MODELING THE VOLATILITY OF NIGERIAN STOCK MARKET USING GARCH FAMILY MODELS

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ABSTRACT

Stock market contributes to the growth process of any economy. However, volatility in stock market can generate a rise in cost of capital which is capable of affecting economic growth negatively. Investors, academics and regulators are interested in understanding the nature of volatility. In this study, the effects of volatility clustering and leverage of Nigerian stock market was investigated using GARCH models. All-share index monthly data collected from CBN office (OkeMosun, Abeokuta) which covers the period of ten year data (1986-2017) was modeled using GARCH, EGARCH and TARCH models. The best fitted model for All-share index is the model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (SIC). It was found that the E-GARCH model is the best model with the lowest AIC and BIC. The model shows that there is volatility clustering and existences of leverage effect in Nigerian Stock market All-share Index.

Keywords: All share index, GARCH models, ARCH effect, Model selection, Volatility.

Introduction

Volatility of stock return is a measure of dispersion around the average return of a security or an index. Investigating behaviors of stock returns volatility gained momentum with the introduction of the Auto-regressive conditional Heteroskedasticity (ARCH) model by Engle (1982) and its generalization by Bollerslev (1986). As a result, many variants of the GARCH model have evolved and understanding of volatility has improved steadily. The understanding of volatility of stock returns is crucial to stock market participants as variation of returns from expectation could mean huge losses or gain and hence greater uncertainty (Gujarati, 2003). Stock market regulators are interested in understanding volatility behavior because high volatile stock market increases uncertainty, which reduced investor's confidence in the market, and lead to high cost of capital. The implication of volatility clustering, according to Engle and Paton (2001), is that volatility shocks today will influence the expectation of volatility in many periods in the future. Another feature of equity volatility is asymmetry in volatility innovation. Asymmetric phenomenon occurs when a fall in return is followed by an increase in volatility greater than the volatility induced by an increase in return.

The volatility clustering has extensively been studied, surveyed and many stylized facts documented. One of the first stylized facts of volatility of asset prices is volatility clustering. Mandelbrot (1963) and Fama (1965) both provide evidence to show that large changes in price of an asset are followed by large changes (of either sign) and small changes are often followed by small changes. Black (1976), Christie (1982), Nelson (1991), Glosten, Jagannathan and Runkle (1993) all find evidence of negative relation between volatility and stock returns. Evidence also abounds to show that the unconditional distribution of asset prices have fatter tails than the normal distribution. This feature of asset price increases the probability of extreme values in asset returns.
The first break-through in volatility modeling was Engle (1982), where it was shown that conditional Heteroskedasticity can be modeled using an autoregressive condition Heteroskedasticity (ARCH) Model. ARCH model relates the conditional variance of the disturbance term to the linear combination of the squared disturbance in the recent past. Having realized the potentials ARCH model, studies have used it to model financial time series. Determining the optimal lag length is cumbersome, oftentimes, engender over-parameterization. Rydberg (2000) argued that large lag values are required in ARCH Models, thus the need for many parameters. However, Bollerslev (1986) and Taylor independently proposed the extension of ARCH Model with an Autoregressive Moving Average (ARMA) formulation, with a view to achieving parsimony. The model is called the generalized ARCH (GARCH), which models conditional variance as a function of its lagged values as well as Squared lagged values of the disturbance term. Although GARCH model has proven useful in capturing symmetric effect of volatility, it is bedeviled with some limitations, such as the violation of non-negativity constraints imposed on the parameters to be estimated. To overcome these constraints, some extensions of the original GARCH model were proposed. This includes asymmetric GARCH family models such as Threshold GARCH (TGARCH) proposed by Zakoian (1994), Exponential GARCH (EGARCH)

proposed by Nelson (1991). The idea of the proponents of these models is based on the understanding that good news (positive shocks) and bad news (negative shock) of the same magnitude have differential effects on the conditional variance.

The EGARCH which captures asymmetric properties between returns and volatility was proposed to address three major deficiencies of GARCH model. They are

i. Parameter restrictions that ensures conditional variance positivity
ii. Non-sensitivity to asymmetric response of volatility to shock and
iii. Difficulty in measuring persistence in a strongly stationary series.

The log of the conditional variance in the EGARCH model signifies that the leverage effect is exponential and not quadratic. According to Majose (2010), the specification of volatility in terms of its logarithmic transformation implies the non-restriction on the parameters to guarantee the positivity of the variance which is a key advantage of EGARCH model over the symmetric GARCH model. Zakoian (1994) specified the TGARCH model by allowing the conditional standard deviation to depend on sign of lagged innovation. The specification does not show parameter restrictions to guarantee the positivity of the conditional variance. However, to ensure Stationary of the TGARCH model, the parameters of the model have to be restricted and the choice of error distribution account for the stationary.

Furthermore, Bollerslev et al. (1994) established that a GARCH model with normally distributed errors could not be sufficient model for explaining kurtosis and slowly decaying autocorrelations in return series.

Nelson (1991) assumed that EGARCH model is stationary if the innovation has a generalized error distribution (GED), he therefore recommended GED in EGARCH model. And Majose (2010) argued that the stationary of TGARCH model depends on the distribution of the disturbance term, which is usually assumed to follow Gaussian or Student-t. Furthermore, as the fat-tailed of the error distribution increases, the leverage effect captured in TGARCH model get smaller and losses more flexibility.

Some related works

Several empirical works on volatility modeling have been done since the seminar paper of Engle (1982), especially in finance. Jayasuriya (2002) examined the effect of stock market liberalization on stock return volatility using Nigeria and fourteen other emerging market data, from December 1984 to March 2000 to estimate asymmetric GARCH Model. The study inferred that positive (negative) changes in prices have been followed by negative (positive) changes. Engle (2003) examined the risk and volatility of stock returns in Nigeria banking sector using Econometric Models and Financial Practice. Ogum et al. (2005) applied the Nigeria and Kenya stock data on EGARCH Model to capture the emerging market volatility. Frimpong and Oteng-Abayie (2006) studied the stock exchange of Ghana using GARCH models by modeling and forecasting the volatility of their returns. He discovered that the model is the best used for stock exchange and can be used to study the variation that might occur due to some climate changes overtime. Okpara and Nwezeaku (2009) randomly selected forty-one companies from the Nigeria stock Exchange to examine the effect of the idiosyncratic risk and beta risk on returns using data from 1996 to 2005 by applying EGARCH (1, 3) model, the result shows less volatility persistence and establishes the existence of leverage effect in the Nigeria Stock market, implying that bad news drives volatility more than good news. Hamadu and Ibiwoye (2010) examined the volatility of daily stock returns of Nigeria insurance stocks using twenty-six insurance companies' daily data from December 15, 2000 to June 9 of 2008 as training data set and from June 10, 2008 to September 9, 2008 as out of sample data set. The result of ARCH (1), GARCH (1, 1), TGARCH (1, 1) and EGARCH (1, 1) show that EGARCH is more suitable in modeling stock price returns as it out performs the other models in model evaluation and out-of-sample forecast. Sanusi (2011) examined the volatility of financial crisis on Nigeria capital market, while studying it he observed that the crisis comes from the Federal Civilians because the Federal Government spend their 70% earning on their Civilians salary instead of investing it.

Ahmed and Suliman (2011)used the Generalized Autoregressive Conditional Heteroscedastic models to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan namely, Khartoum Stock Exchange (KSE) over the period from January 2006 to November 2010. The models include both symmetric and asymmetric models that capture the most common stylized facts about index returns such as volatility clustering and leverage effect. The empirical results show that the conditional variance process is highly persistent and provide evidence on the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns. The results also showed that the asymmetric models provide better fit than the symmetric models, which confirms the presence of leverage effect. Alawiye (2013) studied the volatility of banking sector and reported the account of 57.98% of total trades in 2013. Osazevbaru (2014) tested for the presence or otherwise of volatility clustering in the Nigerian stock market. Using time series data of share prices for the period 1995 to 2009, the Autoregressive

Conditional Heteroscedasticity (ARCH) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model were estimated. The estimates indicate that the market exhibits volatility clustering.

MATERIALS AND METHODS

The sample data used for this study are the monthly closing prices of the Nigerian Stock Exchange (NSE) All Share Index over the period January 1986 to December 2017 collected from the Central Bank of Nigeria office at OkeIlewo, Abeokuta.
The following tools and techniques have been used to achieve the objective of the study:

Unit Root Test:
In order to check whether or not the series are stationary, Augmented Dickey-Fuller (ADF) Unit root test was applied to examine the stationarity of the time series of the study and to find the order of integration between them. The ADF unit root test has been performed by estimating the regression:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{j=1}^{n} \gamma_j \, \Delta Y_{t-j} + \varepsilon_t \,. \qquad (1)$$

The ADF unit root test is based on the null hypothesis H_0: Y_t is not $I_{(0)}$. If the calculated ADF statistics is less than the critical value, then the null hypothesis is rejected; otherwise accepted.

ARCH Model
Every ARCH or GARCH family model requires two distinct specifications, namely, the mean and variance equations. According to Engle, Conditional Heteroskedasticity in a return series $y_t$can be modeled using ARCH model expressing the mean equation in the form:

$$y_t = \mathbf{E}\left(y_{t\backslash t-1}\right) + \mathcal{E}_t \,. \qquad (2)$$

Such that $\boldsymbol{\mathcal{E}}_t = \nu_t \sigma$

Equation (2) is the mean equation which also applies to other GARCH family models. $\mathbf{E}\left(y_{t\backslash t-1}\right)$ is the expected conditional information available at time $t-1$, $\mathcal{E}_t$ is error generated from the mean equation at time t andν_t is a sequence of unit variance. E $\left(\frac{\mathcal{E}_t}{\Omega_{t-1}}\right) = 0$ and $\sigma_t^2 = \mathrm{E}\left(\frac{\varepsilon_t^2}{\Omega_{\{t-1\}}}\right)$is a non-trivial positive value parameter function of n_{t-1}.
The variance equation for an ARCH Model of order q is given as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \varepsilon_{\{t-1\}}^2 \alpha_i + \mu_t \,. \qquad (3)$$

where = $\alpha_0 > 0$; $\alpha_i \geq 0$; $i = 1, \dots, (q-1)$ and $\alpha_q > 0$.
In practical application of ARCH (q) model, the decay rate is usually more rapid than what actually applies to financial time series data. To account for this, the order of the ARCH must be at maximum, a process that is strenuous and more cumbersome.

Generalized ARCH (GARCH) Model:
The conditional variance for GARCH (p, q) model is expressed generally as

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_i \mathcal{E}_{\{t-i\}}^2 + \sum_{j=1}^{p} \beta_j \sigma_{\{t-j\}}^2 \qquad (4)$$

where p is the order of the GARCH terms, σ^2 and q is the order of the ARCH terms, $\square^2$.
And i=1,…,q-1, j=1,…,p-1 and β_p , α_q>0. σ^2_t is the conditional variance and $\square^2_t$ disturbance term. The reduced form of equation 3 is the GARCH (1, 1) represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mathcal{E}_{\{t-1\}}^2 + \beta_1 \sigma_{\{t-1\}}^2 \qquad (5)$$

The three parameters $(\alpha_0, \alpha_1$ and $\beta_1)$ are non-negative and $\alpha_0 + \alpha_1 < 1$ to achieve stationary.

Threshold GARCH (TGARCH) Model:
The generalized specification for the conditional variance using TGARCH (p, q) is given as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \mathcal{E}_{\{t-i\}}^2 + \sum_{k=1}^{r} \gamma_k \sigma_{\{t-k\}}^2 I_{t-k} + \sum_{j=1}^{p} \beta_j \sigma_{\{t-j\}}^2 \qquad (6)$$

where $I_{t-k} = 1$ if $\square_t$<0 and $I_{t-k} = 0$ otherwise.
In this model, good news implies that $\square^2_{t-i}$> 0 and bad news implies bad that $\square^2_{t-i}$< 0 and these two stocks of equal size have differential effects on the conditional variance. Good news has an impact of $\alpha_i$and bad news has an impact of $\alpha_i + \gamma_i$. Bad news Increases volatility when $\gamma_i > 0$, which implies the existence of leverage effect in the i^{th}order and when $\gamma_i \neq 0$ the news impact is a symmetric. However, the First order representation is of TGARCH (p, q) is

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mathcal{E}_{\{t-1\}}^2 + \gamma_1 \sigma_{\{t-1\}}^2 I_{\{t-1\}} + \beta_1 \sigma_{\{t-1\}}^2 \qquad (7)$$

Then, good news has an impact of $\alpha_1$and bad news has an impact of $\alpha_1 + \gamma_1$

Exponential GARCH (EGARCH) Model:
The Conditional Variance of EGARCH (p, q) model is specified generally

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q}\left(\alpha_i\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)\right) + \sum_{j=1}^{p}\beta_j \ln(\sigma_{\{t-j\}}^2) \qquad (8)$$

$\mathcal{E}_{t-i} > 0$ and $\mathcal{E}_{t-i}^2 < 0$ implies good news and bad news respectively and their total effects are $(1+\gamma_i)\,|\mathcal{E}_{t-i}|$and $(I-\gamma_i)\,|\mathcal{E}_{t-i}|$respectively. When$\gamma_i < 0$, the expectation is that bad news would have higher impact on volatility. The EGARCH model achieves covariance stationary when$\sum_{j=1}^{p}\beta_j < 1$. The interest of this paper is to model the conditional variance using EGARCH (1, 1) model, which is specified as

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_1 \ln(\sigma_{\{t-1\}}^2) \qquad (9)$$

The total effects of goods news and bad news for EGARC H (1, 1) are $(1+\gamma_1)\,|\mathcal{E}_{t-1}|$and $(I-\gamma_1)\,|\mathcal{E}_{t-1}|$respectively, Failing to accept the null hypothesis that $\gamma_1 = 0$shows the presence of leverage effect, that is bad news have stronger effect than good news on the volatility of stock index return.

Model Selection/Forecasting Evaluation:
Model selection is done using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) and the model with the lowest AIC and BIC value across the error distribution is adjudged the best fitted. This selection produces the best fitted conditional variance models for the shares Index.
Let c be the number of estimated parameters in the model and n be the sample size. Let $\hat{J}$ be the maximum value of the likelihood function for the model. Then the AIC value of the model

$$AIC = 2c - 2\ln(\hat{J}). \qquad (10)$$

The BIC is formally defined as

$$BIC = \ln(n)c - 2\ln(\hat{J}). \qquad (11)$$

Another way of evaluating the adequacy of asymmetric volatility models is the ability to show the presence of leverage effect, that equal magnitude of bad news (negative shocks) have stronger impact than good news (positive shocks) on the volatility of stock Index returns. The diagnostic test for standardized residuals of the stock returns in each of the four fitted volatility models is conducted. The test for remaining ARCH effect and serial correlation in the residual of the mean equation (standardized residual) reduces the efficiency of the conditional variance model.

On the predictive ability of volatility models, Clement (2005) proposed that out-of-sample forecasting ability remains the criterion for selecting the best predictive model. Therefore, out-of-sample model selection criteria (Root Mean Square Error (RMSE) will be used to test before forecasting the model. If σ^2_t and cap σ^2_t represent the actual and forecasted volatility of share index stock returns at time t, then

$$RMSE = \sqrt{\frac{\sum_{t=T+1}^{T+K}\left(\hat{\sigma}_t^2 - \sigma_t^2\right)^2}{k}} \qquad (12)$$

RESULTS AND DISCUSSION

Data collected for this research work is based on chronological sequence of observations. The data collected is a secondary data and analysis carried out with the aid of R Statistical Package. Here models are compared to find out which one is the best using AIC and SIC Criterion. The lower the value of AIC and SIC the better fitted the model.

Unit Root Test

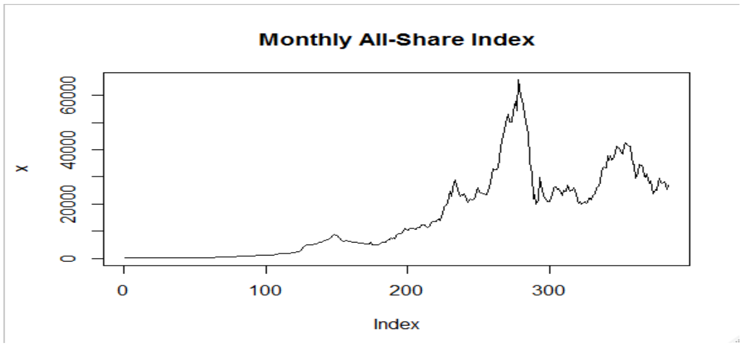

Figure 1: Monthly All-Share Index between 1986 and 2017

Figure 1 shows the time series plot of monthly All-Share Index between 1986 and 2017. It is clearly shown that the data is not stationary. This is confirmed using Augmented Dickey-Fuller Test with p-value of 0.07256. Therefore, there will be need to convert non-stationary series to stationary by differencing the log All-Share Index which represents the returns of the monthly All-Share Index.

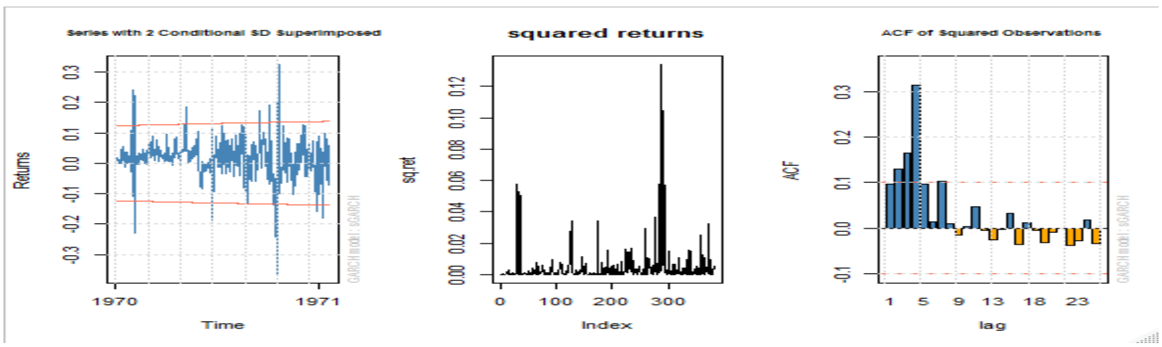

Figure 2: Monthly All-Share Index Returns, Squared Returns and ACF of Squared Returns

Figure 2 shows the plots of monthly All-share index returns, squared returns and the Auto Correlation Function (ACF) of squared returns. The Augmented Dickey-Fuller Test with p-value of 0.01 indicates that the monthly All-share index returns is stationary at 5% level of significance. The squared returns plot shows cluster of volatility at some point in time and the ACF
seems to die down; hence the residuals show some patterns that might be modeled using GARCH family models.

ARCH MODEL

The Autoregressive Conditional Heteroscedastic Model parameters with their standard errors and p-values are given in the table below

Table 1: Parameter estimate, Standard error and p-value of ARCH Model

	Estimate	Std. Error	t value	Pr(>|t|)
μ	0.014860	0.003110	4.7779	$2x10^{-06}$*
α_1	0.000007	0.000000	49.9446	0.00*
α_2	0.999000	0.000028	35944.034	0.00*

*significant at 5% significant level

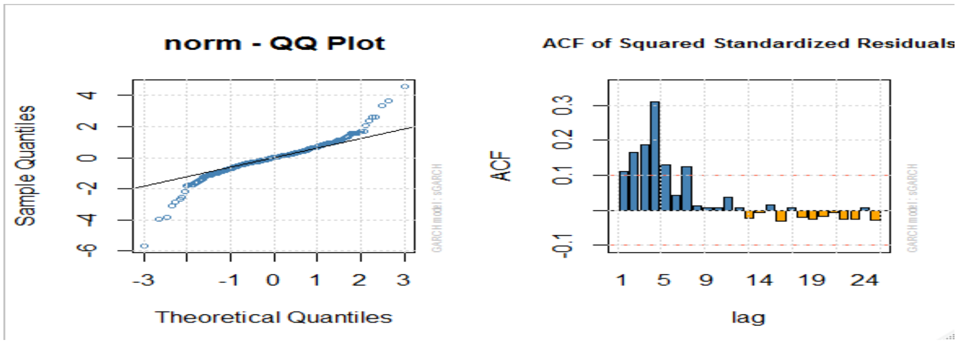

Figure 3: Q-Q plot and ACF of Squared Standardized Residuals of ARCH Model

Figure 3 shows the Q-Q plot and the ACF of squared residual of ARCH model. It is clearly shown that the residual of the model is not normal. The Augmented Dickey-Fuller Test with p-value of 0.01 indicates that the residual of the model is stationary at 5% level of significance Weighted Ljung-Box Test on standardized residuals with p-value of 5.258e-03 indicates non-normality of the residuals. The ACF of the squared residuals which die down indicates serial correlation of the residuals and weighted ARCH LM-test with p-value = 1.330e-03 indicates the presence of ARCH effects. The fitted model has AIC= -2.7361 and BIC=-2.7052.

4.3 GARCH (1, 1) MODEL

Table 2: Parameter estimate, Standard error and p-value of GARCH Model

	Estimate	Std. Error	t value	Pr(>|t|)
μ	0.023663	0.001949	12.1398	0.00000*
ω	0.000213	0.000076	2.8184	0.00483*
α_1	0.446325	0.070891	6.2960	0.00000*
β_1	0.552675	0.045516	12.1424	0.00000*

*significant at 5% significant level

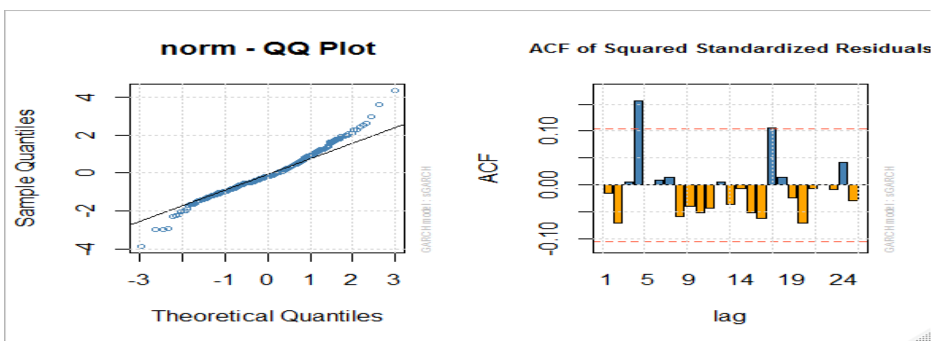

Figure 4: Q-Q plot and ACF of Squared Standardized Residuals of GARCH Model

Figure 4 shows the Q-Q plot and the ACF of squared residual of GARCH model. The residual of the model is approximately normal. The Augmented Dickey-Fuller Test with p-value of 0.004621indicates that the residual of the model is stationary at 5% level of significance. Weighted Ljung-Box test on standardized residuals with p-value of 6.579e-05 indicates non-normality of the residuals. The ACF of the squared residuals does not die down indicates no serial correlation of the residuals and the weightedARCH LM-test with p-value = 0.4822 indicates the absence of ARCH effects. The fitted model has AIC= -3.1982 and BIC= -3.1544.

4.4 EGARCH (1,1) MODEL

Table 3: Parameter estimate, Standard error and p-value of EGARCH Model

	Estimate	Std. Error	t value	Pr(>|t|)
μ	0.02362	0.0017	13.653	0.00000*
ω	-0.5360	0.1621	-3.305	0.00095*

α_1	-0.0433	0.0503	-0.860	0.38946
β_1	0.9052	0.0269	33.639	0.00000*
γ_1	0.7426	0.1036	7.168	0.00000*

*significant at 5% significant level

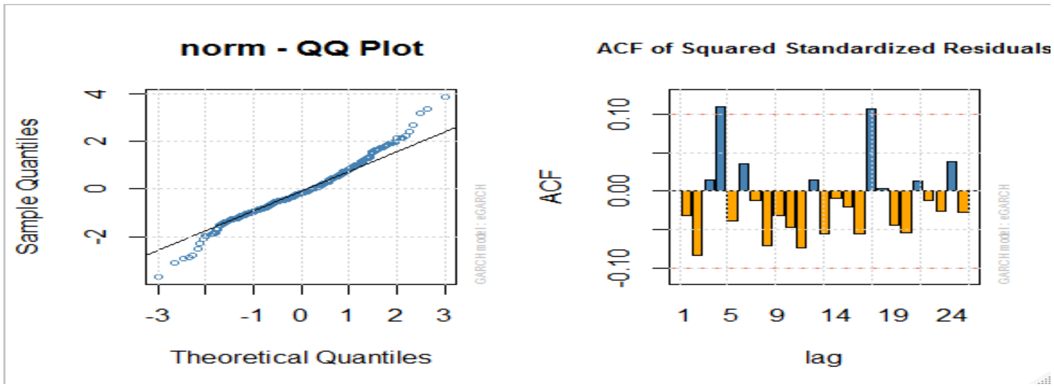

Figure 5: Q-Q plot and ACF of Squared Standardized Residuals of EGARCH Model

Figure 5 shows the Q-Q plot and the ACF of squared residual of EGARCH model. The Augmented Dickey-Fuller test with p-value of 0.01 indicates that the residuals of the model is stationary at 5% level of significance. Weighted Ljung-Box test on standardized residuals with p-value of 2.780e-05 indicates non-normality of the residuals. The ACF of the squared residuals does not die down indicates no serial correlation of the residuals and the weightedARCH LM-test with p-value = 0.7667indicates the absence of ARCH effects. The fitted model has AIC= -3.2101 and BIC= -3.1553.

4.5 TARCH (1, 1) MODEL OR SOMETIME IT IS CALLED GJR-GARCH (1, 1) MODEL

Table 4: Parameter estimate, Standard error and p-value of TGARCH Model

	Estimate	Std. Error	t value	Pr(>|t|)
μ	0.0229	0.00203	11.3268	0.00000*
ω	0.0002	0.00008	2.8162	0.00486*
α_1	0.3712	0.08888	4.1759	0.00003*
β_1	0.5523	0.04629	11.9315	0.00000*
γ_1	0.1511	0.10563	1.4309	0.15247

*significant at 5% significant level

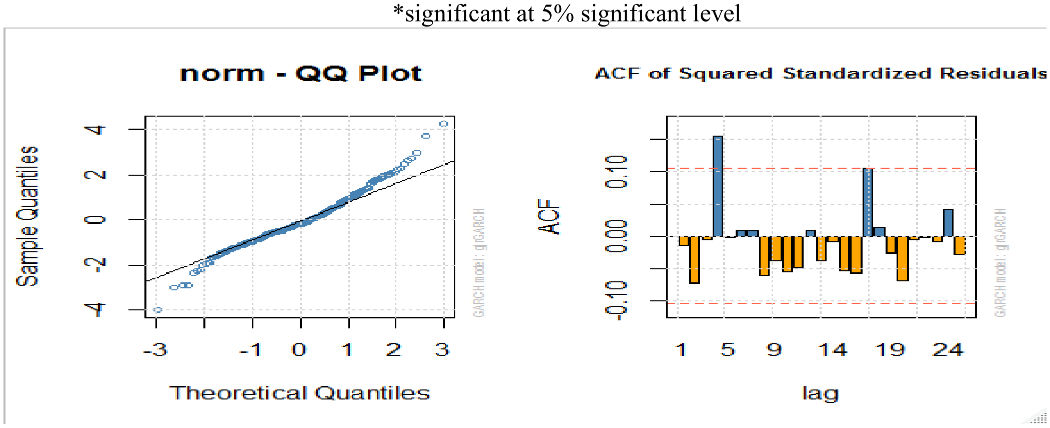

Figure 6: Q-Q plot and ACF of Squared Standardized Residuals of TGARCH Model

Figure 6 shows the Q-Q plot and the ACF of squared residual of EGARCH model. The Augmented Dickey-Fuller test with p-value of 0.01 indicates that the residuals of the model is stationary at 5% level of significance. Weighted Ljung-Box test on standardized residuals with p-value of 5.119e-05 indicates non-normality of the residuals. The ACF of the squared residuals does not die down indicates no serial correlation of the residuals and the weightedARCH LM-test with p-value = 0.7799 indicates the absence of ARCH effects. The fitted model has AIC= -3.1941 and BIC= -3.1394.

4.6 MODEL SELECTION

Table 5: AIC and BIC of Competing Models

Model	ARCH	GARCH	EGARCH	TARCH
AIC	-2.7361	-3.1982	-3.2101	-3.1941
BIC	-2.7052	-3.1544	-3.1553	-3.1394

The best model for Nigerian Stock Market Monthly All-Share Index with the lowest AIC and BIC is the EGARCH Model. All its parameters are significant at 5% significant level except alpha1. Omega and alpha1 have negative effects on Monthly All-Share Index.
The competing fitted models were used to estimate the 1-step forecast series with unconditional 1-sigma band. The adequacies of the models to forecast future value of Nigerian Stock Market Monthly All-Share Index were tested using RMSE. The model with the lowest RMSE is the best model to forecast the Monthly All-Share Index.

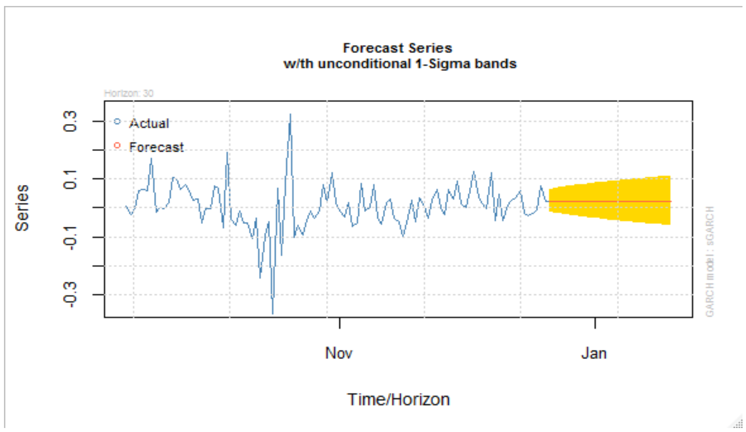

Figure 7: GARCH (1, 1) forecast with RMSE=0.0648

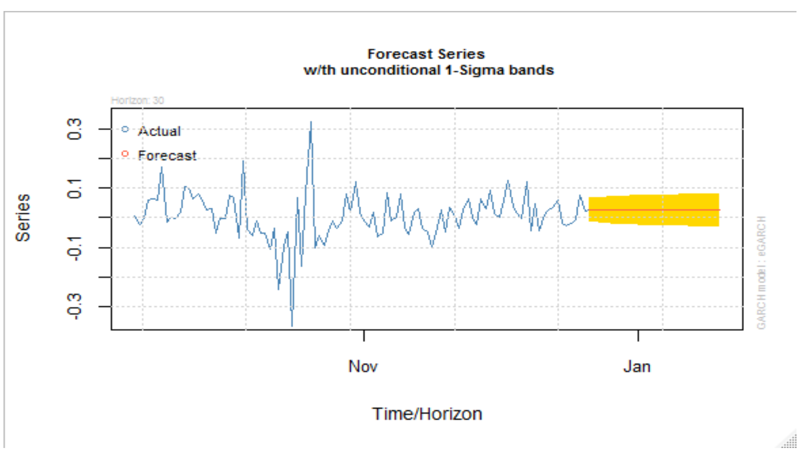

Figure 8: EGARCH (1, 1) forecast with RMSE= 0.05017

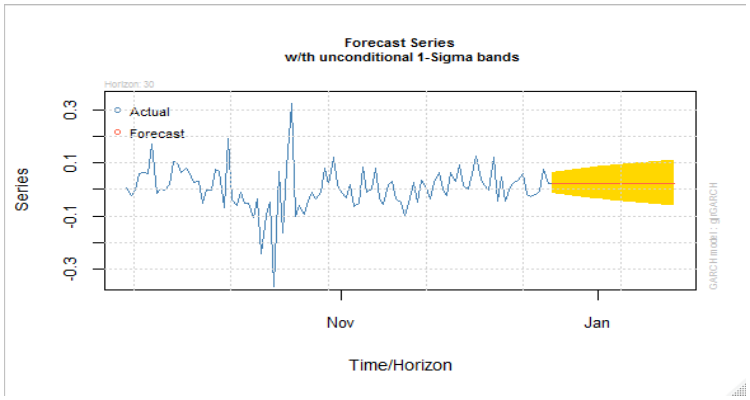

Figure 9: TGARCH (1, 1) forecast with RMSE= 0.0649

Figures 7, 8 and 9 show GARCH (1, 1) forecast with RMSE=0.0648, EGARCH (1, 1) forecast with RMSE= 0.05017 andTGARCH (1, 1) forecast with RMSE= 0.0649 respectively. The EGARCH (1, 1) model with the lowest RMSE is the best model to forecast Nigerian Stock Market All-share Index.

CONCLUSION

This study tests the volatility of Nigerian Stock Market Monthly All-Share Index using the GARCH family models. The stationary Monthly All-Share Index returns were used to test if there is ARCH effect and Heteroskedasticity in the model. The squared returns plot shows cluster of volatility at some point in time and the ACF of returns seems to die down; hence the residuals show some patterns that might be modeled using GARCH family models. The GARCH family models were then fitted to the data to determine the best fitted model using AIC and BIC. The analysis shows that E-GARCH model which has the lowest AIC and BIC adjudged the best model. The adequacy of the model was tested using serial correlation test, Heteroskedasticity Test and Normality test. It was discovered that there is no serial correlation, no Arch effect but the residual is not normally distributed. All its parameters are significant at 5% significant level except alpha1. Omega and alpha1 have negative effects on Monthly All-Share Index. This shows that there is volatility clustering and existences of leverage effect in Nigerian Stock market All-share Index. E-GARCH model is the best model to forecast Nigerian Stock market Monthly All-share Index.

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