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Modeling Volatility of The Shariah Index of Chittagong Stock Exchange (CSI), Bangladesh Using GARCH-type Models

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Abstract:
This research work attempts to estimate the volatility of the return of The Shariah Index of Chittagong Stock Exchange, Bangladesh using daily data from 1st January 2015 to 30th December 2021, which includes 1296 observations. After being confirmed about the presence of the 'ARCH effects' using the ARCH-LM test for residuals, and about the stationarity of data, the researcher has employed several GARCH-type models under three error distributions i.e. normal distribution, student's t distribution, and generalized error distribution for finding the best-fitted model(s). Both ARCH and GARCH terms have been found to be highly statistically significant in all models under all forms of error distributions. The evidence of 'leverage effect' has also been detected in both EGARCH(1,1) and TGARCH(1,1) under all distributions. Based on the two widely accepted model selection criteria i.e. The Akaike information criterion (AIC), and The Schwarz Bayesian information criterion (SBIC), as well as log-likelihood value TGARCH(1,1) has been selected under normal distribution, and EGARCH(1,1) has been selected under both student's t distribution, and generalized error distribution as best-fitted models for The Shariah Index of CSE(CSI), Bangladesh.

Key Words: *CSI, Heteroscedasticity, Stationary, GARCH, GARCH-M, EGARCH, TGARCH, Leverage effect.*

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I. Introduction

A vibrant financial market for every economy can play a vital role in meeting the need for capital for industrialization. The larger the industrialization the larger the employment generation and resolving the problem of unemployment. Again, with industrialization the growth of GDP, infrastructure development also correlated directly/indirectly. Hence, it can be stated that there has a substantial linkage between the financial market development and economic growth and development of a country. For developing a vibrant capital market larger participation of various types of traders are essential. But typically the financial markets are volatile in nature. Always there prevails an oscillation of prices of stocks in the market, in the underdeveloped market it is even larger, which acts as a hindrance of the larger participation of traders. This oscillation is treated as volatility. So, an appropriate prediction of this volatility is indispensable. For this prediction, there has extensive usage of the autoregressive conditionally heteroscedastic(ARCH) model, developed by economist Robert F. Engle III in the 1980s, as well as generalized ARCH(GARCH) models developed by Bollerslev (1986) and Taylor (1986) solely. However, further many extensions of GARCH-type models have been made by some other renowned economists for incorporating asymmetry, risk premium, etc. in the volatility models and some new models have emerged with the passes of time.

To the best of the knowledge of the researcher, there are few authors who conducted their research using ARCH/GARCH-type models with CSCX (CSE selective categories' index), or CASPI(CSE all-share price index). But such a study using The CSE Shariah Index(CSI) is rare to found. Hence, the researcher has selected this Shariah index for estimation. (Huq, Karim, & Ali, 2017) Have tried to model and forecast the return volatility of both DSE, and CSE using DSEX, and CSCX index respectively with GARCH-type models. They found the TGARCH model as the appropriate model for both of the markets. (Tasfiq & Jahan, 2021) They tried to explore the linkage between Chittagong and Dhaka Stock Exchanges using various statistical tools and found the long-run relationship among them. (Rokonuzzaman & Hossen, 2018) They analyzed the volatility of fifteen listed banks in CSE and found a positive correlation between banks' returns and their respective risks. (Chowdhury, 2020) His paper tried to unearth the nature of the volatility of CSE based on the

CSCX index, and also measure the impacts of selected macro-economic factors on volatility by applying both GARCH and Vector Autoregression(VAR) models and found that both of these models can successfully forecast the volatility of this market. (Qamruzzaman, 2015) modeled and forecasted the return volatility of CSCX, CASPI, and CSE30 indices using asymmetric GARCH models and found five different models to capture the features of CSE. Besides these studies (Chowdhury, 2017), (Jahur, Quadir, & Khan, January 2014) have studied the influence of some macroeconomic variables on the market volatility of CSE.

The prime endeavor of this study is to employ some GARCH-type models to The Shariah Index of CSE (CSI), Bangladesh, and find out the appropriate model on the basis of different model selection criteria.

II. Material and Methods

Data:

The present study is based on The Shariah Index of CSE, Bangladesh. The website of Chittagong Stock Exchange (www.cse.com.bd) has explained some general information about this index e.g. CSE Shariah Index is originated to provide the investors shariah-compliant investment opportunity, it includes all shariah-compliant stocks listed on CSE, this number of stocks isn't fixed and is reviewed annually, and which one becomes non-shariah compliant is excluded from the index.

This study covers the daily closing index data of The CSE Shariah Index(CSI), Bangladesh from 1st January 2015 to 30th December 2021, which includes 1296 observations. It has transformed the data into logarithmic daily returns using the following formula:

$$r_t = \log\left(\frac{Pt}{P_{t-1}}\right)$$

Wherer_t isthe logarithmic daily return of the CSI index for time t, Pt is the closing values of CSI index at time t, and P_{t-1} is the corresponding previous days' values.

GARCH(1,1):

Two authors named Bollerslev (1986) and Taylor (1986) separately invented the highly accepted GARCH model. This model lets the conditional variance to be contingent on its foregoing own lags. The shape of GARCH (1,1) is as follows-

Mean equation: $r_t = \omega + \epsilon_t$

Variance equation: $\sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$

Here, α_0 is constant, $\sigma^2{}_t$ in variance equation represents the current day's variance of CSI index return.$\sigma^2{}_{t-1}$Represents the previous day's variance and is treated as a GARCH term. The $\epsilon^2{}_{t-1}$ indicates the previous day's return information about volatility and is treated as an ARCH term.

The conditions are α_0, α_1 , and β_1 should be positive, as well as α_1+β_1<1. If α_1 +β_1 are found very close to unity, it is evidence of volatility persistence, and if found more than unity, then it indicates a sign of explosion.

GARCH-M(1,1):

The typical risk-averse investors seek additional returns for assuming extra risks in the form of a risk premium. GARCH-M brings its own conditional variance/standard deviation in its mean equation. In another way it can be stated that this model permits the partial determination of security return by its risks.

Mean equation: $r_t = \omega + \Upsilon \sigma^2{}_{t-1} + \epsilon_t$

Variance equation: $\sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$

If ϒ is found to be significant and positive, the mean return increases due to a rise in the conditional variance thus risk premium is ensured (Brooks, 2008).

EGARCH(1,1):

Nelson (1991) was the first person to recommend the exponential GARCH model. It can be formulated its conditional variance equation in different ways. One possible specification can be as follows-

$$\text{Ln}(\sigma^2{}_t) = \omega + \beta \ln(\sigma^2{}_{t-1}) + \lambda \frac{\mu_{t-1}}{\sqrt{\sigma^2{}_{t-1}}} + \alpha\left[\frac{|\mu_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \sqrt{\frac{2}{\pi}}\right]$$

The Ln($\sigma^2{}_t$) represents the log of conditional variance. Here, λ is the asymmetry parameter. For leverage effect λ is to be statistically significant and negative. It is termed as the negative correlation between the future volatility of return and the past return. Due to the presence of the leverage effect the negative news has larger effects in the conditional variance than positive news. For positive news, the impact on conditional variance will be (α_1 +λ_1) times, whereas for negative news this impact will be [α_1 +($\lambda_1 \times -1$)] times.

TGARCH(1,1):

Zakoian (1994) and Glosten, Jagannathan, and Runkle (1993) were the proponent of the threshold GARCH (TGARCH) model. The TGARCH (1,1) incorporates its conditional variance equation as follows:

$$\sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \lambda \epsilon^2{}_{t-1} I_{t-1}$$

Where I_{t-1} =1, If ϵ_{t-1}<0; = 0 otherwise.

For the presence of the leverage effect, the λ >0 or must be significant as well as positive. Due to the presence of this effect on the data, the impacts on conditional variance will be equal to α_1 for any positive news. On the other hand, if negative news spreads in the market, this impact will be equal to$(\alpha_1 + \lambda_1)$.
As model selection criterion the researcher has adopted the two most widely used criteria i.e. The Akaike information criterion (AIC), and The Schwarz Bayesian information criterion (SBIC) with log-likelihood value.

III. Basic Statistics

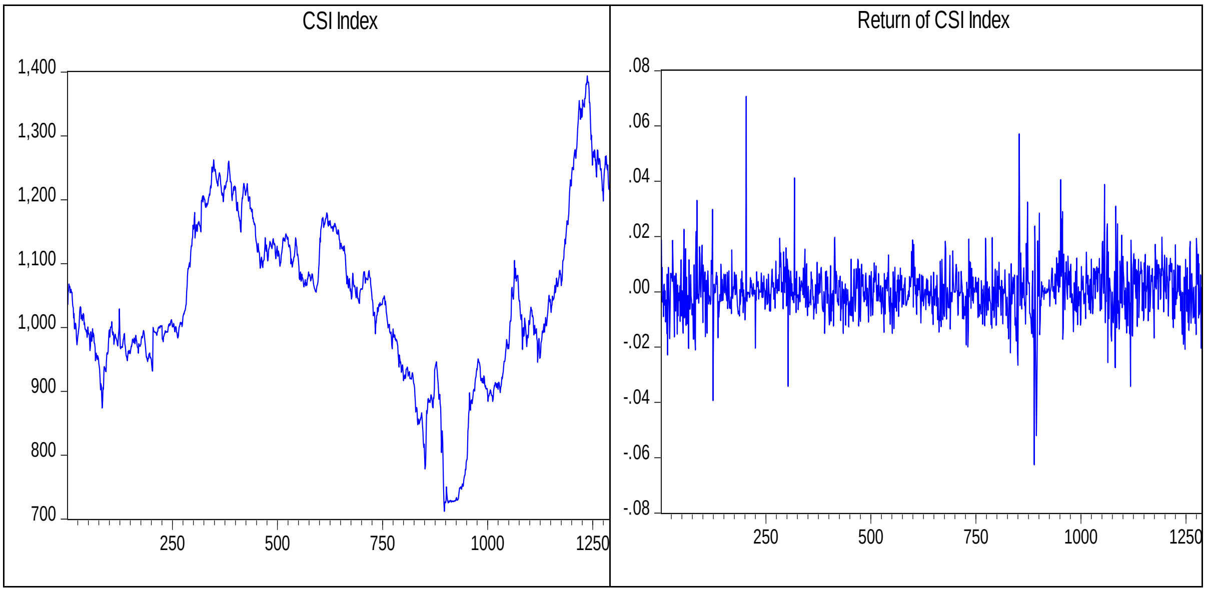
Table 01: Descriptive statistics of the return of The Shariah Index of CSE(CSI)

Items	**Return of CSI Index**
Mean	0.000121
Median	0.0000
Maximum	0.070623
Minimum	-0.062503
Std. Dev.	0.009175
Skewness	0.222972
Kurtosis	10.63835
Jarque-Bera	3158.9
Probability	0.0000
Sum	0.157007
Sum Sq. Dev.	0.108923
Observations	1295

Before finding out the appropriate model for the return series of daily The Shariah Index of CSE Bangladesh for the sample period, it is necessary to observe the descriptive statistics of this series presented in table 01. The index has a remarkable difference between maximum and minimum return having about 7.06%, and -6.25% returns respectively. It has a mean daily return of 0.0121%.The value of skewness and excess kurtosis indicates that the return series is not symmetrically distributed and its nature is leptokurtic. The kurtosis coefficient holds a high value (10.63835) and it is leptokurtic. The Jarque-Bera test statistics with its provability value less than 1% also rejects the null hypothesis of normality.

Both of the daily log returns calculated from The CSE Shariah Index, and this index (in original form) is presented in Figure 01. A return series that contains 'volatility clustering' or 'volatility pooling', acts as a motivation for parameterizing with an ARCH class of model. Volatility clustering can be explained as a situation where large changes in the prices of stocks (of either sign) are followed by large changes and small changes (of either sign) are followed by small changes (Brooks, 2008). Such volatility clustering scenarios are noticed from the graphs presented in the following Figure 01.These graphs can be treated as the primary indications of the existence of 'ARCH effects' in residuals. However, the following section also contains formal tests to confirm it.

Figure 01: Represents the simple line graphs of both The CSE Shariah Index, and Log return data of this index from 01.01.2015 to 30.12.2021



Testing for Heteroscedasticity:

To test 'ARCH-effects' in the residuals firstly it is required to estimate any model, then we have to go for the ARCH-LM tests as residual diagnostic tests. If the value of the test statistic is greater than the critical value from the $\chi 2$ distribution, then the null hypothesis of no ARCH is to be rejected (Brooks, 2008). A test based on arbitrarily selected mean ARMA(1,1) for the presence of ARCH in the residuals is performed by regressing the squared residuals with arbitrarily selected different lags i.e.5,10,15,20, & 25. The result of the heteroskedasticity test presented in table 2.0 suggests that all the probability values with different lags are less than even a 1% level. Hence, there is enough evidence for rejecting null hypothesis which suggests the presence of 'ARCH' in the daily returns series of CSE Shariah Index. Hence, it can be employed the ARCH/GARCH type models on these return data for estimation.

Table 02: ARCH-LM test for residuals of the returns of The CSE Shariah Index(CSI)

Lags		Return of CSI Index
5	LM statistic	83.08
	P-Value	0.0000
10	LM statistic	84.80
	P-Value	0.0000
15	LM statistic	85.78
	P-Value	0.0000
20	LM statistic	88.16
	P-Value	0.0000
25	LM statistic	88.79
	P-Value	0.0000

Testing for *Stationarity:*

Now before ARCH/GARCH type models it is also required to check whether the data is stationary or not. For this purpose, tests like Augmented Dicky Fuller (ADF, 1988) test and Phillips-Perron (P-P, 1987) test have been applied. The (ADF) test with up to 12 lags has been employed on the log return data series with three forms of equations i.e.an intercept but no trend, trend & intercept, and none. For the same purpose Phillips-Perron (P-P) test has also been performed. There are two hypotheses of consideration; H_0: series contains a unit root versus H_1:series is stationary. The results of these two tests are shown in table 3.0. It is found that at level, all the values of test statistics were more negative than the critical values for both ADF and PP tests in all forms of equations. Again all the probability values shown in table 3.0 are statistically significant even a 1% level. So based on these results the null hypothesis, that the series contains a unit root can strongly be rejected. Hence, it may be concluded that the return series of the sample period for The CSE Shariah Index is stationary at level.

Table 03: Results of unit root tests on the daily returns of The CSE Shariah Index(CSI)

Name of Index	Level/ Difference	Test Equation	Augmented Dickey-Fuller Test				Phillips-Perron Test				Comment
			Test-statistic	Critical Value		P-value	T-statistic	Critical Value		P-value	
				1% level	5% level			1% level	5% level		
CSI Index	Level	Intercept	-15.3209	-3.4352	-2.8636	0.0000	-29.8745	-3.4352	-2.8636	0.0000	Stationary at level
		Trend & intercept	-15.3362	-3.9652	-3.4133	0.0000	-29.8649	-3.9652	-3.4133	0.0000	
		None	-15.3234	-2.5668	-1.9411	0.0000	-29.8844	-2.5668	-1.9411	0.0000	

IV. Results and Discussion

Table 04 to table 07 represents the estimated results of all different models under all three error distributions e.g. normal distribution, student's t distribution, and generalized error distribution for The CSE Shariah Index, Bangladesh. Theα_0 (constant), α_1 (ARCH term), and β_1 (GARCH term) are highly statistically significant at 1%,5%,& 10% levels for all models under all of the three error distributions for our return series of CSE Shariah Index. The significance of ARCH and GARCH terms proves that the lagged squared error and lagged conditional variance have significant influencing powers on the return volatility of the CSI Index. The sums of $(\alpha_1 + \beta_1)$ are smaller than one for all the models except EGARCH(1,1), under all error distributions. So, GARCH(1,1), GARCH-M(1,1), and TGARCH(1,1) mean that the variance has a tendency to return back to long-run mean of the volatility for CSI Index, meaning that shocks will decay with time. Table 05 contains the results of GARCH-M(1,1), whereby entering the conditional variance in its mean equation, it hasn't been found any risk premium, as the Υ (risk premium) coefficients are not statistically significant in any level under any distribution.

For EGARCH(1,1) in table 06, λ_1 (asymmetry) coefficients are negative and highly statistically significant under all three error distributions. It is indication of the existence of the 'leverage effect' in the CSI Index. Now for positive news breaks in the market, the parameterμ_{t-1}>0 have $(\alpha_1 + \lambda_1)$ i.e. 0.3092,0.2877, & 0.3032 times the impacts in conditional variance under normal distribution, student's t distribution, and generalized error distribution respectively. On the contrary, if negative news disseminate in the market, the μ_{t-1}<0 have $[\alpha_1 + (\lambda_1 \times -1)]$ i.e. 0.4723, 0.4389, & 0.4643 times the impacts in conditional variance under normal distribution, student's t distribution, and generalized error distribution respectively. So, negative news has larger influential power in affecting the conditional variability than positive one with same magnitude for the CSI Index.

In table 07 the TGARCH(1,1) the λ_1 (asymmetry) coefficients are positive and highly statistically significant under all three error distributions. These ensure the appearance of a 'leverage effect' in the CSI Index. If the positive news spreads in the market, the impacts on conditional variance will be equal to α_1, e.g. 0.1883, 0.1728, &0.1874times under normal distribution, student's t distribution, and generalized error distribution respectively. Whereas, if negative news unveils in the market, the impacts on conditional variance will be equal to $(\alpha_1 + \lambda_1)$, e.g. 0.3726, 0.3520, & 0.3768 times under normal distribution, student's t distribution, and generalized error distribution respectively. Here also, the negative news has more influential power in the conditional variance than positive news. So, both of the EGARCH(1,1), and TGARCH(1,1) confirm the existence of 'leverage effect' in the CSI index.

The results of the ARCH-LM test statistics with their respective probabilities provide the confirmation about non-existence of remaining ARCH effects in the residuals of all the models under all three error distributions. Hence, it might be employed all the models for modeling the volatility of CSI Index, but for finding the best one we should observe some other issues also.

Table 08 represents the summary of all the models under three distributions. The best models have been selected based on the smallest values for AIC, and SBIC, as well as the highest log-likelihood values. Thus, TGARCH(1,1) has been selected under normal distribution, and EGARCH(1,1) has been selected under both student's t distribution, and generalized error distribution for The CSE Shariah Index, Bangladesh. The residual diagnostics for both TGARCH(1,1) and EGARCH(1,1) under all three error distributions also confirm that there are no serial correlations in residuals. But the researcher has observed that their residuals aren't still normally distributed. These are the only weaknesses of these models. However, as the ARCH-LM and the correlogram of squared residuals tests provide satisfactory results still these models can be accepted (Hossain,2012).

V. Conclusion

This study has tried to search for the best-fitted model in modeling the return volatility of The CSE Shariah Index, Bangladesh. In the first part of the analysis, it has been tried to observe the stylized facts of the series. After being confirmed about the presence of the 'ARCH effects' using the ARCH-LM test for residuals, and about the stationarity of data, the researcher became motivated to employ GARCH-type models in modeling. The GARCH(1,1), GARCH-M(1,1), EGARCH(1,1), and TGARCH(1,1) have been applied under three error distributions. These distributions are normal distribution, student's t distribution, and generalized error distribution. Both ARCH and GARCH terms have been found to be highly statistically significant in all models under all forms of error distributions. The evidence of 'leverage effect' has also been detected in both EGARCH(1,1) and TGARCH(1,1) under all distributions. On the basis of the model selection criteria i.e. The Akaike information criterion (AIC), and The Schwarz Bayesian information criterion (SBIC), as well as log-likelihood value TGARCH(1,1) has been selected under normal distribution, and EGARCH(1,1) has been selected under both student's t distribution, and generalized error distribution as best-fitted models for The CSE Shariah Index, Bangladesh. Further study can cover the forecasting ability of these selected models.

Table 04: Results of GARCH(1,1) model under three error distributions for The CSE Shariah Index, Bangladesh

Coefficients	GARCH(1,1) with normal distribution	GARCH(1,1) with student's t distribution	GARCH(1,1) with generalized error distribution
Mean Equation			
ω	0.000369**	0.000108	7.22e-05
ϒ (risk premium)	-	-	-
Variance Equation			
α_0 (constant)	1.50e-05***	1.40e-05***	1.48e-05***
α_1 (ARCH term)	0.28690***	0.282845***	0.297087***
β_1 (GARCH term)	0.55776***	0.561975***	0.544318***
λ_1 (leverage effect)	-	-	-
$\alpha_1 + \beta_1$	0.84466	0.84482	0.841405
AIC	-6.715918	-6.823165	-6.812800
SBIC	-6.699960	-6.803218	-6.792853
Log likelihood	4352.557	4422.999	4416.288
ARCH-LM Test(with lag 5)			
ARCH-LM Statistic	0.616737	0.677459	0.728627
Probability	0.9872	0.9842	0.9814

Comment: ***, **, * represents statistically significant at the 1%, 5% and 10% level respectively.

Table 05: Results of GARCH-M(1,1) models under three error distributions for The CSE Shariah Index, Bangladesh

Coefficients	GARCH-M(1,1) with normal distribution	GARCH-M(1,1) with student's t distribution	GARCH-M(1,1) with generalized error distribution
Mean Equation			
ω	0.000292	-0.000107	-0.000126
ϒ (risk premium)	1.152414	3.212131	3.664012
Variance Equation			
α_0 (constant)	1.51e-05***	1.38e-05***	1.48e-05***

α_1 (ARCH term)	0.286546***	0.278671***	0.294967***
β_1 (GARCH term)	0.557819***	0.567572***	0.545648***
λ_1 (leverage effect)	-	-	-
$\alpha_1 + \beta_1$	0.844265	0.846243	0.840615
AIC	-6.714427	-6.822074	-6.811836
SBIC	-6.694480	-6.798138	-6.787900
Log likelihood	4352.591	4423.293	4416.664
ARCH-LM Test (with lag 5)			
ARCH-LM Statistic	0.613199	0.649969	0.704546
Probability	0.9874	0.9856	0.9827

Comment: ***, **, * represents statistically significant at the 1%, 5% and 10% level respectively.

Table 06: Results of EGARCH(1,1) models under three error distributions for The CSE Shariah Index, Bangladesh

Coefficients	EGARCH(1,1) with normal distribution	EGARCH(1,1) with student's t distribution	EGARCH(1,1) with generalized error distribution
Mean Equation			
ω	0.000228	7.40e-05	4.37e-05
ϒ (risk premium)	-	-	-
Variance Equation			
α_0 (constant)	-1.805788***	-1.524725***	-1.651688***
α_1 (ARCH term)	0.390760 ***	0.363302***	0.383739***
β_1 (GARCH term)	0.841085 ***	0.869182***	0.857225***
λ_1 (leverage effect)	-0.081548***	-0.075613***	-0.080527***
$\alpha_1 + \beta_1$	1.231845	1.232484	1.240964
AIC	-6.722403	-6.832300	-6.820025
SBIC	-6.702456	-6.808364	-6.796088
Log likelihood	4357.756	4429.914	4421.966
ARCH-LM Test (with lag 5)			
ARCH-LM Statistic	0.493174	0.425410	0.457257
Probability	0.9924	0.9946	0.9936

Comment: ***, **, * represents statistically significant at the 1%, 5% and 10% level respectively.

Table 07: Results of TGARCH(1,1) models under three error distributions for The CSE Shariah Index, Bangladesh

Coefficients	TGARCH(1,1) with normal distribution	TGARCH(1,1) with student's t distribution	TGARCH(1,1) with generalized error distribution
Mean Equation			
ω	0.000232	6.77e-05	4.03e-05
ϒ (risk premium)	-	-	-
Variance Equation			
α_0 (constant)	1.27e-05 ***	1.21e-05***	1.25e-05***
α_1 (ARCH term)	0.188325 ***	0.172794***	0.187438***
β_1 (GARCH term)	0.594819 ***	0.606751***	0.590922***
λ_1 (leverage effect)	0.184259***	0.179220***	0.189313***

$\alpha_1 + \beta_1$	0.783144	0.779545	0.77836
AIC	-6.723986	-6.827849	-6.817170
SBIC	-6.704039	-6.803913	-6.793233
Log likelihood	4358.781	4427.032	4420.117
ARCH-LM Test (with lag 5)			
ARCH-LM Statistic	0.742629	0.655917	0.774446
Probability	0.9805	0.9853	0.9786

Comment: ***, **, * represents statistically significant at the 1%, 5% and 10% level respectively.

Table 08: Comparison of models under three different error distributions

Normal Distribution			
Models	**Log Likelihood**	**AIC**	**SBIC**
GARCH(1,1)	4352.591	-6.715918	-6.699960
GARCH-M(1,1)	4352.591	-6.714427	-6.694480
EGARCH(1,1)	4357.756	-6.722403	-6.702456
TGARCH(1,1)	**4358.781**	**-6.723986**	**-6.704039**
Student's t Distribution			
GARCH(1,1)	4422.999	-6.823165	-6.803218
GARCH-M(1,1)	4423.293	-6.822074	-6.798138
EGARCH(1,1)	**4429.914**	**-6.832300**	**-6.808364**
TGARCH(1,1)	4427.032	-6.827849	-6.803913
Generalized Error Distribution(GED)			
GARCH(1,1)	4416.288	-6.812800	-6.792853
GARCH-M(1,1)	4416.664	-6.811836	-6.787900
EGARCH(1,1)	**4421.966**	**-6.820025**	**-6.796088**
TGARCH(1,1)	4420.117	-6.817170	-6.793233

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