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RESEARCH ARTICLE

COMPARING THE PERFORMANCES OF GARCH-TYPE MODELS IN CAPTURING THE BROAD INDEX VOLATILITY IN DHAKA STOCK EXCHANGE.

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Abstract

This study conducted the empirical investigation for the volatility of Broad index of Dhaka stock Exchange (DESX) in Bangladesh. Asymmetric Generalized Autoregressive Conditional Heteroscedastic (GARCH) model was used for DESX index. According to Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), GJR-GARCH (1,1) is found to be the most applicable model to capture the asymmetric volatility. Their performances were also compared under statistical error measurement tools, e.g., root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), theil inequality coefficient and bias proportion analyses.

Introduction:-

Dhaka stock exchange have experienced speedy and substantial growth as investors benefit of the chance to diversify their portfolios internationally in search of the best potential returns to their investments. These developments have motivated empirical analysis into varied aspects of stock return behaviour within the market. The securities market is that the engine of growth for the economy, and performs a vital role in acting as an intermediator between savers and firms seeking further finance for business enlargement. There are two stock exchanges in People's Republic of Bangladesh, e.g., Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE). DSE is that the largest stock market in Bangladesh and play a crucial role for sustainable development goal of the country. DSEX is the main index in DSE. This index started its journey on 27 January 2013. The statistical analysis of financial time series provides proof of diverse conventionalized facts, e.g., volatility clustering, mean reversion, fat tails, leverage impact etc, of which volatility clustering has received extensive attention from academics, researchers and policy makers.

An important and topical space of research issues is the volatility in monetary markets. Volatility refers to the number of uncertainty or risk concerning the dimensions of the changes in a very security's worth. A high volatility means that a security's worth will undoubtly be displayed over a bigger vary of values whereas, lower volatility means that a security's worth doesn't fluctuate dramatically, however changes in worth over a period time. Over the previous few years, modelling volatility of a monetary time series has become a crucial space and has gained a good deal of attention from teachers, researchers and others. The time series is originated to depend upon their own past value (autoregressive), counting on past data (conditional) and exhibit non-constant variance (heteroskedasticity). It's been found that the stock market volatility changes with time and exhibits 'volatility clustering. A series with some periods of low volatility and a few periods of high volatility is supposed to exhibit volatility clustering.

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Variance (or standard deviation) is commonly used because of the risk measure in risk management. Engle (1982) introduced Autoregressive Conditional Heteroskedasticity (ARCH) model to the planet to model monetary time series that exhibit time variable conditional variance. A generalized ARCH (GARCH) model extended by Bollerslev (1986) is another well-liked model for estimating stochastic volatility. However, the GARCH cannot explanation for leverage impact, but they account for volatility clustering and leptokurtosis in a series, this demanded to develop new and extended models over GARCH that resulted in to new models e.g., EGARCH, GJR-GARCH, APARCH, etc. Modelling volatility is widely used by many authors (Engle et al., 1987; Nelson, 1991; Glosten et al., 1993; Schwert, 1989; Ding et al., 1993; French et al., 1987; Chou, 1988). For indices of Dhaka stock exchange, researchers have been working in many dimension also (Basher et al., 2007; Chowdhury, 1994, Chowdhury et al., 2006; Mulla, 2009; Hossain and Uddin, 2011; Rayhan et al., 2011; Islam et al., 2012; Alam et al., 2013; Mukit, 2013; Islam et al., 2014 an so on).

To the best of our knowledge, investigations on broad index of Dhaka Stock Exchange are rare in Bangladesh. Every model is data dependent. A set of models should be tested for selecting few of them on their performance.
Thus, the purpose of the present study is to model and forecast the broad index of DSE through a rigorous comparison of the GARCH family models.

Methodology:-

For assessing volatility on return series (r_t), we can get this series as:
$r_t = (\ln(P_t) - \ln(P_{t-1}))*100$

where r_t is the logarithmic daily return on DSEX index for time t, P_t is the closing index at time t, and P_{t-1} is the corresponding index in the period at time t-1.

The GARCH model (Bollerslev 1986), which permits the conditional variance to be dependent upon previous own lags, confirm to the conditional variance equation in the simplest form as:
$Y_t = X'_t\theta + \varepsilon_t$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}$$

where $\omega > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$

The size of parameters α and β determine the short-run dynamics of the volatility time series. If the calculation of the coefficient is equal to one, then any shock will lead to a permanent change in all future values. Hence, shock to the conditional variance is 'persistence.'

It has already been established that the general GARCH model cannot capture the well-known volatility asymmetry phenomenon in stock markets. To capture this phenomenon, we use the Nelson (1991)'s EGARCH model.

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The left-hand side is the log of the conditional variance. The coefficient γ is known as the asymmetry or leverage term. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is symmetric if $\gamma \neq 0$.
The another asymmetric volatility model is Threshold GARCH. Glosten et al. (1993) proposed the TGARCH or GJR-GARCH model to capture the asymmetry.

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_t^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{i=1}^{p} \gamma_i I_{t-i} \varepsilon_{t-i}^2$$

where

$$I_{t-i} = \begin{cases} 1 & if\ \varepsilon_{t-i} < 0 \\ 0 & if\ \varepsilon_{t-i} \geq 0 \end{cases}$$

The Power ARCH model is

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i (|u_{t-i}| - \eta_i u_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta}$$

where $\delta > 0$, $\eta_i \leq 1$ for $i = 1, \ldots, r$, $\eta_i = 0$ for $i > r$ and $r \leq p$.

We have to estimate the ARCH and different GARCH models. All models (symmetric and asymmetric) are estimated using Maximum Likelihood estimation methodunder Gaussian, Student *t* and Generalized Error Distribution (GED).

Before applying the GARCH methodology, we have to observe the residuals for checking the heteroscedasticity. For this, Lagrange Multiplier (LM) test for Autoregressive conditional heteroscedasticity (ARCH) is used. It is sensible to compute the Engle (1982) test for ARCH effect to ensure that there is no ARCH effect.

Akaike Information Criterion(AIC) and Bayesian Information Criterion(BIC) were applied for model performance whileroot means squared error(RMSE), mean absolute error(MAE), mean absolute percentage error(MAPE), theil inequality coefficient and bias proportion were used for checking forecast performance.

Results and Discussion:-

To find the appropriate model for our given data DSEX index, first the distributional properties of the daily return series of DSEX index during the study period, the descriptive statistics are reported in table 1. Generally the index has a large difference between its maximum and minimum returns. The mean daily return is 0.026592. The volatility (SD) which is 0.866899 indicating a high level of fluctuations. There is an indication of negative skewness (-0.132472) which indicates that the lower tail of the distribution is thicker than the upper tail. It means left tail is particularly extreme, an indication that the DSEX has non-symmetric returns. The kurtosis coefficient having high value (3.3428) which is the pointer of the leptokurtosis or fat taildness in the underlying distribution and does not follow a normal distribution and is further confirmed by Jarque-Bera test statistics, which is highly significant and hence the null hypothesis of normality is rejected.

Table 1:-Descriptive Statistics of daily return of DSEX index

Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera	N
0.0265	0.0097	3.6847	-5.3583	0.8668	-0.1324	3.3428	491.8480 (0.00000)	1045

From Figure 1 it shows that the DSEX index series is non stationary. To make the series stationary, the closing price of the DSEX index is converted into daily logarithmic return series. Figure 2 shows volatility clustering of return series of the DSEX for the study period from 27 January 2013 to 29 May 2017. From the figure 2, it is inferred that the period of low volatility tends to be followed by period of low volatility for a prolonged period and the period of high volatility is followed by period of high volatility for a prolonged period, which means the volatility is clustering and the return series vary around the constant mean but the variance is changing with time.

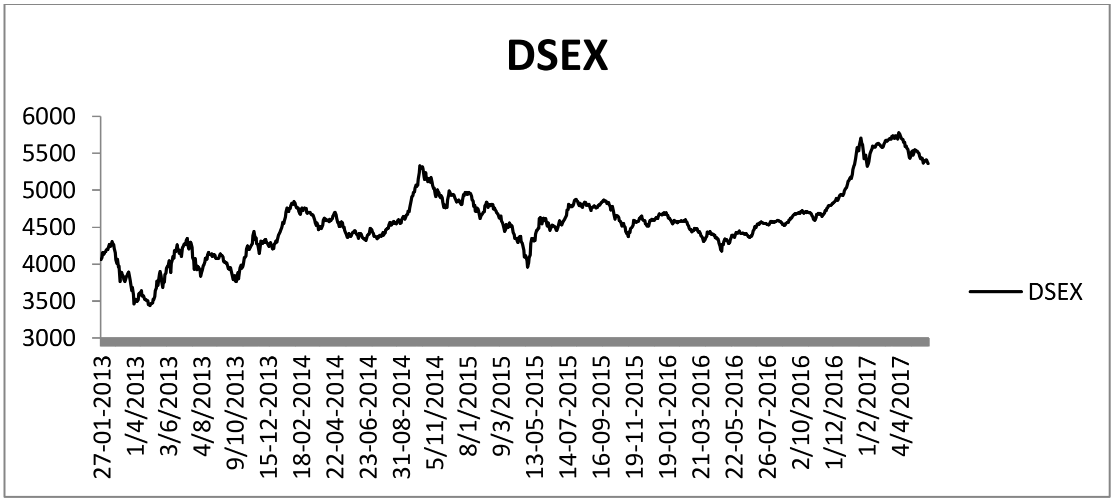

Figure1:-The trend line of DSEX index series.

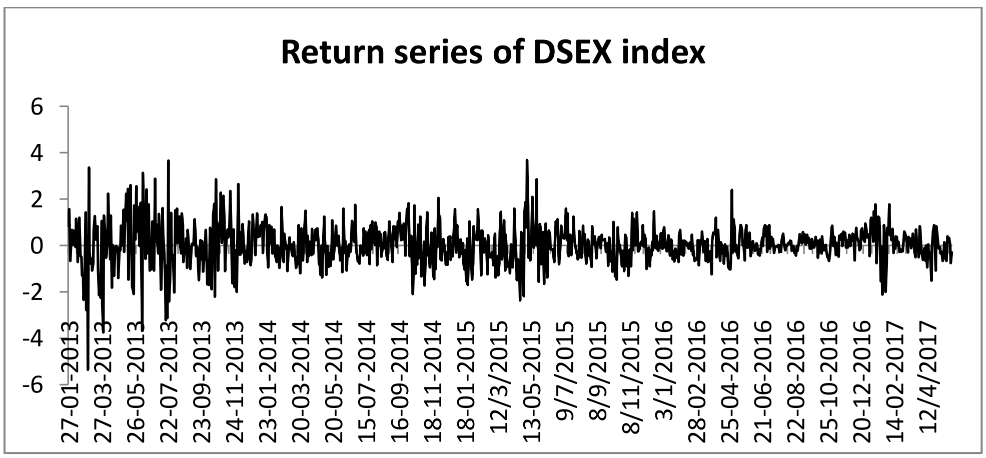

Figure 2:-Volatility clustering of daily return of DSEX index series.

Table 2 shows the presence of unit root in the series tested using ADF and PP tests and the presence of heteroscedasticity tested using ARCH-LM test. The p values of ADF and PP are highly significant, which lead to conclude that the data of the time series for the entire study period is stationary. The ARCH-LM test is applied to find out the presence of ARCH effect in the residuals of the return series. From the table 2, it is inferred that the ARCH-LM test statistics is highly significant, i.e. the null hypothesis of 'no ARCH effect' is rejected, which confirms the presence of ARCH effects in the residuals of time series models in the returns and hence the results warrant for the estimation of GARCH family models.

Table 2:-Result of Unit Root Test and ARCH-LM test

Value	ADF	PP
t- statistic	-29.18617	-29.84357
p value	0.0000	0.0000
ARCH-LM test statistic	132.26	
p value	0.0000	

After volatility clustering is confirmed with return series and stationarity using ADF and PP test, heteroscedasticity effect using ARCH-LM test, the study focuses on determining the best fitted GARCH model to the return series. Therefore, GARCH model is used for modelling the volatility of return series in the Dhaka stock market.

Table 3:-Estimated result under Gaussian error distribution

Parameters	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)	APARCH(1,1)
Mean Model				
AR1	0.626873	0.724883	0.723109	0.711288
MA1	-0.493726	-0.604470	-0.592270	-0.593652
Variance Model				
ω (constant)	0.007136	-0.010736*	0.007756	0.011916
α (ARCH effect)	0.163996	-0.067028	0.094206	0.151137
β (GARCH effect)	0.835004	0.978246	0.840612	0.867244
γ (Leverage effect)		0.292889	0.128365	0.213348
Log likelihood	-1129.43	-1120.772	-1120.047	-1123.424
AIC	2.1712	2.1565	2.1551	2.1635
BIC	2.1949	2.1849	2.1835	2.1967
ARCH-LM test	0.972	1.411	0.4997	1.756
p value	0.32419	0.23483	0.4796	0.1851

Table 4:-Estimated result under Student-t error distribution

Parameters	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)	APARCH(1,1)
Mean Model				
AR1	0.650014	0.713429	0.710415	0.713956
MA1	-0.513377	-0.588993	-0.577496	-0.592883
Variance Model				
ω (constant)	0.007269	-0.013607 *	0.007387	0.012542
α (ARCH effect)	0.163826	-0.065114	0.098510	0.152497
β (GARCH effect)	0.835174	0.977376	0.839568	0.865372
γ (Leverage effect)		0.295668	0.121843	0.212813
Log likelihood	-1126.413	-1120.211	-1119.392	-1122.912
AIC	2.1692	2.1593	2.1577	2.1644
BIC	2.2024	2.1972	2.1956	2.2023
ARCH-LM test	0.9704	1.418	0.5475	1.722
p value	0.3245	0.2336	0.4593	0.1894

Table 5:-Estimated result under GED

Parameters	GARCH(1,1)	EGARCH(1,1)	GJR-GARCH(1,1)	APARCH(1,1)
Mean Model				
AR1	0.631558	0.710979	0.705660	0.709768
MA1	-0.491906	-0.585220	-0.570746	-0.586162
Variance Model				
ω (constant)	0.007324	-0.015212	0.007471	0.012628
α (ARCH effect)	0.164790	-0.065703	0.098651	0.152623
β (GARCH effect)	0.834209	0.977345	0.838982	0.865214
γ (Leverage effect)		0.295763	0.122734	0.215627
Log likelihood	-1125.38	-1119.339	-1118.584	-1121.927
AIC	2.1672	2.1576	2.1561	2.1625
BIC	2.2004	2.1955	2.1941	2.2004
ARCH-LM test	0.9323	1.414	0.5356	1.718
p value	0.3342	0.2344	0.4643	0.1899

We already saw that in our data, the heteroskedastic problem is present. The skewness statistics of the return series which are generated in Table 1 imply the asymmetry in the data set. Therefore, the asymmetric specifications of GARCH model, EGARCH, GJR-GARCH and APARCH are also employed in this dissertation. However, regarding the results of those asymmetric models, the asymmetric effect parameter γ is statistically significant for EGARCH(1,1), GJR-GARCH(1,1) and APARCH(1,1) respectively. Though, the coefficient of mean equation in all models is significant at 1% level. This implies the strong evidence of asymmetry in the return series. In other words, the conditional variance is not higher in the presence of negative innovation or the market seems not nervous when bad news takes place. The finding is interesting because it is likely a phenomenon in many mature markets that the investors react more dramatically to negative shocks than positive shocks. However, the outcome is consistent with the findings in some other emerging markets such as transition markets of Central Europe (Haroutounian and Price, 2001) and Chinese stock markets (Song et al, 1998). For EGARCH(1,1) model constant term is insignificant for Gaussian error distribution, Student-t error distribution.

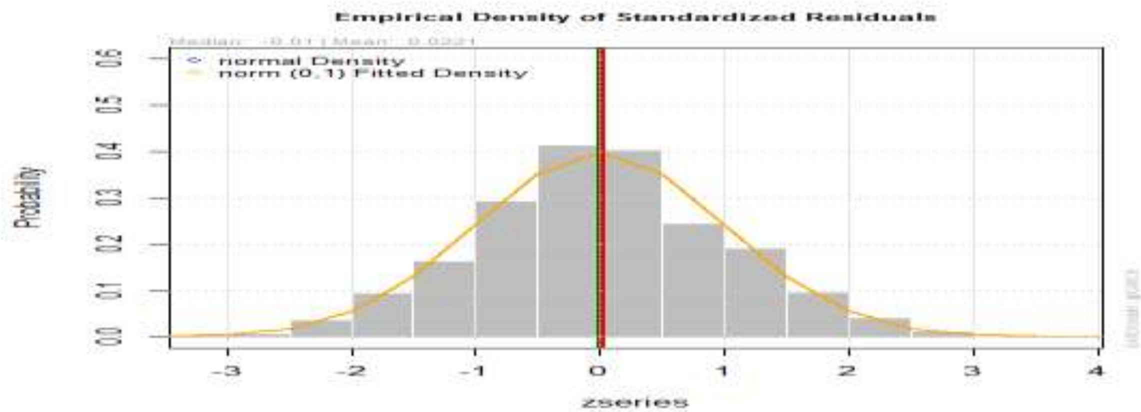

Figure 3:-Density of Standardized Residuals for fitted ARMA(1,1) with GJR-GARCH(1,1) model.

In Table 3, 4 and 5 we examined Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) from different models. From the above tables we found that the value of AIC and BIC of GJR-GARCH(1,1) model is smallest of all the models. So we choose GJR-GARCH(1,1) under Gaussian error distribution model for diagnostic check and forecasting. Also from these tables using ARCH-LM test, there is no remaining ARCH effect.

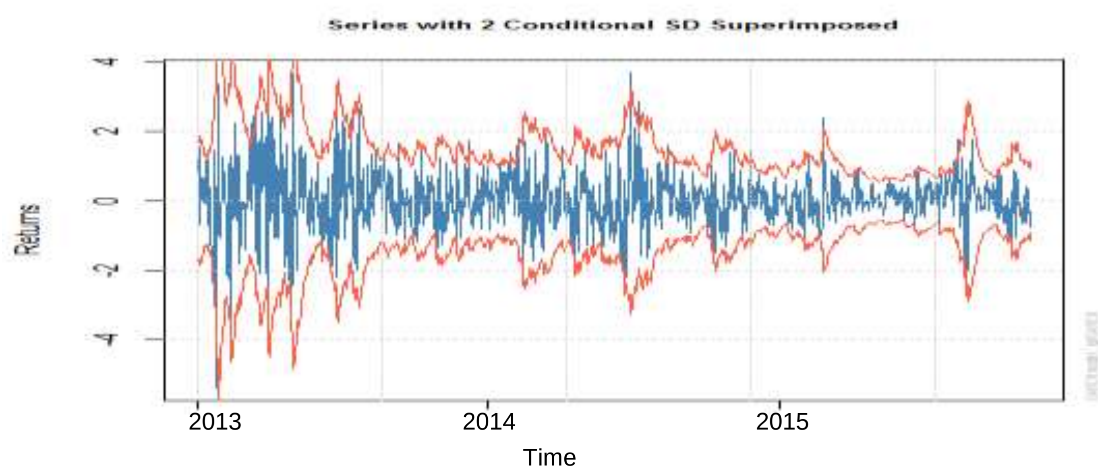

Figure 4:-Series with 2 conditional standard deviation for fitted ARMA(1,1) with GJR-GARCH(1,1) model.

The model GJR-GARCH(1,1), sum of parameters is less than unity but very close, which implies that innovation to the conditional variance will be highly persistent that large changes in returns tend to be followed by large changes and small changes tend to be followed by small changes. This confirms that volatility clustering is observed in the DSEX index in Dhaka Stock Exchange. We also observed from Figure 4 and Figure 5 which is the plot of 2 conditional standard deviation and conditional standard deviation vs absolute return respectively and from these two figure the GJR-GARCH(1,1) model may be appropriate.

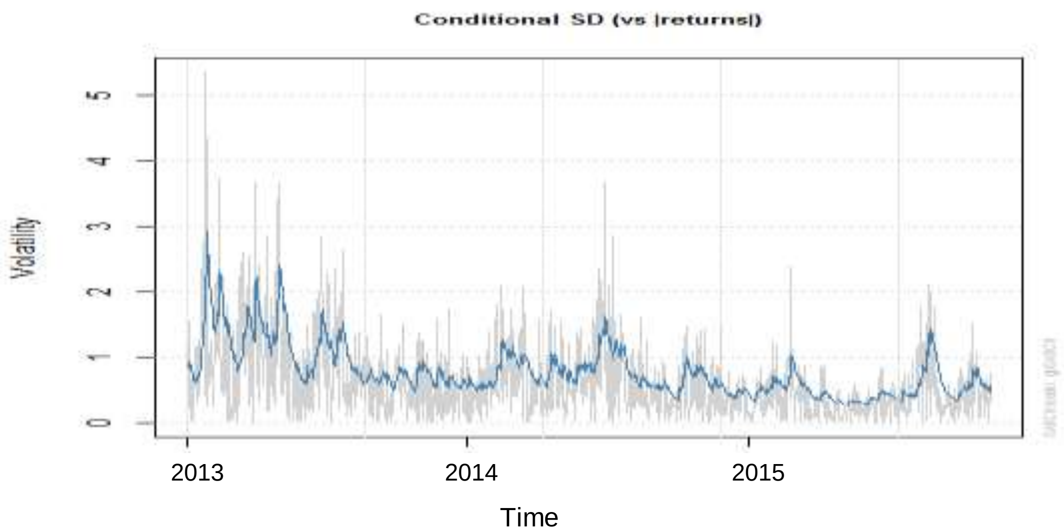

Figure 5:-Series with conditional standard deviation vs absolute return value for fitted ARMA(1,1) with GJR-GARCH(1,1) model.

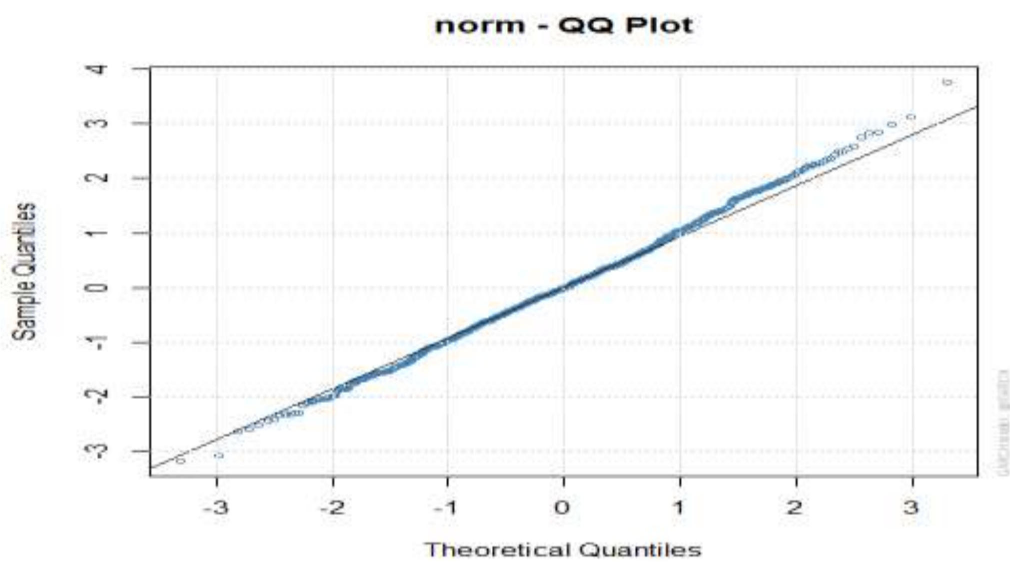

Figure 6:-Normal QQ Plot for fitted ARMA(1,1) with GJR-GARCH(1,1) model.

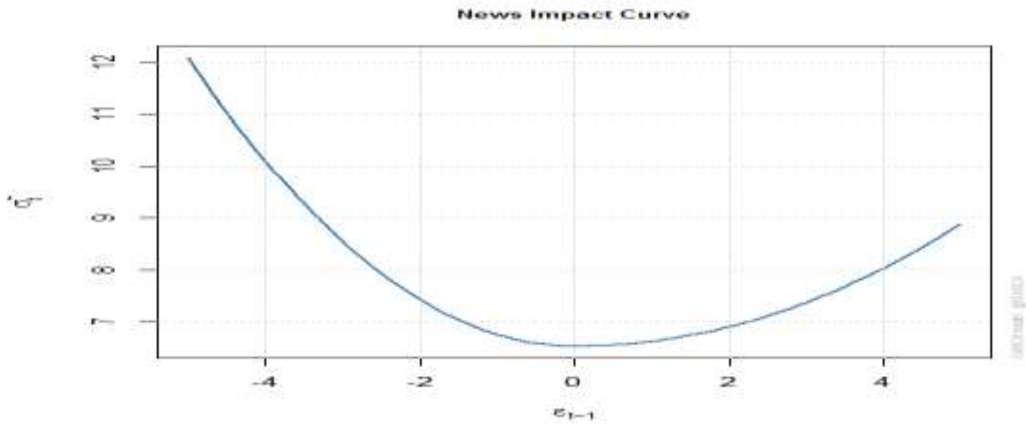

Figure 7:-News impact curve for fitted ARMA(1,1) with GJR-GARCH(1,1) model.

The properties of standardized residuals are employed to define the best fit data models. After estimating the different GARCH-type models, we obtained the standardized residuals from these models to carry out the diagnosis tests to establish the goodness of fit of these alternative models. In theory, the standardized residuals are expected to have a mean of zero and a variance of unity. Figure 3 and 6 represent that the fitted model is reasonably well. In other words, the model considered to best fit data will be the one with the distribution of standardized residuals the most close to normal distribution

A forecast is generally defined as a statement concerning future events. Forecasting is one of the most common uses of econometric methods. According to Akgiray (1989), there are two reasons why forecasting volatility attracts interests of investors. Firstly, good forecast capability of volatility models provides a practical tool for stock market analysis. Secondly, as proxy for risk, volatility is related to expected returns, hence good forecast models enable investors give more appropriate securities pricing strategies. The forecasted values are presented in table 6.

Table 6:-Forecasted value of the fitted model.

Time	**Series**	**Time**	**Series**
T+1	0.076276	T+11	0.027089
T+2	0.071056	T+12	-0.03203
T+3	0.017761	T+13	-0.10193
T+4	-0.05597	T+14	-0.08535
T+5	0.059884	T+15	-0.06419
T+6	0.025049	T+16	-0.12489
T+7	-0.0173	T+17	-0.07378
T+8	-0.07627	T+18	-0.16914
T+9	0.06797	T+19	-0.0904
T+10	0.127286	T+20	-0.11147

Now we shall cheek the adequacy of the fitted model using root mean square error, mean absolute error, mean absolute percent error, Theil inequality coefficient, bias proportion of forecast properties between the two close models. Table 7 show that the GJR-GARCH(1,1) under Gaussian error distribution model performing better than other models. For proving asymmetry information Figure 7 represent the news impact curve. This is the strong indication that the ARMA(1,1) with GJR-GARCH(1,1) model is appropriate.

Table 7:-Forecasting Evaluation properties of fitted models

	GJR-GARCH(1,1) (Normal)	GJR-GARCH(1,1) (GED)
RMSE	0.5304	0.5306
MAE	0.4299	0.4303
MAPE	144.7543	146.2547
Theil Inequality Coefficient	0.8401	0.8409
Bias Proportion	0.0281	0.0282

Conclusion:-

In this study, volatility of DSEX index return is tested using the asymmetric GARCH models. The daily closing prices of DSEX index are collected and modelled using four different GARCH models that capture the volatility clustering and leverage effect for the study period. GARCH (1,1), EGARCH (1,1), GJR_GARCH (1,1), and APARCH (1,1) models are employed in the study after confirming the stationarity test, volatility clustering and arch effect. The results show that the coefficient has the expected sign in the GJR-GARCH (positive and significant) models. Finally, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) suggested that GJR-GARCH (1,1) model be the best fitted model among all to capture the effect. All fitted models of GARCH, EGARCH, GJR-GARCH and APARCH are evaluated by RMSE, MAE, and MAPE, theil inequality coefficient and bias proportion.

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