Modeling Volatility in Selected Nigerian Stock Market

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Abstract
Modeling the volatility in daily stock prices requires to study the particular error distribution that best fits the data, since it is evident that the stock market is now relied upon by investment analysts, economists and policy makers to measure changes in the general economic activities of a nation and globally. This study, therefore aimed at fitting symmetric and asymmetric GARCH models to daily stock prices of selected securities in Nigeria using Access and Fidelity Banks daily closing share prices from April 1, 2010 to December 16, 2016. This study estimates first order symmetric and asymmetric volatility models each in Normal, Student's-t and generalized error distributions (GED) with the view to selecting the best forecasting volatility model with the most appropriate error distribution. The results of the analysis shows that PARCH (1, 1), EGARCH (1, 1) and TGARCH in that order with GED were selected to be the best fitted models based on the Akaike Information Criterion (AIC). The out-of-sample forecasting evaluation result adjudged PGARCH (1, 1) with GED as the best predictive model based on Mean Absolute Error and Theil Inequality Coefficient and EGARCH(1,1) based on root mean square error (RMSE). It is therefore recommended that empirical workers should consider alternative error distributions while specifying predictive volatility model as less contributing error distributions implies incorrect specification, which could lead to loss of efficiency in the model, especially to model the volatility in stock prices.

Keywords: *Asymmetric GARCH; Student's t distribution; Normal distribution; generalized error distribution; Stock prices*

1. Introduction

The stock market is the focus of investment analysts, economists and policy makers because it may be relied upon to measure changes in general economic activities using the stock prices of listed companies of the Nigerian Stock Exchange (NSE). Ogum et al. (1995) mentioned that the stock market provides the fulcrum for capital market activities and it is often cited as a barometer of business direction. The saving sector needs to employ their savings in more beneficial and ambitious projects and the productive sectors always require financial sources to assist them to perform more in the economy. Stock market performance helps to transfer funds from people who have amassed surplus to those who have a paucity of funds (Jayasuriya, 2002).

Time series analysis is one of the best methods of analyzing stock market because the data are collected on daily basis ordered by time. A time series is a set of data collected at equal intervals. In finance, time series data could be data on daily exchange rate, daily shares prices, daily shares index and so on. Time series data could be stationary or non-stationary. A sequence or series is stationary or strictly stationary if there is no systematic change in its mean and variance. This stationarity calls for volatility model. Thus, the volatility of stock markets has been the object of numerous developments and applications over the past two decades. In this respect, the most widely used class of time series models is certainly that of generalized autoregressive conditional heteroscedastic (GARCH) (Rao, 2016).

GARCH models usually indicate a high persistence of the conditional variance. The ARCH as well as the GARCH models captures volatility clustering and leptokurtosis. In situations where their distributions are symmetric, they fail to model the leverage effect. To address this problem, many nonlinear extensions of GARCH have been proposed, such as the Exponential GARCH (EGARCH), GJR-GARCH, PGARCH and TGARCH. Thus, the estimates of a GARCH model in the persistence parameter may suffer from a substantial upward bias. Therefore, models in which the parameters are allowed to change over time may be more appropriate for modeling volatility (Berkes et al., 2003).

Dallah and Ade (2010) examined the volatility of daily stock returns of Nigerian insurance stocks using twenty six insurance companies' daily data from December 15, 2000 to June 9, 2008 as training data set and from June 10, 2008 to September 9, 2008 as out-of-sample dataset. Their result of ARCH (1), GARCH (1, 1) TARCH (1, 1) and EGARCH (1, 1) shows that in model evaluation and out-of-sample forecast of stock price returns, EGARCH is more suitable as it performed better than other models.

This study focuses on the behavior of stock returns volatility of Nigeria stock market using daily share price data for the period July 2011 to June 2016. It is expected that in a volatile stock market, the value of the magnitude of the disturbance terms should be greater at certain periods than others. However, this study models stock return using generalized autoregressive conditional heteroscedasticity (GARCH) models and it is hoped that the findings of this study will be of immense benefit for policy formulation.

In order to achieve the aim of this study, which is modeling of Nigeria stock market price volatility, we set the following objectives:

(i) Estimate the stock price volatility using the generalized autoregressive conditional heteroscedasticity (GARCH) models and

(ii) Selecting the best forecasting volatility model with the most appropriate error distribution.

This study is organized into sections. Section one comprises introduction to the study, which includes the objectives of the study. Section two explores theoretical review of GARCH models and empirical review of related literature. Section three comprises method and materials and model specification. Section four consists of data analysis, results and discussion of findings and finally section five is where we do the conclusion and recommendations.

2. Materials and Methods

2.1 Data Description

In this research, we collected secondary data on daily closing price list of Access and

Fidelity Banks in Nigeria. The data was collected online from www.capitalbancorpng.com/research /pricelist on December 17, 2016 covering April 1, 2010 to December 16, 2016 spanning 1,693 data point. Trading does not take place on Public Holidays at the floor of Nigerian Stock Exchange (NSE), so figures are not available for holidays. The data were entered into Microsoft Excel sheet and subsequently transferred to Eviews 7 for the data analysis.

2.2 Volatility Models Used

2.2.1 GARCH Models

The Generalized autoregressive conditional heteroscedasticity (GARCH) (*p*,*q*) model of Bollerslev (1986) includes *p* lags of the conditional variance in the linear ARCH(*q*) conditional variance equation, The basic model of representing non-correlated series with excess kurtosis and auto correlated squares, proposed by Engle (1982), is given as

$$y_t = E_{t-1}(y_t) + \varepsilon_t \tag{1}$$

Such that $\varepsilon_t = z_t\sigma_t$

Wherez_t is an i.i.d process with mean zero and variance 1 and σ_t is the volatility that evolves over time. Equation (1) is the mean equation, which also applies to other GARCH family model. $E_{t-1}(.)$ is expectation conditional on information available at time *t-1*, $\varepsilon_t$is error generated from the mean equation at time *t*. The volatility σ_t^2 in the basic ARCH (q) model is defined as

$$\sigma_t^2 = c + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + u_t \tag{2}$$

Where $c > 0;\ \alpha_i \geq 0;\ i = 1\ to q - 1$ and $q > 0$.

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. As a result, Bollerslev (1986) proposed the GARCH (*p*, *q*) model given as

$$\sigma_t^2 = c + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

Where*p* is the order of the GARCH terms, σ^2 and *q*are the order of the ARCH terms, ε^2, where $c > 0;\ \alpha_i \geq 0;\ i = 1, \dots, q-1;\ j = 1, \dots, p - 1and\beta_p, \alpha_q > 0$, and σ_t^2 is the conditional variance and ε_t^2, disturbance term.

Conditions on the parameters to ensure that the GARCH(*p*,*q*) conditional variance is always positive are given in Nelson and Cao (1992). The GARCH(*p*,*q*) model may alternative be represented as an ARMA(max{*p*,*q*},*p*) model for the squared innovation:

$$\varepsilon_t^2 = c + \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i)\varepsilon_{t-i}^2 - \sum_{i=1}^{p} \beta_i v_{t-i} \tag{4}$$

where$v_t = \varepsilon_t^2 - \sigma_t^2$, so that by definition $E_{t-i}(v_t) = 0$. The relatively simple GARCH(1,1) model, is simply represented as

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

The three parameters ($c > 0$, $\alpha \geq 0$and$\beta \geq 0$) and $\alpha + \beta < 1$ to achieve stationarity.

The GARCH(1,1) model often provides a good fit in empirical applications. This particular parameterization was also proposed independently by Taylor (1986). The GARCH(1,1) model is well-defined and the conditional variance positive almost surely provided that $c > 0$, $\alpha \geq 0$and$\beta \geq 0$. The GARCH(1,1) model may alternatively be express as an ARCH(∞) model,

$$\sigma_t^2 = c(1-\beta)^{-1} + \alpha \sum_{i=1}^{\infty} \beta^{t-i} \varepsilon_{t-i}^2 \tag{6}$$

provided that $\beta < 1$. If $\alpha + \beta < 1$the model is covariance stationary and the unconditional variance equals $\sigma^2 = c(1 - \alpha - \beta)$. Multi-period conditional variance forecasts from the GARCH(1,1) model may readily be calculated as:

$$\sigma_{t+h|t}^2 = \sigma^2 + (\alpha + \beta)^{h-1}(\sigma_{t+1}^2 - \sigma^2), \tag{7}$$

where $h > 2$ denotes the horizon of the forecast.

2.2.2 The Threshold GARCH (TGARCH) Model

The TGARCH(p,q) model proposed by Zakoian (1994) extends the TS-GARCH(p,q) model to allow the conditional standard deviation to depend upon the sign of the lagged innovations. The generalized specification for the conditional variance using TGARCH (p, q) is given as

$$\sigma_t^2 = c + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i I_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_J \sigma_{t-j}^2 \tag{8}$$

Where $I_{t-i} = 1$, if $\varepsilon_{t-1}^2 < 0$, and 0 otherwise.

In this model, good news implies that $\varepsilon_{t-i}^2 > 0$ and bad news implies that $\varepsilon_{t-i}^2 < 0$ and these two shocks of equal size have differential effects on the conditional variance. Good news has an impact of α_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 asymmetric. However, the first order representation of TGARCH is TGARCH(1, 1). In particular, it may be expressed as:

$$\sigma_t^2 = c + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{9}$$

Glosten, Jagannathan and Runkle (1993).

2.2.3 The Power GARCH (PGARCH) Model

Ding et al (1993) expressed conditional variance using PGARCH (p, d, q) as

$$\sigma_t^d = c + \sum_{i=1}^{p} \alpha_i [|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}]^d + \sum_{t-j}^{q} \beta_j \sigma_{t-j}^d \tag{10}$$

Here, $d > 0$ and $\Re^+$, $\gamma_i < 1$ establishes the existence of leverage effects. If d is set at 2, the PGARCH (p, q) replicate a GARCH (p, q) with a leverage effect. If d is set at 1, the standard deviation is modeled. The first order of equation (7) is PGARCH (1, d, 1), expressed as:

$$\sigma_t^d = c + \alpha[|\varepsilon_{t-1}| + \gamma\varepsilon_{t-1}]^d + \beta\sigma_{t-1}^d \tag{11}$$

2.2.4The Exponential GARCH (EGARCH) Model

The standard GARCH model has a number of potential pitfalls. Such models cannot take into consideration asymmetry, leverage effects, and coefficient restrictions. Nelson (1991) proposed the exponential GARCH or EGARCH model to resolve these limitations. Unlike the standard GARCH model, the EGARCH model can capture size effects as well as sign effects of shocks. The variance equation of EGARCH model is given as

$$ln(\sigma_t^2) = c + \sum_{i=1}^{q} \left\{ \alpha_i \left| \frac{\varepsilon_{t-i}^2}{\sigma_{t-i}} \right| + \gamma_i \left(\frac{\varepsilon_{t-i}^2}{\sigma_{t-i}} \right) \right\} + \sum_{j=1}^{p} \beta_J ln(\sigma_{t-j}^2) \tag{12}$$

$\varepsilon_{t-i} > 0$and$\varepsilon_{t-i} < 0$ implies good news and bad news and their total effects are $(1 + \gamma_i)\lceil\varepsilon_{t-i}\rceil$ and $(1 - \gamma_i)\lceil\varepsilon_{t-i}\rceil$ respectively. When$\gamma_i < 0$, the expectation is that bad news would have higher impact on volatility. The EGARCH model achieves covariance stationarity when $\sum_{j=1}^{p} \beta_J < 1$. Besides, this model captures the leverage effect, which exhibits the negative association between lagged stock returns and contemporaneous volatility. The presence of leverage effects can be tested by the hypothesis that $\delta < 0$. If $\delta \neq 0$ then the impact is asymmetric. The simplest form is the EGARCH (1,1) model, which is specified as

$$ln(\sigma_t^2) = c + \alpha \left|\frac{\varepsilon_{t-1}^2}{\sigma_{t-1}}\right| + \gamma\left(\frac{\varepsilon_{t-1}^2}{\sigma_{t-1}}\right) + \beta ln(\sigma_{t-1}^2) \quad (13)$$

2.3 Error Distributions Hypothesis

The probability distribution of stock prices often exhibits fatter tails than the standard normal distribution. The existence of heavy-tailedness is probably due to a volatility clustering in stock markets. In addition, another source for heavy-tailedness seems to be the sudden changes in stock returns. An excess kurtosis also might be originated from fat tailedness. Moreover, in practice, the returns are typically negatively skewed. In order to capture this phenomenon (e.g., heavy-tailedness), the t and GED distributions are also considered in our analysis.

To further prove that modeling of the return series is inefficient with a Gaussian process for high frequency financial time series, equations 5, 7, 9 and 13 are estimated with a normal distribution by maximizing the likelihood function

$$L(\theta_t) = -\frac{1}{2}\sum_{t-1}^{T}\left(ln2\pi + ln\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2}\right) \quad (14)$$

whereσ_t^2 is specified in each of the GARCH models.

The assumption that GARCH models follow GED[2] tends to account for the kurtosis in returns, which are not adequately captured with normality assumption. As in (3.9) above, the volatility models are estimated with GED by maximizing the likelihood function below:

$$L(\theta_t) = -\frac{1}{2} ln\left(\frac{\Gamma(1/v^3)}{\Gamma(3/v)(v/2)^2}\right) - \frac{1}{2} ln\sigma_t^2 - \frac{1}{2}\left(\frac{\Gamma(3/v)(y_t - X_t'\theta)^2}{\sigma_t^2\Gamma(1/v)}\right)^{v/2} \quad (15)$$

where$v$ is the shape parameter which accounts for the skewness of the returns and $v > 0$. The higher the value of v, the greater the weight of tail. GED reverts to normal distribution if v = 0.In the case of t-distribution, the volatility models considered are estimated to maximize the likelihood function of a Student's t distribution:

$$L(\theta_t) = -\frac{1}{2} ln\left(\frac{\pi(r)\Gamma(r/2^2)}{\Gamma[(r+1)/2]^2}\right) - \frac{1}{2} ln\sigma_t^2 - \frac{(r+1)}{2}\left(1 + \frac{(y_t - X_t'\theta)^2}{\sigma_t^2(r-2)}\right) \quad (16)$$

Here, r is the degree of freedom and controls the tail behavior, r > 2.

2.4 Model Selection/Forecasting Evaluation

The first order volatility models in equations 4, 6, 8 and 10 are estimated by allowing ε_t in (20) for each of the variance equation to follow normal, student's t and generalized error distributions. The value of the positive exponent in equation 13 is set at 1, 2 and 4. This process generates eighteen volatility models. Model selection is done using AIC, and the model with the least AIC value across the error distributions is adjudged the best fitted. This selection produces the best-fitted conditional variance models for stock prices.

The diagnostic test for standardized residuals of the stock returns in each of the best-fitted volatility models is conducted. The tests for remaining ARCH effect and serial correlation using ARCH-LM test and Q-Statistics (Correlogram of Residuals), respectively are conducted. The presence of ARCH effect and serial correlation in the residual of the mean equation (standardized residual) reduces the efficiency of the conditional variance model. Hence, the expectation is that the two null hypotheses that "there is no ARCH effect" and "there is no serial correlation" must not be rejected at 5% significance level. QQ-plot is used to check the normality of the standardized residuals. For a Gaussian process, the points in the QQ-plots will lie on a straight line.

On the predictive ability of volatility models, Clement (2005) proposes that out-of-sample forecasting ability remains the criterion for selecting the best predictive model. Therefore, two out-of-sample model selection criteria (Root Mean Square Error (RMSE) and Theil Inequality Coefficient (TIC)) are applied to evaluate the predictive ability of the best competing models. If σ_t^2 and $\hat{\sigma}_t^2$ represent the actual and forecasted volatility of stock returns at time *t*, then

$$RMSE = \sqrt{\sum_{t=T+1}^{T+k} (\hat{\sigma}_t^2 - \sigma_t^2)^2 / k} \quad (17)$$

and

$$TIC = \frac{\sqrt{\sum_{t=T+1}^{T+k} (\hat{\sigma}_t^2 - \sigma_t^2)^2 / k}}{\sqrt{\sum_{t=T+1}^{T+k} (\hat{\sigma}_t^2)^2 / k}\ \sqrt{\sum_{t=T+1}^{T+k} (\sigma_t^2)^2 / k}} \quad (18)$$

The smaller the RMSE and TIC, the higher the forecasting ability of the model.

3. Result and Discussion of Findings

3.1Exploratory Data Analysis (EDA)

In this section, data are presented in tables and charts and the data presented are then analyzed and the results of the analysis discussed. The descriptive analysis of the data shown in Table 1 reveals that the daily average shares prices of Access and Fidelity Banks are ₦7.61 and ₦2.02 respectively over the period under review, with standard deviations 2.15 and 0.68 respectively. The Fidelity Bank dataset is more skewed and peaked than that of Access Bank but the volatility of Access Bank is more than that of Fidelity Bank. This shows that Fidelity Bank shares price is more stable than that of Access Bank. The shares price of Access Bank fluctuates between ₦3.59 minimum and ₦12.39 maximum under the period in review, while that of Fidelity Bank fluctuates between ₦0.78 minimum and ₦3.50 maximum under the same period.

The time plot depicted in Figure 1 shows that there is a high volatility in Access Bank shares price as a result of the high spike in the movement compared to that of Fidelity Bank. However, both shares prices seem to be moving in a general direction downward, which is not obvious to depict from the raw data except from the time plot. Figure 2 and Figure 3 shows the histogram of the Access Bank data and that of Fidelity Bank, which are bimodal in shape.

Table 2 shows the linear deterministic test for unrestricted cointegration rank test between daily shares prices of Access and Fidelity Banks with Lags interval (in first differences) 1 to 4. The trace and eigen value tests are significant at 5% level. The trace test is significant for none at 5% but not significant for at most 1. Also, the maximum eigen value test is significant for none but not significant for at most 1 at 5% level of significance. The reported log likelihood is 2859.462.

Table 1: Descriptive Statistics

Statistic	ACCESS	FIDELITY
Mean	7.613680	2.025145
Median	7.730000	2.000000
Maximum	12.39000	3.500000
Minimum	3.590000	0.780000
Std. Dev.	2.150051	0.684891
Skewness	0.021149	0.157003
Kurtosis	1.795659	1.869386
Jarque-Bera	102.4425	97.12801
Probability	0.000000	0.000000
Observations	1,693	1,693

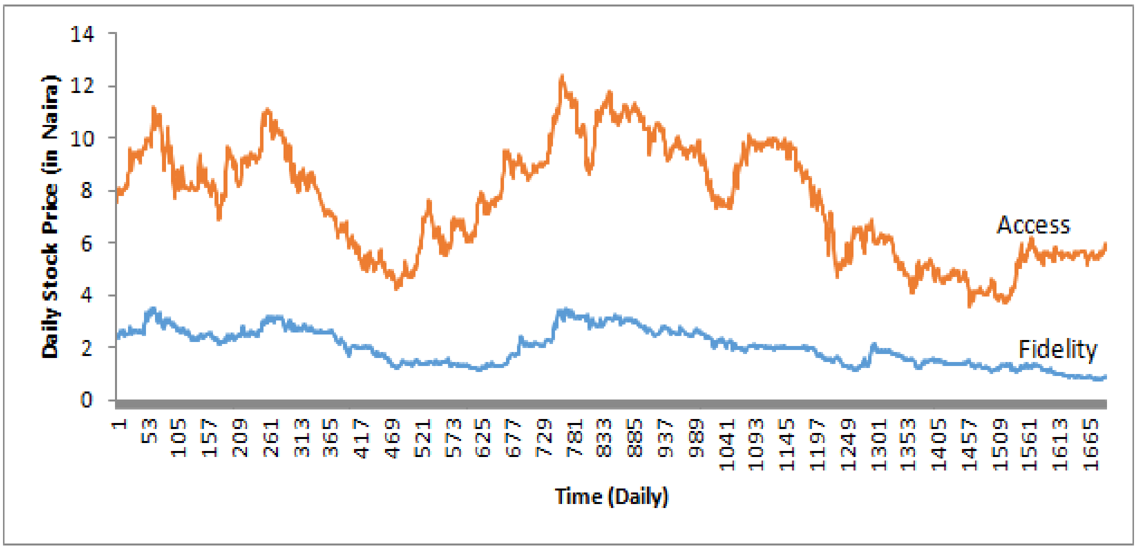
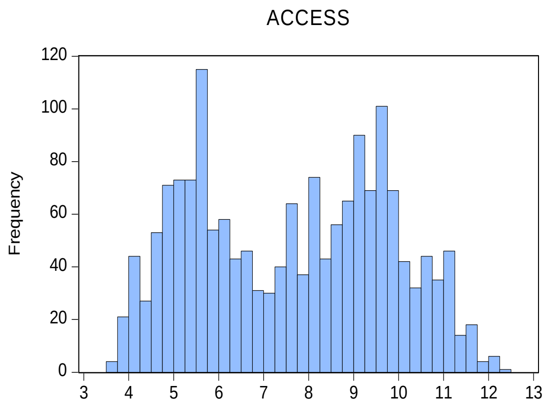


Figure 1: Time Plot of Access and Fidelity Bank



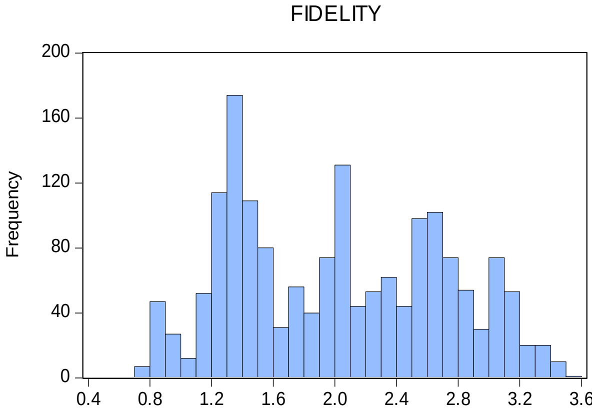


Figure 2: Access Bank spread

Table 2: Linear Deterministic Test for Unrestricted Cointegration Rank Test

	None				**At most 1**			
Test	Eigenvalue	Test Statistic	Critical Value	P-vale	Eigenvalue	Test Statistic	Critical Value	P-vale
Trace	0.015715	29.47487	15.49471	0.0002	0.001620	2.737105	3.841466	0.0980
Maximum Eigenvalue	0.015715	26.73777	14.26460	0.0003	0.001620	2.737105	3.841466	0.0980

Log likelihood = 2859.462
Adjustment cointegration coefficients (standard error in parentheses)
D(ACCESS) = -0.002235 (0.00391) D(FIDELITY) = 0.005920 (0.00117)

Result of Table 3 shows that Fidelity Bank daily shares price does not granger cause Access Bank daily shares price at 5% level of significance while on the other hand, Access Bank daily shares price significantly granger cause Fidelity Bank daily shares price at 5% level of significance.

Table 3: Pairwise Granger Causality Tests at Lag 5

Null Hypothesis:	F-Statistic	P-value
FIDELITY does not Granger Cause ACCESS	1.16589	0.32370
ACCESS does not Granger Cause FIDELITY	5.30493	0.00008

3.2 Model Selection

The model selection is based on the best AIC to the estimation of GARCH family models with the three error distributions to determine the best volatility-forecasting model.#

Table 4 presents the results of the nine volatility models for Access Bank daily shares price. Some parameter estimates are significant at 5% while some are not. Among the nine volatility models TGARCH(1,1) and EGARCH(1,1) for GED have all their parameters significant. So, TGARCH(1,1) with GED and followed by EGARCH(1,1) with GED will be selected as the best volatility models based on the P-value. However, judging by the least AIC, we selected PGARCH(1,1) with GED followed by TGARCH(1,1) with GED. We can conclude for Access Bank daily shares price, generalized error distribution (GED) is the best error distribution model, better than normal and student's t distributions.

Table 5 presents the results of the nine volatility models for Fidelity Bank daily shares price. The parameter estimates are significant at 5% except for $\gamma 1$ for all normal and student's t error distribution models. Among the nine volatility models for Fidelity Bank daily shares price, TGARCH(1,1), EGARCH(1,1) and PGARCH(1,1) all in GED have all their parameters significant and are selected as the best volatility models based on the P-value. Also, judging by the least AIC, we selected EGARCH(1,1) in GED as the best volatility model for Fidelity Bank daily shares price. We now conclude for Fidelity Bank daily shares price that generalized error distribution (GED) is the best error distribution model, better than normal and student's t distributions.

Table 4: Access Bank Estimation Results of First Order GARCH Family Models

	Normal				Student's t			GED			
Model	Parameter	Estimate	P-value	AIC	Estimate	P-value	AIC	Estimate	P-value	AIC	Best
TGARCH(1, 1)	β_0	0.0360	0.0001	3.6702	0.0360	0.0001	3.6714	0.1452	0.0000	2.9184	GED
	α_1	0.9777	0.0000		0.9780	0.0000		0.5266	0.0000		
	γ_1	-0.0206	0.9466		-0.0208	0.9463		-0.0955	0.0000		
	β_1	0.0379	0.6353		0.0380	0.6351		0.0195	0.0821		
EGARCH(1, 1)	$\beta 0$	-1.3881	0.0000	3.6951	-0.5155	0.0023	3.9602	-1.4784	0.0000	2.9814	GED
	$\alpha 1$	1.5680	0.0000		1.6244	0.0000		1.2873	0.0000		
	$\gamma 1$	-0.0468	0.7135		-0.1017	0.5263		0.0575	0.0002		
	$\beta 1$	0.8542	0.0000		0.1389	0.0287		0.6371	0.0000		
PGARCH(1, 1)	β_0	0.1010	0.0002	3.7164	0.1827	0.0000	3.7614	0.2324	0.0000	2.8547	GED
	α_1	0.9014	0.0000		1.0919	0.0000		0.5990	0.0000		
	γ_1	-0.0017	0.9851		-0.0027	0.9798		-0.0272	0.0008		
	β_1	0.0461	0.6382		-0.1925	0.0768		-0.0016	0.9331		

Table 5: Fidelity Bank Estimation Results of First Order GARCH Family Models

	Normal				Student's t			GED			
Model	Parameter	Estimate	P-value	AIC	Estimate	P-value	AIC	Estimate	P-value	AIC	Best
TGARCH(1,1)	β_0	0.0005	0.0001	1.2177	0.0005	0.0001	1.2202	0.0116	0.0000	0.5871	GED
	α_1	0.7847	0.0000		0.7868	0.0000		0.6335	0.0000		
	γ_1	0.0132	0.9491		0.0133	0.9490		-0.1012	0.0000		
	β_1	0.2288	0.0001		0.2291	0.0001		-0.1665	0.0000		
EGARCH(1,1)	β_0	-1.1536	0.0000	1.2354	-1.1536	0.0000	1.2392	-1.5307	0.0000	0.5802	GED
	$\alpha 1$	1.0994	0.0000		1.1030	0.0000		0.8933	0.0000		
	$\gamma 1$	-0.0090	0.9050		-0.0092	0.9040		0.0439	0.0000		
	$\beta 1$	0.9428	0.0000		0.9430	0.0000		0.7808	0.0000		
PGARCH(1,1)	β_0	0.0119	0.0000	1.2197	0.0102	0.0006	1.2406	0.1051	0.0000	0.6028	GED
	α_1	0.7258	0.0000		0.5360	0.0000		0.8001	0.0000		
	γ_1	0.0040	0.9575		0.0052	0.9456		-0.0423	0.0000		
	β_1	0.2598	0.0000		0.4519	0.0000		-0.3381	0.0000		

There are eighteen volatility models estimated, nine for Access Bank while the other nine are for Fidelity Bank. From the nine models for Access Bank, TGARCH (1, 1), EGARCH (1, 1) and PGARCH (1, 1) in GED were selected for forecasting. This result is presented in table 4.8 alongside the percentage improvement of the three volatility models in normal (Gaussian) distribution by student's t and generalized error distributions (Non-Gaussian).

Table 6 shows that the Student's t error distribution does not improve the fitness of first order TGARCH, EGARCH and PGARCH models with normal error assumption, but the generalized error assumption improved the adequacy of the models with Gaussian processes by 20.51, 24.72 and 24.11 per cent.

Therefore, based on the specification of these volatility models, Gaussian process and student's t process are not adequate to capture the variability in Access Bank daily shares prices. Their application could lead to misspecification as other non-Gaussian processes such as GED could contribute more to the fitness of these models than the Gaussian processes and student's t process.

Table 6: Access Bank Model Fit and Improvement of Non-Gaussian Process over Gaussian Process

First Order GARCH Models	Akaike Information Criterion (AIC)			Percentage improvement of Gaussian process by non-Gaussian process	
	Normal Distribution	Student's t Distribution	Generalized Error Distribution	Student's t Distribution	Generalized Error Distribution
TGARCH(1,1)	3.6702	3.6714	2.9184	-0.03%	20.48%
EGARCH(1,1)	3.6951	3.9602	2.9814	-7.17%	19.31%
PGARCH(1,1)	3.7164	3.7614	2.8547	-1.21%	23.19%

Table 7: Fidelity Bank Model Fit and Improvement of Non-Gaussian Process over Gaussian Process

First Order GARCH Models	Akaike Information Criterion (AIC)			Percentage improvement of Gaussian process by non-Gaussian process	
	Normal Distribution	Student's t Distribution	Generalized Error Distribution	Student's t Distribution	Generalized Error Distribution
TGARCH(1,1)	1.2177	1.2202	0.5871	-0.21%	51.79%
EGARCH(1,1)	1.2354	1.2392	0.5802	-0.31%	53.04%
PGARCH(1,1)	1.2197	1.2406	0.6028	-1.71%	50.58%

From the nine models for Fidelity Bank, TGARCH (1, 1), EGARCH (1, 1) and PGARCH (1, 1) in GED were selected for forecasting. This result is presented in table 7 alongside the percentage improvement of the three volatility models in normal (Gaussian) distribution by student's t and generalized error distributions (Non-Gaussian). The table shows that the Student's t error distribution does not improve the fitness of first order TGARCH, EGARCH and PGARCH models with normal error assumption, but the generalized error assumption improved the adequacy of the models with Gaussian processes by 51.79, 53.04 and 50.58 per cent.

Therefore, based on the specification of these volatility models, Gaussian process and student's t process are not adequate to capture the variability in Fidelity Bank daily shares prices. Their application could lead to misspecification as other non-Gaussian processes such as GED could contribute more to the fitness of these models than the Gaussian processes and student's t process.

3.3 Forecast Performance

The result of 30 trading days out of sample forecast of Access Bank daily shares price used in determining the predictive abilities of the three models using the loss function are presented in Table 8.

On the basis of RMSE, EGARCH (1, 1) in GED model is selected as it yielded the least forecast error. While for MAE and Theil coefficient PGARCH (1,1) in GED is selected as it yield the least forecast error. Based on these three criteria, PGARCH(1,1) is selected as the best forecasting volatility model for Access Bank daily shares price, followed by EGARCH and the least is TGARCH. It is worthy to note that the closeness of the forecast evaluation statistics in terms of RMSE and Theil coefficient justifies the adequacy of the conditional volatility models considered.

Table 8: Access Bank Loss Function for Generalized Error Distribution

LOSS FUNCTION (LF)	TGARCH	EGARCH	PGARCH	MIN LF
Root Mean Square Error	2.25072	2.15628	2.18987	EGARCH
Mean Absolute Error (MAE)	1.92171	1.90098	1.89594	PGARCH
THEIL Coefficient	0.13900	0.14045	0.13735	PGARCH

The result of 30 trading days out of sample forecast of Fidelity Bank daily shares price used in determining the predictive abilities of the three models using the loss function are presented in Table 9. On the basis of RMSE, EGARCH (1, 1) in GED model is selected as it yielded the least forecast error. While for MAE and Theil coefficient PGARCH (1,1) in GED is selected as it yield the least forecast error. Based on these three criteria, PGARCH(1,1) is selected as the best forecasting volatility model for Fidelity Bank daily shares price, followed by EGARCH and the least is TGARCH.

It is worthy to note that the closeness of the forecast evaluation statistics in terms of RMSE and Theil coefficient justifies the adequacy of the conditional volatility models considered.

Table 9: Fidelity Bank Loss Function for Generalized Error Distribution

LOSS FUNCTION (LF)	TGARCH	EGARCH	PGARCH	MIN LF
Root Mean Square Error	0.68624	0.68553	0.68826	EGARCH
Mean Absolute Error (MAE)	0.59473	0.59153	0.59334	PGARCH
THEIL Coefficient	0.16304	0.16603	0.16816	PGARCH

4. Conclusion and Recommendations

To estimate the stock price volatility using the generalized autoregressive conditional heteroscadasticity (GARCH) using the daily closing shares prices of Access Bank and Fidelity Banks to model the volatility of stock returns, PARCH (1, 1), EGARCH (1, 1) and

TGARCH in that order with GED were selected to be the best fitted models based on their Akaike Information Criterion (AIC). Thus, generalized error distribution (GED) improved the fitness of first order TGARCH, EGARCH and PGARCH models with normal error assumption for the two selected banks. This corroborates previous studies that GED process is a better volatility model than Gaussian process, due to the asymmetricity of the data. In order to selecting the best forecasting volatility model with the most appropriate error distribution, the out-of-sample forecasting evaluation result adjudged PGARCH (1, 1) with generalized error distribution as the best predictive model based on Mean Absolute Error and Theil Inequality Coefficient and EGARCH(1,1) based on root mean square error.

Given the level of risk associated in investment in stocks, investors, financial analyst and empirical workers should consider alternative error distributions while specifying predictive volatility model as less contributing error distributions implies incorrect specification, which could lead to loss of efficiency in the model. We recommend that GARCH models with generalized error distributions should be used to model the volatility in stock prices in Nigeria market because they are better than both Normal and student’s t error distributions. However, other error distributions can be exploited in subsequent work and results compared with that of generalized error distribution. We also recommend that empirical works should consider alternative error distributions with a view to achieving a robust volatility forecasting model that could guarantee a sound policy decisions.

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