | 0.029 | 0.029 | 1.1976 | 0.274 |
| | | 2 | 0.009 | 0.008 | 1.3079 | 0.520 |
| | | 3 | -0.020 | -0.020 | 1.8706 | 0.600 |
| | | 4 | 0.003 | 0.004 | 1.8856 | 0.757 |
| | | 5 | -0.014 | -0.014 | 2.1582 | 0.827 |
| | | 6 | -0.015 | -0.015 | 2.4914 | 0.869 |
| | | 7 | -0.009 | -0.007 | 2.6032 | 0.919 |
| | | 8 | -0.017 | -0.017 | 3.0348 | 0.932 |
| | | 9 | -0.026 | -0.026 | 4.0376 | 0.909 |
| | | 10 | -0.017 | -0.016 | 4.4741 | 0.923 |
| | | 11 | 0.065 | 0.065 | 10.686 | 0.470 |
| | | 12 | -0.011 | -0.016 | 10.879 | 0.539 |
| | | 13 | -0.015 | -0.017 | 11.221 | 0.592 |
| | | 14 | -0.012 | -0.009 | 11.427 | 0.652 |
| | | 15 | 0.004 | 0.003 | 11.454 | 0.720 |
| | | 16 | 0.013 | 0.013 | 11.690 | 0.765 |
| | | 17 | 0.032 | 0.032 | 13.233 | 0.720 |
| | | 18 | -0.003 | -0.006 | 13.244 | 0.777 |
| | | 19 | 0.005 | 0.005 | 13.282 | 0.824 |
| | | 20 | 0.008 | 0.012 | 13.389 | 0.860 |
| | | 21 | 0.022 | 0.022 | 14.091 | 0.866 |
| | | 22 | -0.012 | -0.018 | 14.295 | 0.891 |
| | | 23 | -0.018 | -0.016 | 14.788 | 0.902 |
| | | 24 | -0.018 | -0.013 | 15.261 | 0.913 |
| | | 25 | -0.003 | 0.001 | 15.274 | 0.935 |
| | | 26 | -0.004 | -0.002 | 15.299 | 0.952 |
| | | 27 | -0.006 | -0.006 | 15.349 | 0.964 |
| | | 28 | -0.003 | -0.007 | 15.361 | 0.974 |
| | | 29 | 0.014 | 0.016 | 15.643 | 0.979 |
| | | 30 | 0.005 | 0.005 | 15.687 | 0.985 |
| | | 31 | -0.015 | -0.017 | 16.023 | 0.988 |
| | | 32 | 0.027 | 0.024 | 17.121 | 0.985 |
| | | 33 | -0.013 | -0.014 | 17.369 | 0.988 |
| | | 34 | -0.007 | -0.007 | 17.451 | 0.992 |
| | | 35 | -0.004 | -0.000 | 17.475 | 0.994 |
| | | 36 | -0.000 | -0.003 | 17.475 | 0.996 |

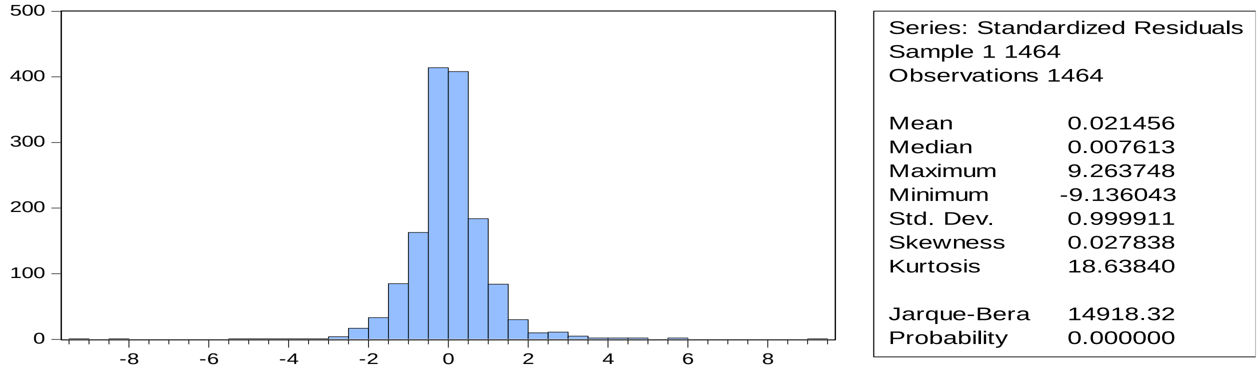
**Source:** Econometric output from Eviews.10

**Appendix-1(b).** Correlogram of Standardized Residuals Squared for EGARCH model.

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | 0.051 | 0.051 | 3.8894 | 0.049 |
| | | 2 | 0.011 | 0.008 | 4.0520 | 0.132 |
| | | 3 | -0.017 | -0.018 | 4.4969 | 0.213 |
| | | 4 | -0.003 | -0.001 | 4.5104 | 0.341 |
| | | 5 | -0.018 | -0.017 | 4.9818 | 0.418 |
| | | 6 | -0.007 | -0.006 | 5.0576 | 0.536 |
| | | 7 | -0.006 | -0.005 | 5.1161 | 0.646 |
| | | 8 | -0.017 | -0.017 | 5.5287 | 0.700 |
| | | 9 | -0.027 | -0.026 | 6.6178 | 0.677 |
| | | 10 | -0.016 | -0.014 | 7.0002 | 0.725 |
| | | 11 | 0.067 | 0.068 | 13.533 | 0.260 |
| | | 12 | -0.008 | -0.016 | 13.639 | 0.324 |

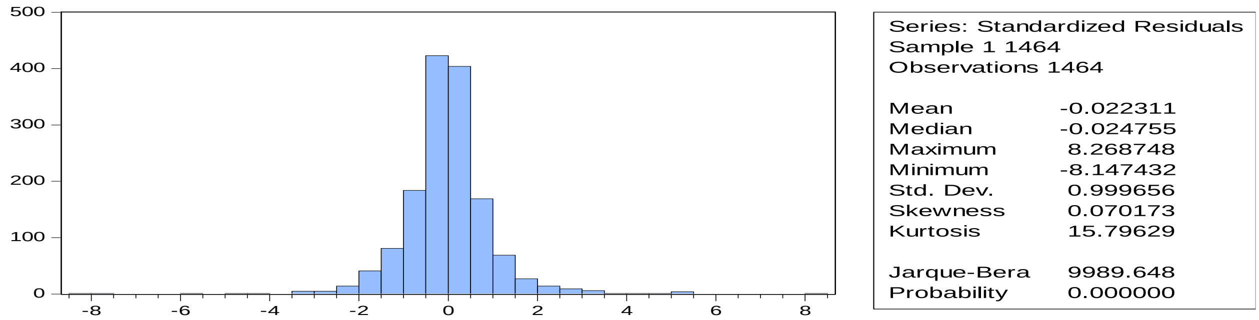
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | 13 | -0.013 | -0.015 | 13.895 | 0.381 |
| | | | | | | 14 | -0.014 | -0.011 | 14.185 | 0.436 |
| | | | | | | 15 | 0.005 | 0.006 | 14.225 | 0.509 |
| | | | | | | 16 | 0.003 | 0.004 | 14.242 | 0.581 |
| | | | | | | 17 | 0.062 | 0.061 | 19.983 | 0.275 |
| | | | | | | 18 | 0.001 | -0.006 | 19.986 | 0.334 |
| | | | | | | 19 | 0.013 | 0.013 | 20.248 | 0.380 |
| | | | | | | 20 | 0.018 | 0.022 | 20.716 | 0.414 |
| | | | | | | 21 | 0.020 | 0.019 | 21.315 | 0.440 |
| | | | | | | 22 | -0.014 | -0.020 | 21.601 | 0.484 |
| | | | | | | 23 | -0.022 | -0.019 | 22.354 | 0.499 |
| | | | | | | 24 | -0.023 | -0.017 | 23.133 | 0.512 |
| | | | | | | 25 | -0.005 | 0.001 | 23.172 | 0.568 |
| | | | | | | 26 | -0.007 | -0.004 | 23.240 | 0.619 |
| | | | | | | 27 | -0.008 | -0.007 | 23.344 | 0.666 |
| | | | | | | 28 | -0.009 | -0.016 | 23.460 | 0.710 |
| | | | | | | 29 | 0.017 | 0.022 | 23.902 | 0.734 |
| | | | | | | 30 | 0.004 | 0.003 | 23.930 | 0.775 |
| | | | | | | 31 | -0.015 | -0.019 | 24.279 | 0.799 |
| | | | | | | 32 | 0.023 | 0.020 | 25.089 | 0.802 |
| | | | | | | 33 | -0.014 | -0.016 | 25.403 | 0.825 |
| | | | | | | 34 | -0.006 | -0.007 | 25.460 | 0.854 |
| | | | | | | 35 | -0.007 | -0.003 | 25.540 | 0.879 |
| | | | | | | 36 | 0.002 | -0.002 | 25.545 | 0.903 |

**Source:** Econometric output from Eviews.10



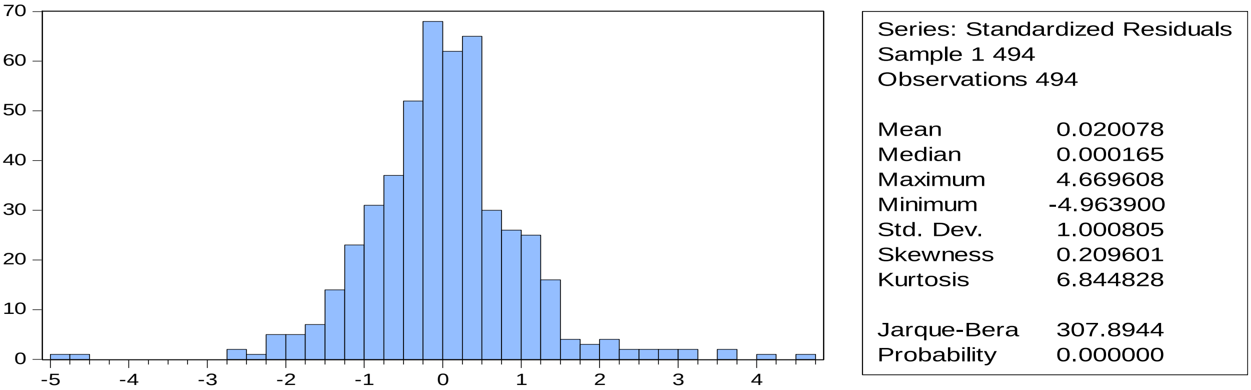

**Appendix-2(a)**. Normality Test of GARCH (1, 1) Model (Series A).

**Source:** Eviews 10



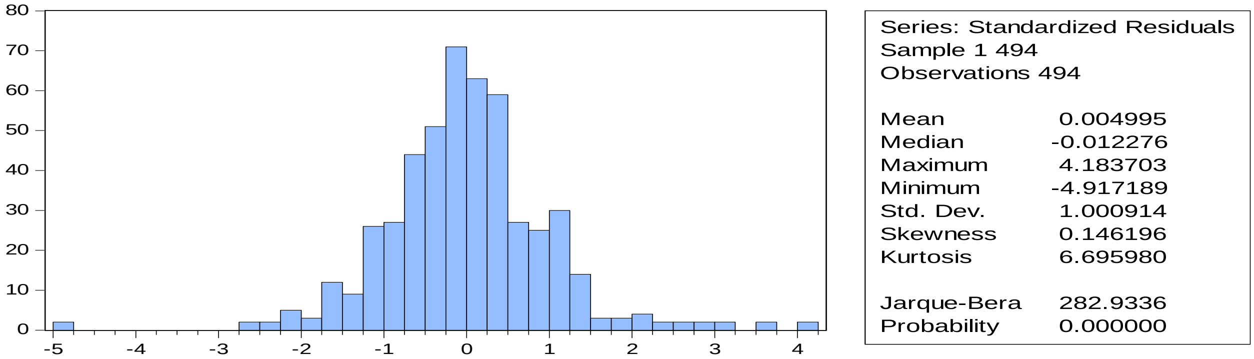

**Appendix-2(b)**. Normality Test of EGARCH Model (Series A).

**Source:** Eviews 10



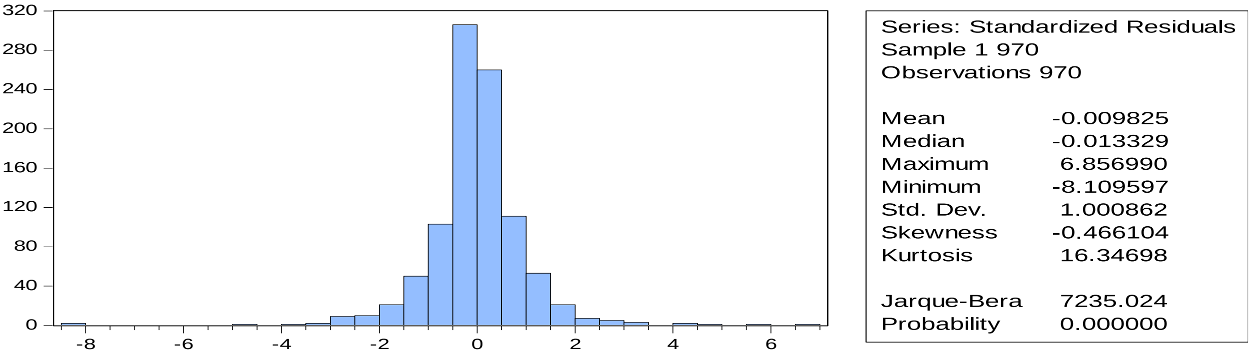

**Appendix-2(c)**. Normality Test of GARCH (1,1) Model (Series B).

**Source:** Eviews 10



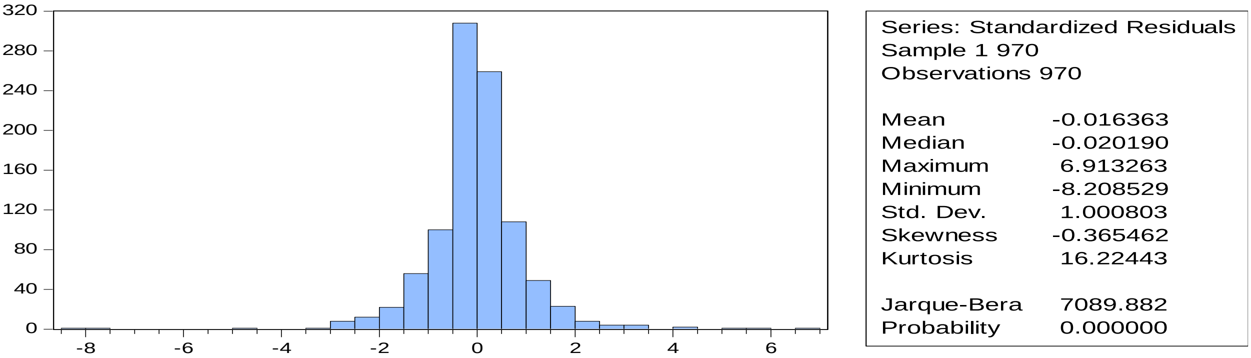

**Appendix-2(d)**. Normality Test of EGARCH Model (Series B).

**Source:** Eviews 10



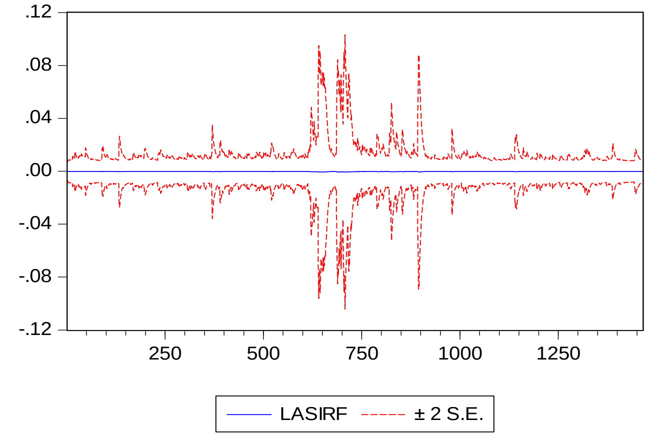

**Appendix-2(e)**. Normality Test of GARCH (1,1) Model (Series C).

**Source:** Eviews 10

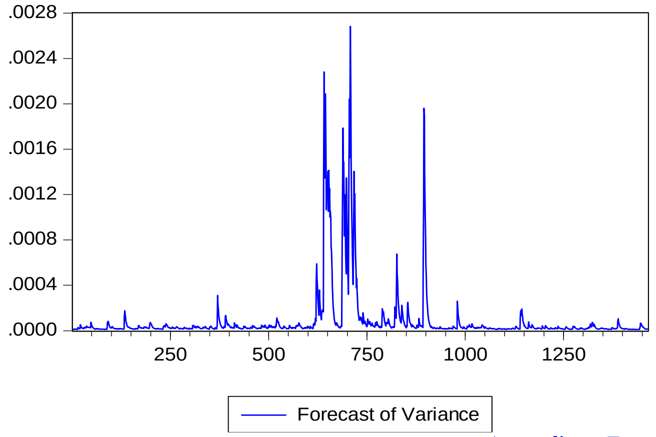



**Appendix-2(e)**. Normality Test of EGARCH Model (Series C).

**Source:** Eviews 10




| | |
|---|---|
| Forecast: LASIRF | |
| Actual: LASIR | |
| Forecast sample: 1 1465 | |
| Included observations: 1465 | |
| Root Mean Squared Error | 0.009278 |
| Mean Absolute Error | 0.004465 |
| Mean Abs. Percent Error | NA |
| Theil Inequality Coefficient | 0.978282 |
| Bias Proportion | 0.000338 |
| Variance Proportion | 0.982541 |
| Covariance Proportion | 0.017121 |
| Theil U2 Coefficient | NA |
| Symmetric MAPE | 179.5920 |




**Appendix-3.** Forecasted Variance.

**Source:** Eviews 10