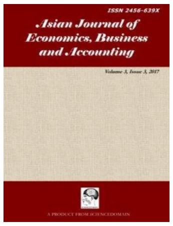

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Modeling Stock Returns Volatility in Nigeria: Applications of GARCH Family Models

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Authors' contributions

This work was carried out in collaboration between all authors. Author MJ designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Authors MAC and DAK managed the analyses of the study. Author DAK managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

This study examines volatility and its stylized facts in Nigerian stock market using daily quotations of Guinness Plc and 7UP Plc stock prices for the period 2nd January 1995 to 31st December, 2016. The study employs basic GARCH (1,1) to examine the symmetric properties of the series while the asymmetric EGARCH (1,1) and Asymmetric Power ARCH, APACH (1,1) are employed to investigate asymmetry and leverage effects in the return series. The results of symmetric GARCH (1,1) shows volatility clustering, high persistence of shocks and mean reverting behaviour for both returns. The results of the asymmetric EGARCH (1,1) and asymmetric power ARCH, APARCH (1,1) showed the presence of asymmetry with absence of leverage effects in Guinness Plc stock returns and the presence of asymmetry and leverage effects in 7UP Plc stock returns. This result suggests that positive shocks increase volatility more than negative shocks of the same magnitude in Guinness Plc whereas negative shocks generate more volatility than positive shocks of the same magnitude in 7UP Plc returns. The choice of heavy-tailed distributions (GED and student's t) in

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estimating volatility in this study confirmed the existence of fat tails in Nigerian stock returns. The study recommends some policy implications for investors and policymakers in Nigerian stock market.

Keywords: Asymmetry; heavy-tailed distributions; stylized facts; shock persistence; stock market; volatility; Nigeria.

1. INTRODUCTION

Volatility modeling is a measure of risk exposure of any company including financial institutions. Providing good volatility estimates avails investors, traders, stock market policymakers and government the opportunity to make better monetary policies and financial decisions. If the cause of the volatility of stock market price is identified, corrected, and controlled, the economy will rapidly grow and develop into an advanced one, and Government will make good reforms that will have good impacts and direct bearing on both the financial institutions and the entire economy at large. There is also need to check stock prices in order to minimize the unstable and volatile nature of the market especially in an emerging economy like ours.

Modeling volatility of financial time series is a complex problem. This complexity is partly due to the variety of the series in use such as stocks, exchange rates, interest rates, inflation rate etc., and partly due to the frequency of observation of the series such as second, minute, hourly, weekly, daily, monthly, etc or due to the availability of very large datasets. This is mainly as a result of the existence of statistical regularities called *stylized facts* which are common to a large number of financial series and are difficult to reproduce artificially using stochastic models.

Most of these stylized facts were first documented by [1] and later by [2] and [3] when they noticed that large changes in stock prices were followed by large changes in prices of both signs and small stock price changes were followed by periods of small changes in prices. This property of financial time series data was described as volatility clustering. Other stylized facts of financial returns such as leptokurtosis, shock persistence, non-normality, mean reversion, asymmetry and leverage effect, etc., are also documented in studies conducted by [4,5,6,7,8] among others. These stylized facts can be observed more or less clearly depending on the nature of the series and its frequency. The properties that we now present here are mainly concerned with daily stock prices.

Several empirical works have been documented in the literature following the introduction of ARCH model by [9], GARCH model by [10] and their extensions by [11,12,13,14] among others on volatility modeling, especially in finance, even though a number of theoretical issues still unfolds. Jagajeevan [15] investigated the persistence of volatility, risk-return trade off and asymmetric volatility in returns on daily and monthly returns on the All Share Price Index of the Colombo stock exchange. The results of his study could only identify volatility clustering in daily returns, but not in monthly returns. He also investigated the existence of leverage effects in daily returns and found that negative shocks increase volatility as compared to positive shocks of the same magnitude.

Floros [16] conducted a study to examine volatility clustering in the Egyptian stock market. He used daily data for Egypt's CMA general index, he also employs GARCH –type models and found strong evidence of volatility clustering in the Egyptian market. He also found that leverage effects exist in the Egyptian market and that bad news increased volatility more than good news of the same magnitude. Ahmed & Suliman [17] investigated conditional variance in daily returns of the Khartoum Stock Exchange (KSE) using both symmetric and asymmetric GARCH models. They found a high degree of persistence in the conditional volatility of stock returns on the KSE. Olivier & Tewari [18] examined the existence and nature of volatility clustering phenomenon in South Africa using the Johannesburg Stock Exchange (JSE). They used GARCH-type models to detect volatility clustering and also to examine the asymmetric effect of positive and negative shocks in the JSE. The results indicate the presence of volatility clustering in the JSE. However, their study failed to identify the asymmetric effect of positive and negative shocks on the conditional volatility.

In Nigeria, Jayasuriya [19] examines 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. The Nigerian session of the result tilted more to business cycle of behaviour of return series than volatility clustering. Ogum et al. [20] apply the Nigeria and Kenya stock data on EGARCH model to capture the emerging market volatility. The result of the study differed from [19]. Though volatility persistence is evidenced in both markets; volatility responds more to negative shocks in the Nigeria market and the reverse is the case for Kenya market.

Okpara and Nwezeaku [21] randomly selected forty one companies from the Nigerian 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 Nigeria stock market, implying that bad news drives volatility more than good news. Dallah & Ade [22] examine the volatility of daily stock returns of Nigerian insurance stocks using twenty six insurance companies' daily data from December 15, 2000 to June 9 of 2008 as training data set and from 10th June 2008 to 9th September 2008 as out-of-sample dataset. The result of ARCH (1), GARCH (1, 1) TARCH (1, 1) and EGARCH (1, 1) shows that EGARCH is more suitable in modeling stock price returns as it outperforms the other models in model evaluation and out-of-sample forecast. Bala & Asemota [23] employed GARCH models with exogenous breaks to examine exchange rate returns series from January 1985 to July 2011 for Naira/US Dollar return and from January 2004 to July 2011 for Naira/British pounds and Naira/Euro returns. The study compared different estimates of variants of GARCH models with break in respect of the three exchange rates. They found the presence of volatility clustering in the three currencies and most of the asymmetric models rejected the existence of leverage effect except for models with volatility break.

2. MATERIALS AND METHODS

In this section, we present the source of data and methods of data analysis.

2.1 Source of Data

The data used in this work are secondary data on daily closing share prices of Guinness Plc and 7UP Plc obtained from the Nigerian Stock Exchange from 2nd January 1995 to 31st December, 2016. The daily share prices are in Nigerian naira. The daily share prices are converted to daily returns r_t as:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \times 100 = [\log(P_t) - \log(P_{t-1})] \times 100 \qquad (2.1)$$

where P_t denotes the closing market index at the current day (t) and P_{t-1} denotes the closing market index on the previous day ($t-1$).

2.2 Methods of Data Analysis

The following statistical tools are used in the analysis of data in this work.

2.2.1 Augmented Dickey-fuller (ADF) unit root test

A series is said to be weakly or covariance stationary if the mean, variance and autocovariance of the series do not depend on time. In this work, we employ ADF unit root test [24]. The Augmented Dickey-Fuller (ADF) unit root test constructs a parametric correction for higher-order correlation by assuming that the series follows an AR(p) process:

$$Y_t = \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \cdots + \theta_p Y_{t-p} + u_t \qquad (2.2)$$

If $\theta^* = 0$, against the alternative $\theta^* < 0$, then Y_t contains a unit root. To test the null hypothesis, the ADF test is evaluated using the t –statistic:

$$t_\theta = \theta^*/SE(\theta^*) \qquad (2.3)$$

where θ^* is the estimate of θ, and $\mathrm{SE}(\theta^*)$ is the coefficient standard error. We also employ KPSS stationarity test due to [25] which has higher power as a confirmatory test to ADF unit root test.

2.3 Model Specification

The following autoregressive conditional heteroskedasticity models are specified for this study.

2.3.1 ARCH model

Engle [9] introduced the ARCH (p) model in which the conditional variance σ_t^2 is a linear function of lagged squared residuals ε_t

$$r_t = \mu + \varepsilon_t; \;\; \varepsilon_t = e_t \sigma_t^2 \qquad (2.4)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 \qquad (2.5)$$

where $\omega > 0, \text{and } \alpha_i \geq 0$

2.3.2 GARCH Models

The ARCH model takes the highest persistence volatility into consideration and so has become one of the most common tools for characterizing changing variance and volatility. This observation led [10] in order to achieve a more parsimonious parameterization, then, introduced the Generalized ARCH (p, q) Model (GARCH (p, q)).Thus , the volatility model, GARCH (p, q) process ε_t can be written as:

$$r_t = \mu + \varepsilon_t; \;\; \varepsilon_t = e_t \sigma_t^2 \qquad (2.6)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{j=1}^{p} \beta_j \sigma_{t-j}^2 t \in Z \qquad (2.7)$$

where $\alpha_i > 0$ and $\beta_j > 0$ for all values of i and j . GARCH (1,1) model is the most commonly available, the most commonly used, and sometimes good enough and is given by:

$$r_t = \mu + \varepsilon_t \qquad (2.8)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (2.9)$$

The stationarity condition of basic GARCH (1,1) is that $\alpha_1 + \beta_1 < 1$.

2.3.3 Exponential GARCH (EGARCH) model

To overcome the drawbacks of basic GARCH of [9,11] introduced the Exponential GARCH given as:

$$r_t = \mu + \varepsilon_t; \;\; \varepsilon_t = e_t \sigma_t^2 \qquad (2.10)$$

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \left[\alpha_i \left| \frac{\varepsilon_{t-i}}{\alpha_{t-i}} \right| + \gamma_i \left[\frac{\varepsilon_{t-i}}{\alpha_{t-i}} \right] \right] + \sum_{j=1}^{p} (\beta_j \, ln(\sigma_{t-1}^2) \qquad (2.11)$$

The conditional variance of the EGARCH (1,1) specification is given by:

$$ln(\sigma_t^2) = \omega + \beta_1 ln\left((\sigma_{t-1}^2)\right) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\alpha_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\alpha_{t-1}} \qquad (2.12)$$

where γ represents the asymmetric coefficient in the model. If the relationship between variance and returns is negative then the value of γ must be negative and significant. The difference between α_1 and γ is expressed as impact of shocks on conditional volatility. β_1 coefficient represents the measure of volatility persistence. The sufficient condition for the stationarity of the EGARCH model is that $|\beta_1| < 1$.

2.3.4 The asymmetric power ARCH (APARCH) model

Ding et al. [12] expressed conditional variance using APARCH (p,d,q) as:

$$r_t = \mu + \varepsilon_t; \;\; \varepsilon_t = e_t \sigma_t^2 \qquad (2.13)$$

$$\sigma_t^d = \omega + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-1}| + \gamma_i \varepsilon_{t-i})^d + \sum_{j=1}^{q} \beta_j \sigma_{t-1}^d \qquad (2.14)$$

here, d > 0 and $\gamma_i < 1$ establishes the existence of leverage effects. If $d = 2$, the APARCH (p,q) replicate a GARCH (p , q) with a leverage effect. If $d = 1$, the standard deviation is modeled. The first order of equation (2.14) is APARCH (1,d,1) which is expressed as:

$$\sigma_t^d = \omega + \alpha_1 \sum_{i=1}^{p} (|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1})^d + \beta_1 \sigma_{t-1}^d \qquad (2.15)$$

2.4 Error Distribution

We obtain the estimates of GARCH process by maximizing the log likelihood function:

$$L\theta_t = -\, {}^{1}\!/_{2} \sum_{t-1}^{T} \left(\ln 2\pi + ln\sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2} \right) \qquad (2.16)$$

(i) Normal (Gaussian) distribution to the log likelihood for observation t is:

$$l_t = \frac{-\frac{1}{2}\log(2\pi) - \frac{1}{2}\log\sigma_t^2 - \frac{1}{2}(y_t - X_t'\theta)^2}{\sigma_t^2} \qquad (2.17)$$

(ii) For student's $t-$ distribution, the log-likelihood contributions are of the form:

$$l_t = \frac{1}{2}\log\left[\frac{\pi(v-2)\Gamma({}^{v}\!/_{2})^2}{\Gamma\left({}^{(v+1)}\!/_{2}\right)} \right] - \frac{1}{2}\log\sigma_t^2 - \frac{(v+1)}{2}\log\left[1 + \frac{(y_t - X_t'\theta)^2}{\sigma_t^2(v-2)}\right] \quad (2.18)$$

where the degree of freedom $v > 2$ controls the tail behaviour. The $t-$distribution approaches the normal distribution as $v \to \infty$.

(iii) For the Generalized Error Distribution (GED), we have

$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma(^1/_r)^3}{\Gamma(^3/_r)(^r/_2)^2}\right] - \frac{1}{2}\log\sigma_t^2 - [\frac{\Gamma(^3/_r)(y_t - X_t'\theta)^2}{\sigma_t^2\Gamma(^1/_r)}]^{\frac{r}{2}} \qquad (2.19)$$

where the tail parameter $r > 0$. The GED is a normal distribution if $r = 2$, and fat-tailed if $r < 2$.

2.5 Mean Reversion and Volatility Half-life

For a stationary GARCH models, the mean reverting form of the GARCH model is given as $(\alpha_1 + \beta_1)$. The magnitude of $(\alpha_1 + \beta_1)$ controls the speed of mean reversion. The half-life of a volatility shock is given by the formula:

$$H_{life} = \frac{\ln\left(\frac{1}{2}\right)}{\ln(\alpha_1 + \beta_1)} \qquad (2.20)$$

The half-life measures the average time it takes for $|\varepsilon_t^2 - \hat{\sigma}^2|$ to decrease by one half. The closer $(\alpha_1 + \beta_1)$ is to one the longer the half-life of a volatility shock. If $(\alpha_1 + \beta_1) > 1$, the GARCH model is non-stationary and the volatility explodes to infinity.

3. RESULTS AND DISCUSSION

3.1 Some Stylized Facts of Stock Prices and Returns

To observe some of the stylized facts and graphical properties of the stock prices and returns, and as a first step in analyzing time series data, we plot the original series in level against time which helps us in understanding the trend as well as pattern of movement of the original series. Here we plot the daily closing share prices and returns of Guinness Plc and 7UP Plc as function of time. The time plots are presented in Fig. 1.

From the time plots of the daily closing share prices of Guinness Plc and 7UP Plc reported in Fig. 1. (left) it is clearly seen that the trend movements in both plots are not smooth. This indicates that their means and variances are heteroskedastic and the series seems to be non-stationary. We, therefore, transform the series to log returns. The time plots of the returns presented in Fig. 1 (right) indicate that some periods are riskier than others. The risky times are randomly scattered and there are some degrees of autocorrelation in the riskiness of the financial returns. The amplitudes of the returns vary over time as large changes in returns tend to be followed by large changes and small changes are followed by small changes. This phenomenon is described as *volatility clustering,* [26] and is one of the *stylized facts* of the financial time series. There is high level of volatility clustering in the Guinness and 7UP returns indicating that both returns are being driven by the same market forces. Periods of high volatility clustering implies frequent changes in stock prices in the stock market while periods

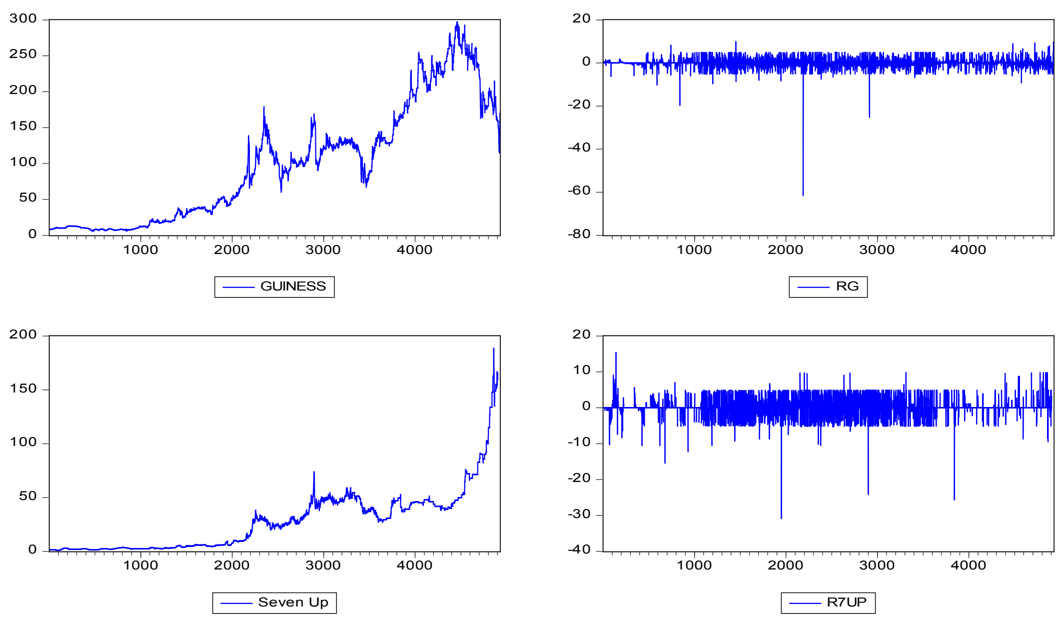

Fig. 1. Time plot of daily prices and returns of guinness Plc and 7UP Plc

Table 1. Descriptive statistics of returns

Variable	Guinness Plc returns	7UP Plc returns
Mean	0.615	0.096
Maximum	9.844	15.52
Minimum	-61.502	-30.866
Standard Deviation	2.2983	2.4737
Variance	5.2822	6.1192
Skewness	-4.2882	-0.8271
Kurtosis	111.87	14.055
Jarque-Bera	2448311	25646.85
P-value	0.0000	0.0000
Number of Observations	4927	4927

Source: Researcher's computations

of low volatility clustering entails either persistence of constant prices of stock over time or persistence of shocks in the stock market. Thus both volatility clustering and persistence of shocks are evidenced in the two returns.

3.2 Descriptive Statistics of Returns

To better understand the nature and distributional properties of Guinness Plc and 7UP Plc returns series, we consider the descriptive statistics of both return series. The result is presented in Table 1.

The descriptive statistics reveal that the average daily returns are 0.615% and 0.096% for Guinness Plc and 7UP Plc respectively. The daily standard deviations are 2.298% and 2.474% for Guinness Plc and 7UP Plc respectively with daily variances of 5.28% and 6.12%. These reflect high levels of dispersion from the average returns in the market over the period under review. The wide gaps between the maximum return 9.844% and 15.52% and minimum returns -61.502% and -30.866% for Guinness Plc and 7UP Plc respectively give supportive evidence to the high levels of variability of price changes in the individual companies over the study period.

The high kurtosis values of 111.87 and 14.055 for Guinness Plc and 7UP Plc respectively suggest that big shocks of either sign are more likely to be present in the series and that the returns series are clearly leptokurtic. The skewness coefficients are -4.2882 for Guinness Plc and -0.8271 for 7UP Plc. The negative skewness suggests an asymmetry in both return series. The high values of Jarque-Bera statistics in both returns with zero p-values indicate that the return series are non-normally distributed, one of the *stylized facts* prominent in all financial time series data.

3.3 Unit Root and Stationarity Test Results

To examine the unit root and stationarity characteristics of the daily stock prices and returns of Guinness Plc and 7UP Plc, we employ the popular Augmented Dickey-Fuller (ADF) unit root test and KPSS Lagrange Multiplier stationarity test. The results of the ADF and KPSS tests are reported in Tables 2.

The ADF unit root test results presented in Table 2 show that the daily prices of Guinness Plc and 7UP Plc are non-stationary at all conventional test sizes both with intercept only and with

Table 2. Unit root and stationarity test results

Variable	Option	ADF test statistic	KPSS test statistic
Daily Guinness price	Intercept only	-1.41961	8.047593
	Intercept and Trend	-3.365996	0.517693
Return Guinness	Intercept only	-59.82926**	0.134104**
	Intercept and Trend	-59.83319**	0.051767**
Daily 7Up Price	Intercept only	3.055790	6.481644
	Intercept and Trend	1.473525	0.490601
Daily Return7Up	Intercept only	-63.91568**	0.053331**
	Intercept and Trend	-63.90947**	0.055663**

*Note: ** denotes the significant of ADF and KPSS test statistics at 1% marginal significance level* intercept and linear trend. However, the ADF unit root test of both returns shows evidence of stationarity at 1%, 5% and 10% significance levels both with constant only and with constant and linear trend. Since ADF parametric unit root test suffers from severe size distortions and low power, we employ KPSS non-parametric stationarity test to confirm the result of ADF unit root test. The KPSS stationarity test presented in Table 2 confirmed the result of ADF unit root test that the daily share prices of both Guinness Plc and 7UP Plc are non-stationary while their log returns are stationary. It is therefore worth concluding that the stock returns for both series are integrated of order one, I(1).

3.4 Heteroskedasticity Test Result

Having shown that the returns series are stationary, we now test for the ARCH effects in the residuals of returns. To test for ARCH effects we employ Engle's LM ARCH test. The result is presented in Table 3.

The Engle's LM ARCH test result presented in Table 3 shows that the returns series for both Guinness Plc and 7UP Plc exhibit the presence of ARCH effects since the p-values of both F-statistics and nR^2 are strictly less than 0.05 significance levels. This means that the variances of returns are non-constant (heteroskedastic) and can only be modeled using heteroskedastic models such as ARCH and GARCH.

3.5 Optimal Symmetric and Asymmetric GARCH Models Selection

In order to select optimal symmetric and asymmetric GARCH models with different distributional assumptions that best model the Guinness Plc and 7UP Plc returns series, we use the log-likelihood in conjunction with some selected information criteria such as Akaike Information Criterion (AIC) due to [27], Schwarz Information Criterion (SIC) due to [28] and Hannan Quinn Criterion due to [29]. The best fitting model is one with highest log-likelihood and lowest information criteria. The result of the estimates is reported in Table 4.

Table 3. Heteroske dasticity test of ARCH effects in the returns

Return	Parameter	Lag Order	Test Statistic	P-value
Guinness Plc	F-statistic	1	12.49555	0.0000
	nR^2	15	12.47404	0.0000
7UP Plc	F-statistic	1	0.693047	0.0000
	nR^2	15	14.79074	0.0000

Table 4. Symmetric and asymmetric GARCH model order selection

	Model	Distribution	LogL	AIC	SIC	HQC
Guinness Plc	GARCH (1,1)	ND	-10262.53	4.167457	4.172736	4.169309
	GARCH (1,1)	STD	-10219.52	4.150404	4.157003	4.389011
	GARCH (1,1)	**GED**	**-10010.37**	**4.043146**	**4.067106**	**4.064535**
	EGARCH (1,1)	ND	-10122.03	4.110830	4.117429	4.113910
	EGARCH (1,1)	STD	-8626.284	3.504073	3.511992	3.506850
	EGARCH (1,1)*	**GED**	**-4603.752**	**1.871220**	**1.879139**	**1.873998**
	APARCH (1,1)	ND	-10131.54	4.115098	4.123017	4.117876
	APARCH (1,1)	**STD**	**-8524.872**	**3.463313**	**3.472552**	**3.466554**
	APARCH (1,1)	GED	-10743.16	4.362558	4.367837	4.364410
7UP Plc	GARCH (1,1)	ND	-11034.40	4.480374	4.484334	4.481763
	GARCH (1,1)	STD	-10938.74	4.442354	4.448953	4.444669
	GARCH (1,1)	**GED**	**-10604.79**	**4.312814**	**4.316773**	**4.314202**
	EGARCH (1,1)	ND	-10674.98	4.335287	4.341886	4.337602
	EGARCH (1,1)	STD	-6580.060	2.673456	2.681375	2.676234
	EGARCH (1,1)	**GED**	**3651.629**	**-1.47986**	**-1.47194**	**-1.47708**
	APARCH (1,1)	ND	-10794.84	4.384348	4.392266	4.387125
	APARCH (1,1)	STD	-9989.360	4.057788	4.067026	4.061028
	APARCH (1,1)*	**GED**	**8447.597**	**-3.42626**	**-3.41702**	**-3.42302**

*Note: *denotes the GARCH model selected by the criteria*

From the results of symmetric and asymmetric GARCH models selection presented in Table 4, the search criteria have selected symmetric GARCH (1,1) models with generalized error distribution (GED) as the best model for both Guinness Plc and 7UP Plc log returns. In case of asymmetric models EGARCH (1,1) with GED and APACH (1,1) with student-t distribution has been selected to fit Guinness Plc stock returns while EGARCH (1,1) and APACH (1,1) both with GED has been selected to model the volatility of 7UP Plc stock returns.

3.6 Parameter Estimates of Symmetric and Asymmetric Volatility Models

We estimate the symmetric GARCH (1,1), asymmetric EGARCH (1,1) and APARCH (1,1) models for Guinness Plc and 7UP Plc stock return series. The results are presented in Tables 5 and 6.

The results of Tables 5 and 6 indicate that all the coefficients in the conditional variance equations of the symmetric GARCH (1,1) models are highly statistically significant at 1% significance levels and all satisfied the non-negativity restrictions of the models. The significance of the ARCH parameters (α_1) indicates that the news about volatility from previous periods has explanatory powers on current volatilities. In the same way, the statistical significance of the GARCH parameters (β_1) does not only indicates that news about volatility from previous periods has explanatory powers on current volatilities but also suggests volatility clustering in the daily returns of Guinness Plc and 7UP Plc. The lagged conditional variance estimates (β_1) has coefficients 0.729802 and 0.589932 for Guinness Plc and 7UP Plc stock returns respectively implying that 73% and 59% of variance shock remains the next day for Guinness Plc and 7UP Plc respectively. The symmetric GARCH (1,1) models for Guinness Plc and 7UP Plc returns both show evidence of volatility clustering and shock persistence as measured by the sum of ARCH and GARCH terms ($\alpha_1 + \beta_1$). From our estimates in Table 5, Guinness Plc daily returns have a higher volatility persistence of $\alpha_1 + \beta_1 = 0.933636$ and 7UP Plc daily returns has a high volatility persistence of $\alpha_1 + \beta_1 = 0.911945$. High volatility persistence implies that the average

Table 5. Parameter estimates of volatility models of daily stock returns for guinness Plc

Parameter	GARCH (1,1) with GED	EGARCH (1,1) with GED	PARCH (1,1) with STD
μ	1.14E-07	5.84E-08	-4.82E-08
	(0.9961)	(0.9967)	(0.9840)
	[0.0048]	[0.0041]	[-0.020]
ω	0.022048	-0.189004	0.001347
	(0.0000)	(0.0000)	(0.9097)
	[5.3156]	[-30.46]	[0.1134]
α_1	0.203834	0.008916	0.190954
	(0.0000)	(0.0000)	(0.0000)
	[7.0320]	[15.101]	[4.8227]
γ		0.130897	-0.004666
	---	(0.0000)	(0.8279)
		[7.0158]	[-0.217]
β_1	0.729802	0.969214	0.780745
	(0.0000)	(0.0000)	(0.0000)
	[64.109]	[364.38]	[254.94]
δ		----	0.460587
	----		(0.0000)
			[82.8834]
v	0.319375	0.304642	2.001914
	(0.0000)	(0.0000)	(0.0000)
	[34.163]	[37.181]	[1167.3]
$\alpha_1 + \beta_1$	0.9336	0.9781	0.9717
ARCH LM Test	0.005210	0.112196	0.076432
	(0.9425)	(0.7377)	(0.7376)

Note: values in (.) are p-values while values in [.] are z-statistics

Table 6. Parameter estimates of volatility models of daily stock returns for 7UP Plc with GED

Parameter	GARCH (1,1)	EGARCH (1,1)	PARCH (1,1)
μ	-8.81E-14	-1.26E-12	1.81E-14
	(0.9981)	(0.9044)	(0.9999)
	[-0.003]	[-0.120]	[0.0002]
ω	0.007355	-0.062994	0.010370
	(0.0000)	(0.0000)	(0.0000)
	[9.7295]	[-40.46]	[4.6462]
α_1	0.322013	0.092861	0.092570
	(0.0000)	(0.0000)	(0.0000)
	[5.5794]	[16.603]	[5.2385]
γ	---	-1.64E-05	0.052988
		(0.9974)	(0.0306)
		[-0.003]	[-2.1628]
β_1	0.589932	0.893071	0.544092
	(0.0000)	(0.0000)	(0.0000)
	[58.265]	[1057.5]	[23.415]
δ			1.705637
	----	-----	(0.0000)
			[14.402]
v	0.184942	0.183370	0.173249
	(0.0000)	(0.0000)	(0.0000)
	[39.519]	[68.769]	[40.749]
$\alpha_1 + \beta_1$	0.9119	0.9859	0.6367
ARCH LM Test	0.660365	0.055789	0.183799
	(0.4165)	(0.5321)	(0.6681)

Note: values in (.) are p-values while values in [.] are z-statistics

variance will remain high since increases in conditional variance due to shocks will decay only slowly.

The parameter estimates of asymmetric EGARCH (1,1) with GED and APARCH (1,1) with STD for Guinness Plc stock returns as shown in Table 5 indicate that the volatility shocks are quite persistence in both EGARCH (1,1) and APARCH (1,1) models, although all the models are stable and mean reverting. The asymmetric effect parameter γ captured by EGARCH (1,1) is positive and significant indicating the presence of asymmetry without leverage effect. The asymmetric effect parameter γ captured by APARCH (1,1) is negative and insignificant indicating the presence of asymmetry but the absence of leverage effect for Guinness Plc stock returns. This implies that previous period's positive shocks have more impacts on the conditional variance. In other words, good news (positive shocks) increases volatility more than negative shocks (bad news) of the same magnitude.

For the parameter estimates of the asymmetric EGARCH (1,1) and APARCH (1,1) models which are all estimated with GED for 7UP Plc stock returns shown in Table 6, most parameters of the models are statistically significant, the volatility shocks are quite persistence in both models and the models are stable and mean reverting. The asymmetric effect parameter γ captured by EGARCH (1,1) is negative indicating the presence of asymmetry and leverage effect. The asymmetric effect parameter γ captured by APARCH (1,1) is positive and significant indicating the presence of asymmetry and leverage effect for 7UP Plc stock returns. This implies that previous period's negative shocks have more impacts on the conditional volatility. In other words, bad news (negative shocks) increases volatility more than positive shocks (good news) of the same modulus.

Table 7. Volatility mean reversion rate and half life

Return	Model	Mean Reversion Rate	Volatility Half-Life	Remark
Guinness Plc	GARCH (1,1)	0.9336	10 days	Stationary
	EGARCH (1,1)	0.9781	31 days	Stationary
	APARCH (1,1)	0.9717	24 days	Stationary
7UP Plc	GARCH (1,1)	0.9119	8 days	Stationary
	EGARCH (1,1)	0.9859	49 days	Stationary
	APARCH (1,1)	0.6367	2 days	Stationary

The results of the ARCH LM test reported in the lower panel of Tables 5 and 6 show that our estimated GARCH-type models have captured all the ARCH effects and none is remaining in the residuals. This is justified by the p-values of the ARCH LM tests statistics which are highly statistically insignificant. This shows that our estimated GARCH-type models are good, adequate, valid and accurate in describing the volatility situation in Nigeria.

3.7 Volatility Mean Reversion and Half-Life

To test for mean reversion in volatility for Guinness Plc and 7UP Plc, we apply two tests. The first tests are the ADF unit root test and KPSS stationarity test presented in Table 2, the second test is the estimates from GARCH models presented in Table 7 above.

The ADF unit root test and KPSS stationarity test results reported in Table 2 revealed that the returns of both Guiness Plc and 7UP Plc are stationary (contain no unit roots) and hence mean reverting. When stock returns are mean reverting it indicates that the volatility of returns finally reverts to its long-run average no matter how high or low it fluctuates.

We also test for mean reversion in volatility using estimates from GARCH-type models as presented in Table 7. From the results of our estimated GARCH models in Table 7, the volatility mean reversion rates for Guinness Plc are given as $\alpha_1 + \beta_1 = 0.9336$ for standard GARCH (1,1), $\alpha_1 + \beta_1 = 0.9781$ for EGARCH (1,1) and $\alpha_1 + \beta_1 = 0.9717$ for APARCH (1,1). For the 7UP Plc the volatility mean reversion rates are given as $\alpha_1 + \beta_1 = 0.9119$ for standard GARCH (1,1), $\alpha_1 + \beta_1 = 0.9859$ for EGARCH (1,1) and $\alpha_1 + \beta_1 = 0.6367$ for APARCH (1,1). These mean reversion rates are all very close to unity.

The half-life of volatility shock which is estimated by equation (2.20) measures the average number of time periods it takes the volatility to revert to its long run average. When the value of $\alpha_1 + \beta_1$ is close to unity, the half-life of a volatility shock will be longer. If $(\alpha_1 + \beta_1) > 1$, the GARCH model is said to be non-stationary and the volatility eventually explodes to infinity, and the series will follow a random walk. In our estimated GARCH-type models for Guinness Plc, the volatility half-lives are 10 days for basic GARCH (1,1) model, 31 days for EGARCH (1,1) model and 24 days for APARCH (1,1) model. For the 7UP Plc, the half-life of volatility is given as 8 days for basic GARCH (1,1) model 49 days for EGARCH (1,1) and 2 days for APARCH (1,1) model. We, therefore, conclude that the return series under review is stationary and mean reverting. As policy implication for investors, stationary and mean reverting asset returns are better options for long-term investment due to the minimal risk associated with them.

4. CONCLUSION

From the estimates of our GARCH models, all the stock returns exhibit mean-reversion in volatility and there is presence of asymmetry with absence of leverage effects in Guinness plc stock returns while asymmetry and leverage effect exists in 7up plc stock returns. When stock prices exhibit mean reverting behaviour it means that the variance of the returns increases less than proportionally with the investment horizon. Secondly, if stock prices are mean-reverting, stocks are relatively less risky for longer investment horizons, so that a larger share of wealth may be allocated to stocks. The same is true if stock returns show negative autocorrelation. Given the impact of mean-reverting behaviour of stocks on asset allocation decisions and the profitability of trading strategies, it is important for investors to know whether or not stock prices exhibit mean reversion before investing heavily in them as mean reverting stocks are less risky.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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