CHARACTERISTIC RESPONSES OF SYMMETRIC AND ASYMMETRIC VOLATILITY SHOCKS IN THE NIGERIAN STOCK MARKET

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ABSTRACT

This study examines the persistence of shocks, symmetric and asymmetric responses while providing accurate estimates of volatility in the Nigerian stock market using daily and monthly stock returns for the periods 3rd July 1999 to 12th June 2017 and January 1985 to March 2017 respectively. The study employs symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TARCH (1,1) with normal, student-t, skewed student-t, Generalized Error Distribution and skewed Generalized Error Distribution. The estimated symmetric GARCH (1,1) models for both returns show evidence of volatility clustering and higher persistence of volatility shocks with explosive tendencies. The estimated asymmetric EGARCH (1,1) and TARCH (1,1) models for daily returns show evidence of asymmetry with absence of leverage effect whereas the estimated asymmetric EGARCH (1,1) and TARCH (1,1) models for monthly returns show evidence of asymmetry with the presence of leverage effect. Results of the asymmetric models also show evidence of higher volatility shocks persistence giving rise to long memory in Nigerian stock market. The student-t and skewed student-t heavy tailed distributions fitted the daily and monthly stock returns respectively. Due to the higher degree of risk and uncertainty inherent in stock markets with explosive volatility shocks, this study recommends caution in the conduct of trading strategy for securities and an increased market depth in order to make the Nigerian stock market less volatile.

Keywords: Asymmetric Response, GARCH Variants, Shock Persistence, Stock Returns, Symmetric Response, Volatility Clustering, Nigeria.

JEL Classification: E44, GO1, C13

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1. INTRODUCTION

One of the characteristics of asset volatility which makes its Modelling very important is that it is not directly observable. Volatility measures the uncertainty and risk which play significant role in modern financial analysis. Measuring and predicting volatility is crucial for portfolio selection, option pricing, risk management and strategic pair-trading. Banks and other financial institutions make use of volatility assessments as part of monitoring their risk exposure (Engle & Platton, 2011). However, estimates of volatility can only be obtained from well constructed volatility models. Various time varying volatility models such as symmetric Autoregressive Conditional Heteroskedasticity (ARCH) model due to Engle (1982), Generalized ARCH (GARCH) model of Bollerslev (1986), asymmetric Exponential GARCH (EGARCH) introduced by Nelson (1991), asymmetric Power ARCH (PARCH) extended by Ding et al. (1993), Threshold ARCH (TARCH) due to Zakoian (1994) and Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) introduced by Glosten et al. (1993) among others have been applied in the literature to capture the characteristics of stock return series. The characteristics of asset returns popularly recognized in the financial literature include time-varying volatility, volatility clustering, symmetric and asymmetric characteristic, volatility shock persistence, heavy or fat-tailed behaviour, non-normality and leverage effect.

This study is a reappraisal of empirical evidence to critically examine the characteristic responses of symmetric and asymmetric volatility shocks in Nigerian stock return series using the lower order symmetric and asymmetric GARCH models. The objectives of this paper are therefore twofold: to examine the persistence of shocks, symmetric and asymmetric responses while providing accurate estimates of volatility in Nigerian stock market; and to investigate the presence of leverage effects in Nigerian stock returns. The rest of the paper is organized as follows. Section 2 reviews relevant literature on the subject matter while section 3 presents data and methodology. After a discussion of results and empirical findings in section 4, section 5 draws a conclusion proffers some policy implications.

2. LITERATURE REVIEW

Volatility clustering as one of the characteristic features of financial time series was first noticed in studies conducted independently by Mandelbrot (1963), Fama (1965) as well as Black (1976), when they observed the occurrence of large changes in stock prices being followed by large changes in stock prices of both positive and negative signs and the occurrence of small stock price changes being followed by periods of small changes. Sequel to this result, numerous researchers including Poterba & Summer (1986), Tse (1991), McMillan et al. (2000), Najand (2002), Lee (2009), Emenike (2010), and Ezzat (2012) among others have in recent times documented evidence in the literature showing that financial time series normally exhibit volatility clustering and leptokurtosis. Further studies such as Rousan & AL Khouri (2005), Liu & Huang (2010), Kosapattarapim *et al.* (2011), Liu et al. (2009) and Gokbulut &Pekkaya (2014) investigated independently and found asymmetry and leverage effect, one of the characteristics of asset returns which was first observed by Black (1976). Leverage effect occurs when stock returns tend to have a negative correlation with changes in volatility, a situation where negative shocks produce more volatility than positive shocks of the same magnitude.

Recent studies on the subject matter for both developed and emerging stock markets are also documented in the literature. For example, Al-Najjar (2016) applied symmetric and asymmetric GARCH variants to examine the behaviour of stock return volatility in Amman Stock Exchange (ASE) in Jordan for the period 1st January, 2005 to 31st December, 2014. The symmetric GARCH models provided empirical evidence for both volatility clustering and leptokurtosis in ASE, while the asymmetric EGARCH model provided no evidence for the existence of leverage effect in the stock returns of the ASE. Banumathy & Azhagaiah (2016) empirically investigated the pattern of volatility in Indian stock market using daily closing prices of S&P CNX Nifty Index from 1 January, 2003 to 31st December, 2012 and employing both symmetric and asymmetric GARCH models. The estimated GARCH (1,1) and TGARCH (1,1) were found most appropriate in capturing the symmetric and asymmetric volatility respectively. The study also provided no empirical evidence of a significant risk premium using GARCH-M (1,1) model. The asymmetric models showed that negative shocks have more significant effect on conditional volatility than positive shocks.

Regarding the superiority of heavy tailed distributions over Gaussian (normal) errors in GARCH model estimation, Dutta (2014) estimated symmetric GARCH, symmetric EGARCH and GJR-GARCH models using normal and heavy-tailed distributions. The results showed that when the heavy-tailed distribution was considered, the volatility shock persistence was found to reduce in all the models. The findings also revealed that positive shocks generated more volatility than negative ones in the Yen/US Dollar exchange market. Ding (2011) also found that fat-tailed distributions produced better volatility estimates when he examined the ability of APARCH model in Modelling and forecasting the common characteristic features of Standard & Poor 500 and MCSI Europe Index daily stock returns.

There is empirical evidence on the subject matter is also available from the developing countries. For example, Coffie (2015) investigated the symmetric and leverage effect properties of stock returns in the Ghanaian and Nigerian stock markets using lower order GARCH, GJR-GARCH and EGARCH models. Both the GJR-GARCH and EGARCH models captured the leverage effect in Ghana whereas a reverse volatility asymmetry was exhibited in Nigeria. The asymmetric EGARCH provided the best out-of-sample forecast for the Ghanaian stock market while the GJR GARCH gave a better estimation for the Nigerian stock market.

Kuhe & Audu (2016) examined the volatility mean reversion in Nigerian stock market using symmetric GARCH models. They utilized the daily quotations of SevenUpBottling Company Nigeria Plc as a proxy for Nigerian stock market for the period 1st February 1995 to 24th November, 2014. The results of ARCH (5) and GARCH (1,1) models showed evidence of volatility clustering and mean reversion in the Nigerian stock market. The conditional volatility was found to be quite persistent. The estimated basic GARCH (1,1) model was found to be superior over the ARCH (5) model. Kuhe & Ikughur (2017) investigated the well documented stylized facts of asset returns using the daily closing share prices of Guinness Nigerian Plc as proxy for Nigerian stock market for the period 1/02/1995 to 24/11/2014. The study employed symmetric GARCH (1,1), asymmetric TGARCH (1,1) and PGARCH (1,1) models with Gaussian errors. The symmetric GARCH (1,1) model showed evidence of volatility clustering and mean reversion and the conditional volatility shock was found to be quite persistent. The estimated asymmetric TGARCH (1,1) and PGARCH (1,1) models produced evidence in support of the existence of asymmetry and leverage effects in the Nigerian stock market.

This study contributes and extends the existing literature by critically examining the characteristic responses of symmetric and asymmetric volatility shocks in Nigerian stock return series using symmetric and asymmetric GARCH models with more current data.

3. DATA AND METHODOLOGY

The data used in this research work are the daily and monthly closing all share index (ASI) of the Nigerian Stock Exchange (NSE) obtained from the Nigerian Stock Exchange for the period 03/07/1999 to 12/06/2017 and January 1985 to March 2017, making a total of 4726 and 387 observations for daily and monthly prices respectively. The daily and monthly returns r_t are calculated as:

$$r_t = 100.\ln \Delta P_t \qquad (1)$$

where r_t is the stock return series, Δ is the first difference operator and P_t is the closing market index at the current day (t).

3.1 Ng and Perron (NP) Modified Unit Root Test

To check the unit root properties of the daily and monthly stock prices and returns, the Ng & Perron modified unit root test was employed because it has good power property. Ng & Perron (2001) constructed four test statistics which are based on the Generalized Least Squares detrended series Y_t^d. The four test statistics are the modified forms of Phillips & Perron Z_α and $Z_t$statistics, the Bhargava (1986) R_1 statistic, and the Elliot, Rothenberg & Stock Point Optimal statistic (Elliot et al., 1996). First, define the term:

$$k = \sum_{t=2}^{T} (Y_{t-1}^d)^2 / T^2 \qquad (2)$$

The four modified statistics are then written as,

$$\left.\begin{array}{c} MZ_\alpha^d = (T^{-1}(Y_T^d)^2 - f_0)/(2k) \\ MZ_t^d = MZ_\alpha \times MSB \\ MSB^d = (k/f_0)^{0.5} \\ MP_T^d = \begin{cases} (-7^2 k + 7T^{-1}(Y_T^d)^2)/f_0\,, & \text{if } \mathrm{x_t} = \{1\} \\ (-13.5^2 k + (1+13.5)T^{-1}(Y_T^d)^2)/f_0, & \text{if } \mathrm{x_t} = \{1,\mathrm{t}\} \end{cases} \end{array}\right\} \qquad (3)$$

where f_0 is the frequency zero spectrum define as:

$$f_0 = \sum_{j=-(T-1)}^{T-1} \hat{\gamma}(j).K\left(\frac{j}{l}\right) \quad (4)$$

where l is a bandwidth parameter, K is a kernel function and $\hat{\gamma}(j)$ is the j-th sample autocovariance of the residuals $\hat{u}_t$ and is given by:

$$\hat{\gamma}(j) = \sum_{t=j+1}^{T} (\hat{u}_t \hat{u}_{t-j})/T \quad (5)$$

In addition to the MZ_α and MZ_t statistics, Ng and Perron also investigated the size and power properties of the MSB statistic. Critical values for the demeaned and detrended case of this statistic were taken from Stock (1990).

3.2 Test for Heteroskedasticity

Test for heteroskedasticity (or ARCH effect) was conducted using the Lagragian Multiplier test proposed by Engle (1982). The test checks the pair of hypothesis $H_0: \rho_1 = \cdots = \rho_m$ versus $H_1: \rho_1 \neq 0 \text{ for some} i \in \{1, \ldots, m\}$. The F-statistic is estimated as:

$$F = \frac{SSR_0 - SSR_1/m}{SSR_1(n - 2m - 1)} \quad (6)$$

$$\text{where} SSR_1 = \sum_{t=m+1}^{T} e_t^2, SSR_0 = \sum_{t=m+1}^{T} (a_t^2 - \varpi)^2 \text{ and } \varpi = \frac{1}{\mathrm{n}}\sum_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{a}_{\mathrm{t}}^2 \quad (7)$$

$\hat{e}_t$ is the residual obtained from least squares linear regression, ϖ is the sample mean of $\mathrm{a}_{\mathrm{t}}^2$. The ARCH LM test statistic is distributed asymptotically as chi- square distribution with m degrees of freedom under the H_0. The decision is to reject the null hypothesis if the p-value of F-statistic is less than $\alpha = 0.05$.

3.3 Model Specification

The following conditional heteroskedasticity models are specified for this study. While the basic GARCH model captures the symmetric properties of returns, the EGARCH and TARCH models capture the asymmetric characteristics of returns.

3.3.1 The Autoregressive Conditional Heteroskedasticity (ARCH) Model

The ARCH model was first developed by Engle (1982). For the log return series (r_t), the ARCH (p) model is specified as:

$$r_t = \mu + \varepsilon_t \quad (8)$$

$$\varepsilon_t = \sqrt{h_t}u_t, \qquad u_t \sim N(0,1) \quad (9)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \quad (10)$$

where r_t is the return series, ε_t is the innovation or shock at day t which follows heteroskedastic error process, μ is the conditional mean of (r_t), h_t is the volatility (conditional variance) at day t and ε_{t-i}^2 is the square innovation at day $t-i$. For an ARCH (p) process to be stationary, the sum of ARCH terms must be less than one (i.e., $\sum \alpha_i < 1$).

3.3.2 The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The ARCH model was extended by Bollerslev (1986) called Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model. Assuming a log return series $r_t = \mu + \varepsilon_t$ where ε_t is the error term at time t. The ε_t follows a GARCH (p, q) model if:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (11)$$

with constraints $\omega > 0, \alpha_i \geq 0, i = 1, 2, \ldots, q$ and $\beta_j \geq 0, j = 1,2, \ldots, p; \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$ to ensure conditional variance to be positive as well as stationary. The basic GARCH (1,1) model which is sufficient in capturing all volatility in any financial data is given by:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (12)$$

For the stationarity condition of a basic GARCH (1,1) to be satisfied, the sum of ARCH and GARCH terms must be less than one (i.e., $\alpha_1 + \beta_1 < 1$).

3.3.3 The Exponential GARCH (EGARCH) Model

The EGARCH model was extended by Nelson (1991) to capture asymmetric effects between positive and negative stock returns. It is expressed as:

$$\ln(h_t) = \omega + \sum_{i=1}^{p} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right\} + \sum_{k=1}^{r} \gamma_k \left[\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right] + \sum_{j=1}^{q} \beta_j \ln\left(h_{t-j}\right) \qquad (13)$$

where γ represents the asymmetric and leverage effect coefficient in the model, β coefficient represents the measure of shock persistence. Asymmetry exists if $\gamma_k \neq 0$, there is leverage effect if $\gamma_k < 1$. The conditional variance equation for EGARCH (1,1) model specification is given as:

$$\ln(h_t) = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \gamma_1 \left[\frac{\varepsilon_{t-1}}{h_{t-1}} \right] + \beta_1 \ln(h_{t-1}) \qquad (14)$$

3.3.4 Threshold ARCH (TARCH) Model

The TARCH model was extended independently by Glosten, Jagannathan and Runkle, (1993) and Zakoian (1994). The generalized specification of TARCH for the conditional variance is given by:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \sum_{k=1}^{v} \gamma_k \varepsilon_{t-k}^2 \, d_{t-k}^{-} \tag{15}$$

where $d_t^{-} = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In TARCH model, good news is given by $\varepsilon_{t-i} > 0$, and bad news is given by $\varepsilon_{t-i} < 0$. Good news has impact on α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news produces more volatility, an indication of leverage effect. If $\gamma \neq 0$, the impact of news is asymmetric. The conditional variance equation for the TARCH (1,1) model specification is given by:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 d_{t-1}^{-} \tag{16}$$

3.3.5 Estimation and Distributional Assumptions of GARCH family Models

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

$$ln(L\theta_t) = -{}^{1}\!/_{2} \sum_{t-1}^{T} \left(\ln 2\pi + ln h_t + \frac{\varepsilon_t^2}{h_t} \right) \tag{17}$$

The five distributional assumptions employed in the estimation of parameters in this work are given by:

(i) Normal distribution (ND) is given by:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, -\infty < z < \infty \tag{18}$$

(ii) The student-t distribution (STD) is given by:

(iii)

$$f(z) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{z^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, -\infty < z < \infty \tag{19}$$

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

(iv) Skewed Student-t Distribution is given as:

(v)

$$f(z;\ \mu, \sigma, v, \lambda) = \begin{cases} bc\left(1 + \frac{1}{v-2}\left(\frac{b\left(\frac{z-\mu}{\sigma}\right) + a}{1-\lambda}\right)^2\right)^{-\frac{v+1}{2}}, \text{if} z < -\frac{a}{b} \\ bc\left(1 + \frac{1}{v-2}\left(\frac{b\left(\frac{z-\mu}{\sigma}\right) + a}{1+\lambda}\right)^2\right)^{-\frac{v+1}{2}}, \text{if } z \geq -\frac{a}{b} \end{cases} \tag{20}$$

where v is the shape parameter with $2 < v < \infty$ and λ is the skewness parameter with $-1 < \lambda < 1$. The constants a, b and c are given as:

$$a = 4\lambda c\left(\frac{v-2}{v-1}\right), \qquad b = 1 + 3\lambda^2 - a^2, \qquad c = \frac{\Gamma(\frac{v+1}{2})}{\sqrt{\pi(v-2)\Gamma(\frac{v}{2})}},$$

where μ and σ^2 are the mean and variance of the skewed student-t distribution respectively.

(vi) The Generalized Error Distribution (GED) is given as:

$$f(z,\mu,\sigma,v) = \frac{\sigma^{-1} v e^{\left(-\frac{1}{2}\left|\frac{\left(\frac{z-\mu}{\sigma}\right)}{\lambda}\right|^{v}\right)}}{\lambda 2^{(1+(1/v))}\Gamma\left(\frac{1}{v}\right)}, 1 < z < \infty \tag{21}$$

$v > 0$ is the degrees of freedom or tail -thickness parameter and

$$\lambda = \sqrt{2^{(-2/v)}\Gamma\left(\frac{1}{v}\right) \Big/ \Gamma\left(\frac{3}{v}\right)}$$

The GED is a normal distribution if $v = 2$, and fat-tailed if $v < 2$.

(vii) Skewed Generalized Error Distribution (SGED) is given by:

$$f(z; v, \xi) = v\left(\frac{1}{2\theta\Gamma(\frac{1}{v})}\right)\exp\left(\frac{|z-\delta|^v}{[1 - sign(z-\delta)\xi]^v\theta^v}\right) \tag{22}$$

Where $\theta = \Gamma\left(\frac{1}{v}\right)^{0.5}\Gamma\left(\frac{3}{v}\right)^{-0.5}S(\xi)^{-1}$, $\delta = 2\xi A S(\xi)^{-1}$, $S(\xi) = \sqrt{1 + 3\xi^2 - 4A^2\xi^2}$, $A = \Gamma\left(\frac{2}{v}\right)\boldsymbol{\Gamma}\left(\frac{1}{v}\right)^{-0.5}\Gamma\left(\frac{3}{v}\right)^{-0.5}$,$v > 0$ is the shape parameter controlling the height and heavy-tail of the density function while ξ is a skewness parameter of the density with $-1 < \xi < 1$.

4. RESULTS AND DISCUSSION

4.1 Graphical Properties of Daily and monthly Stock Prices and Returns

In order to examine the graphical properties of the series, the original series of daily and monthly stock prices and returns are first plotted against time. The plots are presented in Figures 1and 2.

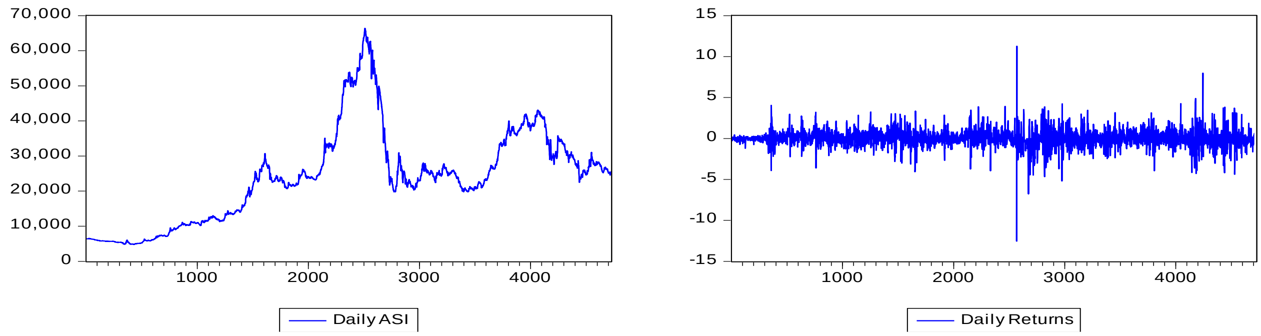

Figure 1: Time Plot of Daily Stock Prices and Returns from 1999 – 2017.

The time plots of the daily and monthly stock prices presented in Figures 1 and 2 (left) suggests that the series have means and variances that change with time and the presence of trends in each series indicating that the series are not weakly or covariance stationary. This also suggests the presence of unit roots in the daily and monthly stock prices in Nigerian stock market.

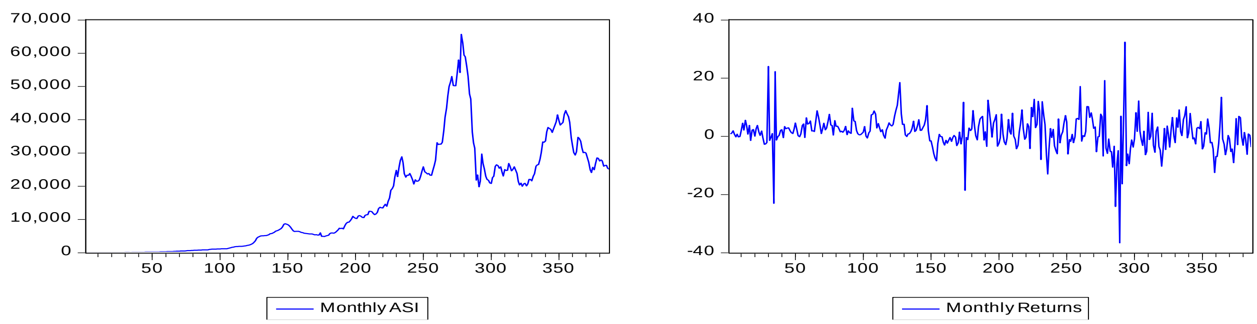

Figure 2: Time Plot of Monthly Prices and Returns in Nigeria from 1999 – 2017

The time plots of the daily and monthly return series presented in Figures 1 and 2 (right) suggests that the series have constant means and variances with absence of trends indicating that they are being generated by random walks and are thus weakly or covariance stationary. This also suggests that the daily and monthly stock return series maynot contain unit roots. Apart from the visual examination of time plots, a unit root test is also employed to further examine the stationarity properties.

4.2 Unit Root and Heteroskedasticity Tests Results

Ng and Perron unit root test is employed to investigate the unit root and stationarity characteristics of both monthly and daily stock prices and returns in this work. The results of Ng and Perron unit root test together with heteroskedasticity test for ARCH effects are presented in Table 1.

The results of Ng – Perron unit root test reported in upper panel of Table 1 indicates that the daily and monthly market prices are non-stationary (contains unit root). This is shown by the Ng–Perron test statistics being higher than their corresponding asymptotic critical values at 1% and 5% levels. However, the Ng–Perron unit root test results of the daily and monthly stock returns show evidence of weakly and covariance stationarity as the test statistics are all smaller than their corresponding asymptotic critical values at all the designated test sizes both for constant only and for constant and linear trend. These results showed that the daily and monthly stock prices are non-stationary while their log returns are stationary.

The lower panel of Table 1 indicates result of the residual test of heteroskedasticity for ARCH effects.

Table 1: Ng – Perron Unit Root Test and ARCH LM Test Results

Variable	Option	Ng-Perron test statistics			
		MZa	MZt	MSB	MPT
Daily Stock Prices	Intercept only	-0.63183	-0.44522	0.70465	26.9371
	Intercept & trend	-3.71650	-1.26353	0.33998	23.1074
Daily Returns	Intercept only	-2102.35*	-32.4217*	0.01542*	0.01169*
	Intercept & trend	-2213.14*	-33.2652*	0.01503*	0.04119*
Monthly Stock Prices	Intercept only	-1.96833	-0.85679	0.43529	11.0584
	Intercept & trend	-14.0863	-2.62508	0.18636	6.64165
Monthly Returns	Intercept only	-63.4120*	-5.62881*	0.08877*	0.39104*
	Intercept & trend	-65.4779*	-5.72073*	0.08737*	1.39656*
Asymptotic Critical Values					
1%	Intercept only	-13.8000	-2.58000	0.17400	1.78000
5%		-8.10000	-1.98000	0.23300	3.17000
1%	Intercept & trend	-23.8000	-3.42000	0.14300	4.03000
5%		-17.3000	-2.91000	0.16800	5.48000
ARCH LM Test for Daily Returns		F-Statistic	1306.912	nR^2	1023.994
		P-value	0.0000	P-value	0.0000
ARCH LM Test for Monthly Returns		F-Statistic	19.11207	nR^2	18.29672
		P-value	0.0000	P-value	0.0000

Note: *denotes the significance of Ng-Perron test statistics at 5% significance levels.

From the results in the Table 1, it is clear that the test rejects the null hypothesis of no ARCH effects in the residuals of returns. This means that the errors are time varying and can only be modeled using heteroskedastic ARCH family models.

4.3 Summary Statistics of Monthly and Daily Stock Prices and Returns

To better understand the distributional characteristics of the monthly and daily stock prices and returns, I compute the summary statistics for all the series and results are presented in Table 2.

The summary statistics shown in Table 2 indicate positive means for both daily and monthly stock prices and returns which indicate gains in the stock market for the trading period under review. The positive standard deviations and high range values for both daily and monthly stock prices and returns shows the dispersion from the means and high level of variability of price changes in the stock market during the study period. The summary statistics also show positive asymmetry for monthly and daily stock prices (skewness = 0.903657 and 0.656391) respectively and negative asymmetry for the monthly and daily returns (skewness = -0.441460 and -0.112892) respectively. The distribution is leptokurtic for all the series as kurtosis = 3.113408 and 10.60535 for monthly stock prices and returns respectively and kurtosis = 3.340807 and 15.11793 for daily stock prices and returns respectively. The distribution is non-normal for all the series as Jarque-Bera statistics are 52.87778 and 942.8187 for monthly stock prices and returns respectively and 362.2371 and 28920 for daily stock prices and returns respectively with the marginal p-values of 0.0000 in all the series.

Table 2: Summary Statistics of Stock Prices and Returns

Statistic	Monthly ASI	Monthly Returns	Daily ASI	Daily Returns
Mean	15109.10	1.404264	23947.77	0.029172
Range	6554.10	68.93965	61578.97	23.81438
Std. Deviation	15072.54	5.997599	13316.67	1.004785
Skewness	0.903657	-0.441460	0.656391	-0.112892
Kurtosis	3.113408	10.60535	3.340807	15.11793
Jarque-Bera	52.87778	942.8187	362.2371	28920
P-value	0.000000	0.000000	0.000000	0.000000
No. of Obs.	387	386	4726	4725

4.4 Searching for Optimal Symmetric and Asymmetric GARCH Models

To select the best fitting symmetric and asymmetric GARCH models with suitable distributional assumptions, Akaike information criterion (AIC) due to Akaike (1974) and Schwarz information criterion (SIC) due to Schwarz (1978) in conjunction with log likelihoods (LogL) are employed. The best fitting model is one with largest log likelihood and minimum information criteria. Results are presented in Table 3.

Table 3: Search for Optimal Volatility Models

S/N	Model	Distribution	LogL	AIC	SIC
		Daily Stock Returns			
1	GARCH (1,1)	ND	-5737.016	2.4301	2.4355
2	**GARCH (1,1)**	**STD**	**-5452.253**	**2.3099**	**2.3168**
3	GARCH (1,1)	GED	-5456.485	2.3117	2.3186
4	GARCH (1,1)	SSTD	-5486.783	2.3241	2.3296
5	GARCH (1,1)	SGED	-5521.276	2.3387	2.3442
6	EGARCH (1,1)	ND	-5688.024	2.4097	2.4166
7	**EGARCH (1,1)**	**STD**	**-5422.339**	**2.2977**	**2.3059**
8	EGARCH (1,1)	GED	-5428.335	2.3002	2.3085
9	EGARCH (1,1)	SSTD	-5450.468	2.3092	2.3160
10	EGARCH (1,1)	SGED	-5483.986	2.3234	2.3302
11	TARCH (1,1)	ND	-5736.786	2.4304	2.4372
12	**TARCH (1,1)**	**STD**	**-5450.401**	**2.3096**	**2.3178**
13	TARCH (1,1)	GED	-5455.145	2.3120	2.3198
14	TARCH (1,1)	SSTD	-5483.981	2.3234	2.3302
15	TARCH (1,1)	SGED	-5520.013	2.3386	2.3455
		Monthly Stock Returns			

1	GARCH (1,1)	ND	-1156.907	6.0151	6.0561
2	GARCH (1,1)	STD	-1150.628	5.9855	6.0368
3	GARCH (1,1)	GED	-1150.869	5.9889	6.0402
4	**GARCH (1,1)**	**SSTD**	**-1150.205**	**5.9825**	**6.0235**
5	GARCH (1,1)	SGED	-1151.368	5.9864	6.0274
6	EGARCH (1,1)	ND	-1155.101	6.0109	6.0621
7	EGARCH (1,1)	STD	-1146.862	5.9734	6.0349
8	EGARCH (1,1)	GED	-1148.438	5.9815	6.0430
9	**EGARCH (1,1)**	**SSTD**	**-1146.796**	**5.9730**	**6.0243**
10	EGARCH (1,1)	SGED	-1148.831	5.9784	6.0296
11	TARCH (1,1)	ND	-1156.399	6.0176	6.0689
12	TARCH (1,1)	STD	-1149.798	5.9855	6.0470
13	TARCH (1,1)	GED	-1149.799	5.9886	6.0501
14	**TARCH (1,1)**	**SSTD**	**-1149.757**	**5.9832**	**6.0244**
15	TARCH (1,1)	SGED	-1150.140	5.9852	6.0364

Note:bold facedenotes the model selected by various criteria.

Table 3 shows results of 15 different symmetric and asymmetric GARCH variants estimated with different innovation densities for both daily and monthly stock returns. The information criteria together with the log likelihood optimally selects symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TARCH (1,1) models all with student-t distributions (STD) for daily stock returns while symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TARCH (1,1) models all with skewed student-t distributions (SSTD) are selected as the best candidates to model the monthly stock return volatility in Nigerian stock market.

4.5 Results of Symmetric and Asymmetric GARCH (1,1) Variants

The parameter estimates of the selected GARCH models for daily and monthly stock returns are respectively presented in Tables 4 and 5.

Table 4: Parameter Estimates of Volatility Models of Daily Stock Returns

Parameter	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
μ	-0.0103	-0.0106	-0.0084
	(0.0087)	**(0.0025)**	**(0.0044)**
	[0.0682]	[0.0081]	[0.0083]
ω	0.0182	-0.3514	0.0170
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.0030]	[0.0175]	[0.0029]
α_1	0.3348	0.4479	0.3517
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.0253]	[0.0243]	[0.0294]
γ	---	0.0329	-0.0555
		(0.0091)	**(0.0279)**
		[0.0126]	[0.0309]
β_1	0.7205	0.9482	0.7281
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.0140]	[0.0064]	[0.0136]

v	4.8793	5.1639	4.9171
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.3134]	[0.3388]	[0.3152]
$\alpha_1 + \beta_1$	1.0553	1.3961	----
$\alpha_1 + \beta_1 + \gamma/2$	----	----	1.0521
ARCH LM Test	0.136101	0.300670	0.202133
	(0.7122)	(0.5835)	(0.6530)

Note: values in (.) are p-values while values in [.] are standard errors

From the results of symmetric GARCH (1,1) models presented in Tables 4 and 5 for daily and monthly stock returns, all the estimated coefficients in the variance equations of both returns are statistically significant and exhibited the expected positive signs. The significance of α_1 and β_1 parameters in both returns indicates that news about volatility from the previous periods have explanatory powers on the current volatility. However, the sum of the shock persistence coefficients $(\alpha_1 + \beta_1)$ in the symmetric GARCH (1,1) models for both daily and monthly stock returns are greater than unity $(\alpha_1 + \beta_1 > 1)$. This suggests that the conditional variance processes are unstable and explosive giving rise to long memory, a departure from many developed markets.

For the estimated asymmetric EGARCH (1,1) and TARCH (1,1) models for daily stock returns presented in Table 4, the asymmetric (leverage) effect parameter γ captured by EGARCH (1,1) model is positive and significance indicating the presence of asymmetry without leverage effect. For leverage effect to exist in EGARCH model the leverage effect parameter must be negative $(\gamma < 0)$. For the TARCH (1,1) model, the asymmetric (leverage) effect parameter $(\gamma = -0.0555)$ and is statistically significant indicating the presence of asymmetry but no leverage effect. Leverage effect exist in TARCH (1,1) model is γ is positive $(\gamma > 0)$. Thus the absence of leverages in the daily stock returns indicates that positive shocks (good news) generate more volatility than negative shocks (bad news) of similar magnitude. See Table 6 for more explanations.

Table 5: Parameter Estimates of Volatility Models of Monthly Stock Returns

Parameter	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
μ	1.9693	2.0321	2.0074
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.1749]	[0.1799]	[0.1901]
ω	2.1309	-0.1008	1.8602
	(0.0120)	**(0.0079)**	**(0.0038)**
	[0.8480]	[0.1193]	[0.6420]
α_1	0.6116	0.6710	0.4420
	(0.0000)	**(0.0000)**	**(0.0001)**
	[0.1330]	[0.1111]	[0.1135]
γ	---	-0.0681	0.2026
		(0.1997)	**(0.1787)**
		[0.0531]	[0.1507]
β_1	0.5091	0.8669	0.5165
	(0.0000)	**(0.0000)**	**(0.0000)**
	[0.0636]	[0.0329]	[0.0546]

v	5.1861	6.7233	4.5738
	(0.0023)	**(0.0038)**	**(0.0005)**
	[0.7024]	[0.3210]	[0.3075]
$\alpha_1 + \beta_1$	1.1207	1.5379	----
$\alpha_1 + \beta_1 + \gamma/2$	----	----	1.0598
ARCH LM Test	0.266509	0.053381	0.110767
	(0.6060)	(0.8174)	(0.7395)

Note: values in (.) are p-values while values in [.] are standard errors

For the asymmetric EGARCH (1,1) and TARCH (1,1) models estimated for monthly stock returns presented in Table 5, the asymmetric (leverage) effect parameter γ is negative for EGARCH (1,1) model and positive for TARCH (1,1) model as expected, although not statistically significant in both models. This indicates a weak form of asymmetry and leverage effect in the monthly stock returns in Nigerian stock market. The implication is that negative shocks (market retreats) tend to produce more volatility than positive shocks (market advances) of the same modulus.

It is important to point out that all the estimated symmetric and asymmetric GARCH-type models for both returns show over persistence of volatility shocks with explosive tendencies since the sum of ARCH and GARCH terms $(\alpha_1 + \beta_1)$ for GARCH (1,1) and EGARCH (1,1) and $(\alpha_1 + \beta_1 + \gamma/2)$ for TARCH (1,1) models are all greater than one in all the models. When the sum of volatility estimates is greater than one in the stock market, it signals potential and excessive gains or losses on the part of traders and investors, a market situation that is not conducive for long term investment.

The results of the ARCH LM test for remaining ARCH effects in residuals of the daily and monthly returns as presented in the lower panels of Tables 4 and 5 shows that there are no ARCH effects remaining in the residuals of returns estimated by different GARCH models with heavy tailed distributions. This is because the p-values of the F-statistics for both daily and monthly returns are highly statistically insignificant for all GARCH-type models. This means that the GARCH models sufficiently captured all the ARCH effects in the residuals of both returns.

4.6 The Magnitude of News Impact on Conditional Volatility

The magnitudes of news impact on the conditional volatility of the two asymmetric GARCH models for the daily and monthly returns are presented in Table 6.

Table 6: News Impact on Conditional Volatility

Return	EGARCH (1,1)		TARCH (1,1)	
	Good news	Bad news	Good news	Bad news
Daily Returns	1.0329	0.9671	0.3517	0.2962
Monthly Returns	0.9319	1.0681	0.4420	0.6446

Note: Asymmetry is calculated as $\frac{|-1+\hat{\gamma}|}{1+\hat{\gamma}}$ for EGARCH (1,1) and $\frac{\hat{\alpha}_1+\hat{\gamma}}{\hat{\alpha}_1}$ for TARCH (1,1), where the numerator represents bad news impact while the denominator represents good news impact on volatility.

The evidence provided in Table 6 shows that good news have more impact on conditional volatility than bad news for daily returns. In the EGARCH (1,1) model for example, the impact of good news on conditional volatility is about 1.07 times more than bad news and about 1.19 times more than bad news for TARCH (1,1) model for daily returns. For monthly returns, it is the other way round as bad news have more impact on conditional volatility than good news for both EGARCH (1,1) and TARCH (1,1) models under heavy tailed skewed student-t distribution. In the EGARCH (1,1) model for instance, the impact of bad news on conditional volatility is about 1.15 times more than good news and about 1.146 times more than good news for TARCH (1,1) model for monthly returns. The results of Table 6 therefore help in confirming the absence of leverage effect in the daily stock returns and the presence of leverages in the monthly stock returns.

5. CONCLUSION AND RECOMMENDATIONS

This paper has attempted to examine the characteristic responses of symmetric and asymmetric volatility shocks persistence in Nigerian stock market. The study used the daily and monthly stock returns for the periods 3rd July 1999 to 12th June 2017 and January 1985 to March 2017 respectively and employed time plots, Ng & Perron modified unit root test, ARCH LM test and symmetric and asymmetric GARCH models with five different distributions as methods of analysis. Results of time plots and unit root test showed that the daily and monthly prices are non-stationary while their stock returns are weakly and covariance stationary. The student-t distribution fitted all the models estimated for daily stock returns while the skewed student-t heavy tailed distribution fitted all the GARCH models estimated for monthly stock returns. The estimated symmetric GARCH (1,1) models for both daily and monthly stock returns showed evidence of volatility clustering and higher persistence of volatility shocks with explosive tendencies. The estimated asymmetric EGARCH (1,1) and TARCH (1,1) models for daily returns showed evidence of asymmetry with the absence of leverage effect indicating that positive shocks generate more volatility than negative shocks for the daily stock return series whereas the estimated asymmetric EGARCH (1,1) and TARCH (1,1) models for monthly returns show evidence of asymmetry with the presence of leverage effect suggesting that negative shocks tend to produce more volatility than positive shocks of the same sign for the monthly stock return series. Results of the asymmetric models also show evidence of higher volatility shocks persistence giving rise to long memory in Nigerian stock market. Higher persistence of volatility shocks in the stock market is associated with higher level of risk and uncertainty as it signaled potential and excessive gains or losses by investors and traders in the stock market. As a policy recommendation, this kind of stock market with explosive volatility shocks needs excessive and aggressive trading strategy for securities and an increased market depth in order to make it less volatile.

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