MODELLING THE EFFECTS OF GLOBAL FINANCIAL CRISIS ON THE NIGERIAN STOCK MARKET USING GARCH MODELS WITH STRUCTURAL BREAKS

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ABSTRACT

In financial risk management and portfolio selection, volatility modeling is important because it improves the efficiency in parameter estimation and the accuracy in interval forecast. However, the accuracy is compromised when structural breaks are ignored. This study examined the behaviour of stock returns in Nigerian stock market in the context of Global Financial Crisis. Data on daily closing all share index for the period of 2nd January 1998 to 9th January 2018 are studied using symmetric and asymmetric GARCH-type models. The data was divided into three sub-periods of pre-crisis period, crisis period and post-crisis period to investigate the behaviour of Nigerian stock market in different sub-periods. The study showed the presence of autoregressive conditional heteroskedasticity (ARCH) effect, volatility clustering, leptokurtosis, high shock persistence and asymmetry across the study periods. Volatility was found to increase during the Global Financial Crisis period of 2007-2009 with evidence of asymmetry without leverage effect. The post crisis period showed less persistence to volatility shocks, presence of asymmetry with leverage effects and faster reactions of volatility to market changes. The impact of market shocks caused by the global financial crisis was found to have negative and significant effect on Nigerian stock market. This study also found significant positive risk-return relationship indicating that investors in Nigerian stock market should be compensated heavily for holding risky assets. The study recommends estimation of volatility in the Nigerian stock market to incorporate structural breaks in the conditional variance to avoid over-estimation of market shocks and restore investor's confidence.

Keywords: Asymmetry, Financial crisis, GARCH, Stock Market, Structural Breaks, Volatility.

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1. INTRODUCTION

Volatility modeling is considered an important tool for many economic and financial applications such as equity pricing, financial risk management, portfolio selection, management and optimization, options trading as well as pair trading strategy. Modeling the variance of the errors can also improves the efficiency in parameter estimation and the accuracy in interval forecast. One of the basic features of volatility is that, it is not directly observable. This makes financial analysts to be keenly interested in obtaining accurate estimates of the conditional variance in order to improve portfolio selection, risk management and valuation of financial derivatives (Tsay, 2002).

The Autoregressive (AR) model, Moving Average (MA) model, Autoregressive Moving Average (ARMA) model and the Autoregressive Integrated Moving Average (ARIMA) model which represent short memory features are inadequate in capturing the long memory in volatility. The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model extended by Bollerslev (1986) and Nelson (1991) then become the most widely used models in studying the volatility of financial return series. The common characteristics found in financial time series such as fat tails, volatility clustering, volatility persistence, asymmetry and leverage effect were easily captured by the GARCH family models. The basic ARCH and GARCH models capture the symmetric properties of return series while their extensions such as EGARCH, TARCH, APARCH, GJR-GARCH models, etc., capture the asymmetry and leverage effects in the return series. In recent times, several empirical evidences in the financial literature found support for the GARCH-type models. This study therefore utilizes the lower GARCH-type models in studying the volatility behaviour of stock returns in Nigerian stock market using the daily quotations of the Nigerian stock exchange (NSE) in the context of Global Financial Crisis.

The recent global financial crisis triggered in 2007 and went on through 2009 had its origin in the US financial markets, spreading rapidly to other developed and emerging financial markets. The crises caused serious and great depression in the real economies around the globe. The crisis which considerably affected financial markets including the Nigerian stock market, is considered the most devastating crisis since the Great Depression of 1929 (Amedeo& Meier, 2010).

The Global Financial Crisis which led to the crash of the Nigerian Stock Market in January, 2009 also affected its market capitalization which dropped from an all-time high of N13.5 trillion in March 2008 to less than N4.6 trillion by the second week of January 2009. The daily All-Share Index (a measure of the magnitude and direction of general price movement) was nose-dived from 66000 basis points to less than 22000 points in the same period. The crash of the Nigerian stock market as a result of the Global Financial Crisis, economic crisis and other local events have created some level shifts in the variance of stock return series. Therefore, the conventional GARCH variants which ignore these shifts may not be adequate in obtaining accurate volatility estimates in the Nigerian stock market (Kuhe and Chiawa, 2017). This study intends to employ both symmetric and asymmetric GARCH family models with exogenous breaks and heavy-tailed distributions to investigate the impact of volatility shock persistence on the conditional variance due to this crash on the Nigerian stock market using daily closing all share index of the Nigerian Stock Exchange.

The main objective of this study is to investigate the behaviour of stock return volatility in Nigerian stock market in the presence of 2007-2009 Global Financial Crisis using GARCH family models. This involves examining the NSE stock return series for evidence of volatility clustering, shock persistence, fat-tails distribution, asymmetry and leverage effects as they provide essential information in the pre-crisis, during the financial crisis, in the post-crisis and the entire study period about the riskiness of asset returns in Nigerian stock market. The study also investigates the impact of exogenous breaks on the conditional variance in Nigerian stock returns.

The rest of the paper is organized as follows: section 2 reviews relevant literature on the subject matter, section 3 presents materials and methods; section 4 discusses results of empirical findings while section 5 hinges on conclusion and policy implications.

2. LITERATURE REVIEW

The available empirical evidence on the subject matter has affirmed that financial crises have influence on the volatility of stock markets. For example, Schwert (1989) found that financial crises increase the volatility of stock markets. In a similar development, Ellis and Lewis (2001) found stock market volatility in the New Zealand and Australian stock markets to be more pronounced in late 1998 than middle of 1997, when the main events of Asian financial crisis occurred. Much empirical evidence on the subject matter across the globe is also documented in the literature. For example, Bartram and Bodnar (2009) conducted a study which provided a broad based analysis on the impact of global financial crises on the overall world equity markets performance. Their findings revealed that the total return index of the world market portfolio declined tremendously in the middle of the year 2008 while the 30 days rolling portfolio of the world markets which measures the normal volatility of the global markets increased during the same period. A more significant decline was noticed among the emerging markets as compared to the developed markets. A study was conducted by Orlowski (2012)on the proliferation of risks in the US and European financial markets before and during the global financial crisis and found significant increase in volatility clustering during financial distress and a significant increase of risk in the Germany, Hungary and Poland equity markets. Kenourgios and Samitas (2011) investigated the long-term relationships between Balkan emerging stock markets and other developed stock markets during the global financial crisis. The result of their study showed supportive evidence for increase in stock market dependence during the period of crises. Mathur *et al.* (2016) examined the impact of global financial crisis on the Indian stock market using daily quotations of the top 20 companies listed on Bombay Stock Exchange (BSE) for the period 2001-2012 using GARCH (0,1) model. Result showed high volatility for all stock returns during the crises period from 2007-2009 indicating that the global financial crisis had affected the Indian economy too.

Chukwuogor and Feridun (2007) examined the shock persistence and volatility behaviour of fifteen countries including emerging and developed markets during the global financial crises and found that the crises affected Asia and Russia including the internet bubble. In assessing the predictability of the volatility behaviour in ten emerging stock markets and comparing them to industrialized markets in the context of global financial crises of 2008, Alper et al. (2009) found similar results. Vitor (2015) employed GARCH family models to investigate the sensitivity of shock persistence and asymmetric effects in the international stock market during the global financial crises using daily data of twelve stock indexes over the period from October 1999 to June 2011. The results showed that the Subprime crisis period turned out to have bigger impact on stock market volatility with high shock persistence and asymmetric effects. Tabajara et al. (2014) compared the stock market behaviour of Brazil, Russia, India and China (BRIC) emerging economies to those of the industrialized economies of USA, Japan, United Kingdom and Germany in the light of 2008 global financial crisis using GARCH, EGARCH and TARCH univariate models. The stock market behaviours of the BRIC's emerging markets and the industrialized economies in terms of shock persistence effects on volatility, asymmetry and delayed reaction of volatility to stock market changes were found to be similar in both markets. However, the BRIC's stock markets showed less persistence of shocks, less asymmetric effects and faster volatility reactions to market changes.

Hassan (2017) examined the sudden changes in volatility of weekly Wednesday-close returns of three major indexes of DJIA (Dow Jones Industrial Average), DAX (*Deutscher Aktienindex* or German Stock Index), and FTSE (Financial Times Stock Exchange 100 Index) from January 2008 to December 2015. The study utilized the

Iterated Cumulative Sums of Squares (ICSS) algorithm to capture structural breaks in the return series. The findings indicate that volatility persistence declines significantly when regime shifts were combined with GARCH model. Abdennadher and Hallara (2018) examined changes in volatility of emerging stock markets for the period April 2005 to March 2015 using different GARCH variants. The study employed the Bai and Perron technique to test for multiple structural breaks in the volatility. The study found evidence of structural breaks in most of the markets. The structural breaks were found to significantly affect the volatility behaviour of the stock markets. There was sharp drop in volatility shock persistence after incorporating the structural changes in the volatility models. Amaefula and Asare (2014), Dutta et al. (2017), Kutu and Ngalawa (2017) also found similar results across different stock markets.

In Nigeria, Onuoha and Nwaiwu (2016) in an attempt to investigate the impact of the global financial crisis on Nigerian stock market employed multiple linear regression model using secondary data from 2008 to 2014. The global financial crisis which is measured by currency crisis, credit crisis, liquidity crisis, and foreign investment crisis was found to have negative and significant impact on Nigerian stock market. Olowe (2009) employed exponential GARCH-in-mean model to investigate the relationship between stock market return series and volatility in Nigerian stock market using daily returns from 4th January, 2004 to 9th January, 2009 in the light of stock market crash, insurance reform, banking reforms and the global financial crisis. The banking reforms of 2004 and the stock market crash of 2008 were found to have negative impacts on stock returns whereas insurance reform and the global financial crisis had no impact on stock returns in Nigeria. However, the stock market crash of 2008 was found to have contributed greatly to high volatility shock persistence in Nigerian stock market especially during the global financial crisis. The stock market crash was also found to have contributed to the sudden change in the conditional variance of returns. In a similar vein, Adamu (2010) found that volatility in Nigerian stock market increased drastically during the global financial crisis period.

Umanhonlen and Lawani (2015) employed econometric approaches to investigate the effect of the global financial meltdown on Nigerian banking industry and economy using quarterly secondary data from 2001Q1 to 2011Q3 covering period of 42 quarters. The global financial meltdown was found to have negative and reverse effect on both the Nigerian banking sector and the economy during the study period. Aliyu (2011) assessed the innovations of monetary policy in Nigerian stock market during the global financial crisis period using monthly data for the period of January 2007 to August 2011. He employed EGARCH model and regressed stock market returns against money stock (M1 and M2) and monetary policy rate (MPR). The empirical findings from the study revealed that, unlike the anticipated components of the monetary innovation, the unanticipated component of the policy innovations on M2 and MPR exerted destabilizing effect on Nigerian stock returns. Njiforti (2015) conducted a study to investigate the impact of the 2007-2008 global financial crisis on the Nigerian capital market using monthly time series data spanning from January 2006 to December 2009. The study employed Vector Error Correction model (VECM) as method of analysis. All Share Index (ASI) was proxy for the performance of the Nigerian Capital market, while Credit to Private Sector (CPS), Price of Crude Oil (POIL), Money Supply (MS) and Dow Jones Industrial Average (DJIA) were used as the set of explanatory variables to ascertain the effects of the crisis on the Nigerian capital market. Based on the results obtained from cointegration and VECM analyses, the study found that the global financial crisis had adverse and significant effect on the Nigerian capital market both in the short-run and long-run leading to the crash of the Nigerian stock market including valuable loss of capital assets and investments.

From the reviewed literature, it is glaring to know that while different authors across the globe employed different methodologies to investigate the impact of Global Financial Crisis on the behaviour of stock market volatility, all have agreed that Global Financial Crises have influence on the volatility of stock markets. However, while some authors found less volatility clustering and shock persistence during financial crises some authors found significant increase in volatility clustering and shock persistence during financial distress. This study examined the behaviour of stock returns in Nigerian stock market in the context of global financial crisis using more recent data. The study went further to examine the effect of ignoring levels shifts and including level shifts in the various GARCH models.

3. MATERIALS AND METHODS

3.1 Source of Data and Integration

The data used in this study are the daily closing all share index (ASI) of the Nigerian Stock Exchange (NSE) obtained from www.nse.ng.org for the period 2nd January 1998 to 9th January 2018 making a total of 4922 observations. The data is further sub-divided into three main sub-periods to consider the impact of global financial crisis: the pre-crisis period(2nd January 1998 to 29th December 2006), the crisis period(4th January 2007 to 31st December 2009)and the post-crisis period (4th January 2010 to 9th January 2018). The daily returns r_t are calculated as:

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

Where r_t denotes the stock return series, Δ is the first difference operator and P_t denotes the closing market index at the current day (t). The natural log of the series is multiply by 100 to convert it to percentage.

3.2 Unit Root, Stationarity and Heteroskedasticity Tests

The presence or absence of unit roots in a series can strongly influence its behaviour and properties. If a series has no unit roots, it is characterized as stationary, and therefore exhibits mean reversion in that it fluctuates around a constant long run mean. Also, the absence of unit roots implies that the series has a finite variance which does not depend on time, and that the effects of shocks dissipate over time. On the other hand, if a series contains a unit root, it is characterized as non-stationary process that has no tendency to return to a long-run deterministic path. Besides, the variance of the series is time-dependent and goes to infinity as time approaches infinity, which results in serious problems for forecasting. Non-stationary series suffer permanent effects from random shocks; series with unit roots follow a random walk. It is therefore reasonable to conduct unit root test and ascertain the stationarity of the return series before proceeding with estimation procedures.

To check for the presence of unit root in stock prices and returns, Dickey-Fuller Generalized Least Squares (DF GLS) unit root due to Elliot, Rothenberg and Stock (1996) was employed. The test results obtained by DF-GLS parametric unit root test are confirmed by the non-parametric stationarity test due to Kwaitkowski, Philips, Schmidt and Shin (1992). To test for the presence of ARCH effects in the return series, Engle's Lagrange Multiplier test due to Engle (1982) is employed. The null hypothesis of no ARCH effects in the return series is rejected if the p-value of the F-statistic associated with the test is less than 0.05.

3.3 Model Specification

The following conditional heteroskedasticity models are specified for this study.

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:

$$r_t = \mu + \varepsilon_t \quad (2)$$

$$\varepsilon_t = \sqrt{h_t}u_t, \qquad u_t \sim N(0,1) \quad (3)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \quad (4)$$

where r_t is the return series, ε_t is the 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 ARCH (GARCH) Model

Bollerslev (1986) extended the ARCH model called Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model. Assuming a log return series

$$r_t = \mu_t + \varepsilon_t \qquad (5)$$

where ε_t is the error term at time t. The innovation ε_t follows a GARCH (1,1) model if:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (6)$$

with constraints $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$ to ensure conditional variance to be positive as well as stationary. The symmetric GARCH (1,1) model is sufficient in capturing all the volatility in any financial data. The GARCH (1,1) model with dummy variable in the conditional variance is specified as:

$$h_t = \omega + \phi_1 d_1 + \cdots + \phi_n d_n + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (7)$$

Where $d_1, \ldots, d_n$ are dummy variables added to the conditional variance equation which takes value 1 as the sudden break appears in conditional volatility onwards and otherwise it takes value 0.

3.3.3 The GARCH-in-Mean (GARCH-M) Model

The GARCH-in mean model was proposed by Engle et al. (1987). The GARCH-in mean model makes a significant change to the role of time-varying volatility by explicitly relating the level of volatility to the expected return. A simple GARCH (1,1)-in mean model can be specified as:

$$r_t = \mu + \lambda h_t + \varepsilon_t, \qquad \varepsilon_t = \sigma_t e_t \qquad (8)$$
$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (9)$$

Where μ and λ are constants. The parameter λ is called the risk premium parameter. A positive λ indicates that the return is positively related to its past volatility. The symmetric GARCH (1,1)-M model which incorporates structural breaks in the conditional variance is given by:

$$h_t = \omega + \phi_1 d_1 + \cdots + \phi_n d_n + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{10}$$

3.3.4 The Exponential GARCH (EGARCH) Model

The EGARCH model was extended by Nelson (1991) to capture asymmetric effects between positive and negative stock returns. The EGARCH (1,1) model is specified as follows:

$$\ln h_t = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma \left[\frac{\varepsilon_{t-1}}{h_{t-1}}\right] + \beta_1 \ln h_{t-1} \tag{11}$$

Where γ denotes the asymmetry or leverage effect parameter. There is presence of asymmetry when $\gamma \neq 0$; leverage effect exists if $\gamma < 0$ indicating that bad news ($\varepsilon_{t-1} < 0$) increases volatility more than good news ($\varepsilon_{t-1} > 0$) of the same magnitude. The EGARCH (1,1) model with dummy variable in the conditional variance is specified as:

$$\ln(h_t) = \omega + \phi_1 d_1 + \cdots + \phi_n d_n + \alpha_1 \left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma \left[\frac{\varepsilon_{t-1}}{h_{t-1}}\right] + \beta_1 \ln(h_{t-1}) \tag{12}$$

3.3.5 Threshold ARCH (TARCH) Model

The TARCH model was extended by Glosten, Jagannathan and Runkle, (1993). The generalized specification of TARCH (1,1) for the conditional variance is given by:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 \mathbb{I}_{t-1}^- \tag{13}$$

Where $\mathbb{I}_1^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In TARCH (1,) model, good news is given by $\varepsilon_{t-1} > 0$, and bad news is given by $\varepsilon_{t-1} < 0$. Good news has impact on α_1, while bad news has an impact of $\alpha_1 + \gamma$. If $\gamma > 0$, bad news produces more volatility, an indication of leverage effect. If $\gamma \neq 0$, the impact of news is asymmetric. The TARCH (1,1) model with dummy variable in the conditional variance is specified as:

$$h_t = \omega + \phi_1 d_1 + \cdots + \phi_n d_n + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma \varepsilon_{t-1}^2 \mathbb{I}_{t-1}^- \tag{14}$$

Lastrapes (1989) and Lamoreux & Lastrapes (1990) argued that when relevant random level shifts in variance are ignored in the standard GARCH variants, they tend to overestimate the persistence in volatility. Thus given the extended GARCH models which take these breakpoints identified by Bai and Perron multiple breakpoint test into consideration, the shock persistence (i.e., $\alpha_1 + \beta_1$) is predicted to be smaller than that found by the conventional GARCH models.

3.4 Estimation and Error Distributions of GARCH family Models

The estimates of GARCH process are obtained by maximizing the log likelihood function:

$$ln(L\theta_t) = -{}^1/_2 \sum_{t-1}^{T} \left(\ln 2\pi + lnh_t + \frac{\varepsilon_t^2}{h_t} \right) \quad (15)$$

This study employs two heavy-tailed distributions in the estimation of GARCH parameters. These distributions are optimally selected using information criteria and maximum log likelihood and are given by:

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

$$f(z) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)} \left(1 + \frac{z^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, -\infty < z < \infty \quad (16)$$

and the student-t distribution to the log-likelihood contributions is of the form:

$$l_t = \frac{1}{2}\log\left[\frac{\pi(v-2)\Gamma\left({}^v/_2\right)^2}{\Gamma\left({}^{(v+1)}/_2\right)}\right] - \frac{1}{2}\log h_t - \frac{(v+1)}{2}\log\left[1 + \frac{\left(y_t - X_t'\theta\right)^2}{h_t(v-2)}\right] (17)$$

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

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

$$f(z, \mu, \sigma, v) = \frac{\sigma^{-1} v e^{\left(-\frac{1}{2}\left|\frac{\left(\frac{z-\mu}{\sigma}\right)}{\lambda}\right|^v\right)}}{\lambda 2^{(1+(1/v))}\Gamma\left(\frac{1}{v}\right)}, 1 < z < \infty \quad (18)$$

$v > 0$ is the degrees of freedom or tail -thickness parameter and $\lambda = \sqrt{2^{(-2/v)}\Gamma\left(\frac{1}{v}\right)/\Gamma\left(\frac{3}{v}\right)}$ and the GED distribution to the log-likelihood contributions is given by:

$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma\left({}^1/_v\right)^3}{\Gamma\left({}^3/_v\right)\left({}^v/_2\right)^2}\right] - \frac{1}{2}\log h_t - \left[\frac{\Gamma\left({}^3/_v\right)\left(y_t - X_t'\theta\right)^2}{h_t\Gamma\left({}^1/_v\right)}\right]^{\frac{v}{2}} \quad (19)$$

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

4. RESULTS AND DISCUSSION

4.1 Summary Statistics and Normality Test for Return Series

To better understand the distributional characteristics of returns in Nigerian stock market for the different study sub-periods, summary statistics such as the daily mean, standard deviation, skewness, kurtosis as well as Jarque-Bera statistic are computed. The results of the summary statistics are reported in Table 1.

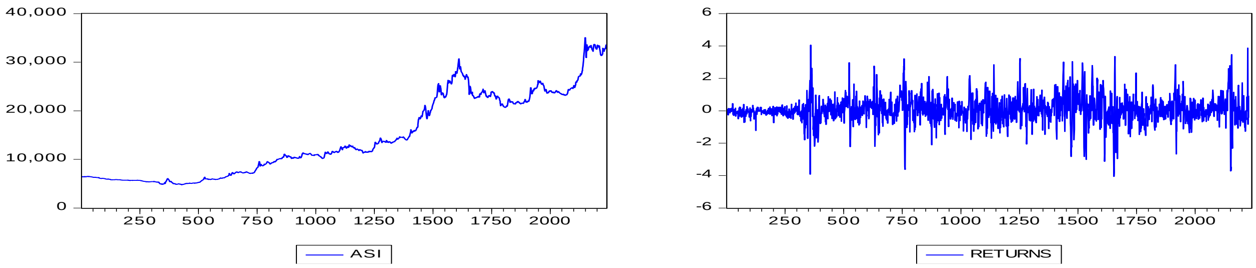
Table 1: Summary Statistics and Normality Test of Returns

Statistic	Pre-Crisis	Crisis Period	Post-Crisis	Full Period
Mean	0.0732	-0.0645	-0.0139	0.0183
Maximum	4.0549	11.2650	7.9750	11.2650
Minimum	-4.0584	-12.5494	-5.1965	-12.5494
Std. Dev.	0.8060	1.4604	1.0134	1.0098
Skewness	0.0577	-0.3186	0.1530	-0.1327
Kurtosis	6.8234	15.5419	8.1122	14.5455
Jarque-Bera	1364.99	4744.33	2143.07	27351.71
P-value	0.0000	0.0000	0.0000	0.0000
No. of Obs.	2239	722	1961	4922

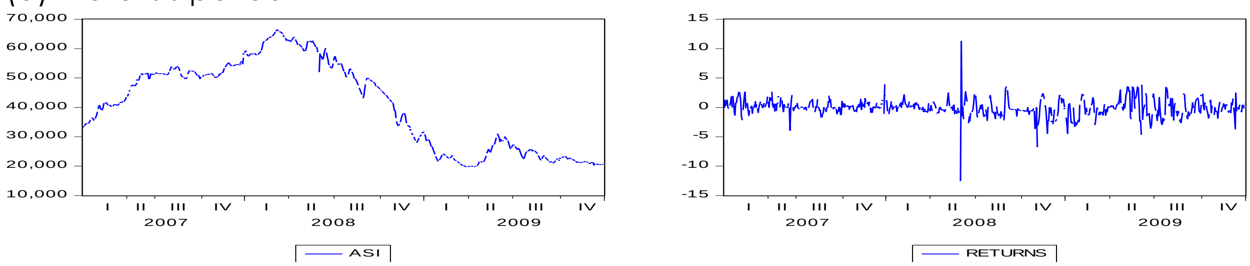
The summary statistics reported in Table 1 showed that the means of daily stock returns during the pre-crisis and the full study periods are positive indicating gains in the stock market for the trading sub-periods under review. The daily means of stock returns during the global financial crisis and post-crisis sub-periods are negative indicating losses in the stock market for the trading sub-periods. The positive standard deviations of stock returns for all sub-periods show the dispersion from the means and high level of variability of price changes in the stock market during the study periods. The summary statistics also show positive asymmetry for daily stock returns during the pre-crisis (skewness = 0.0577) and post-crisis (skewness = 0.1530) sub-periods and negative asymmetry for daily stock returns during the global financial crisis (skewness = -0.3186) and the full study period (skewness = -0.1327). The distributions of the return series are leptokurtic across the sub-periods as the kurtosis values are all very high. The Jarque-Bera test statistics gladly reject the null hypotheses of normality in the return series across the study sub-periods with the marginal p-values of 0.0000 in all series. Since the skewness of the return series is not zero, the kurtosis is greater than 3 and the Jarque-Bera statistic is very high with highly significant p-value across the study periods, it is a clear indication that the stock returns are non-Gaussian.

4.2 Graphical Examination of Stock Prices and Returns across Periods

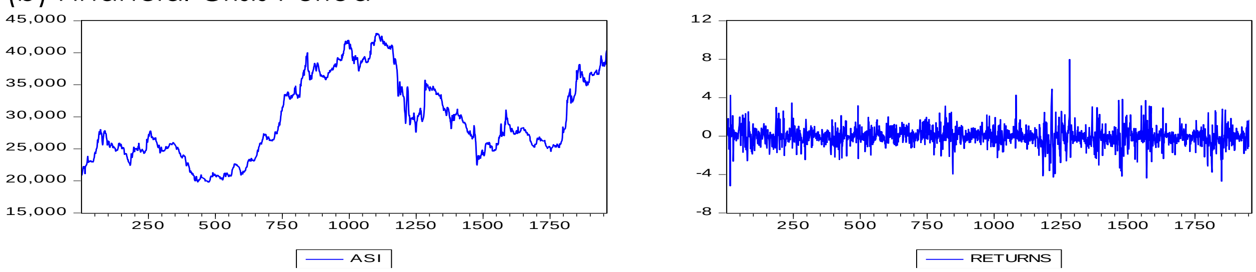
To examine the graphical properties of the return series, the original daily stock prices and returns are plotted against time. The plots are presented in Figure 1.



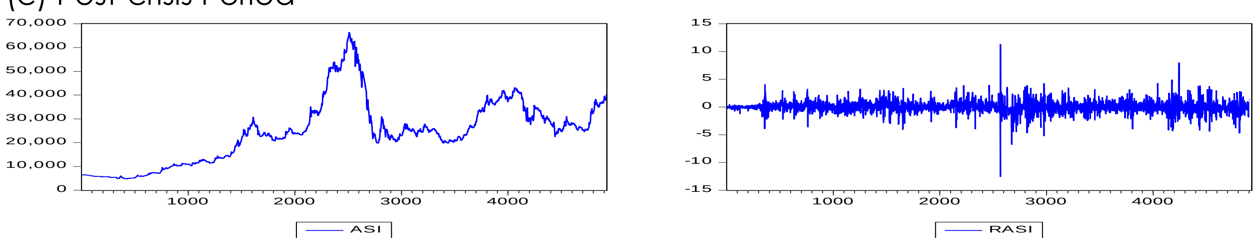
(a) Pre-crisis period



(b) Financial Crisis Period



(c) Post-crisis Period



(d) The Full study period

Figure 1: Time Plots of Daily Stock Prices & Returns across Study Periods

The plots of the daily share prices presented on the left part of Figure 1 appeared to contain trend components which suggest that the series are not covariance stationary. The plots of the daily stock returns presented on the right part of Figure 1 suggest that volatility clustering is quite evident across the sub-periods with less volatility clustering in the financial crisis sub-period and the return series appeared to be stationary. A series with some periods of low volatility and some periods of high volatility is said to exhibit volatility clustering. Volatility clustering implies that the error exhibits time-varying heteroskedasticity (unconditional standard deviations are not constant).

4.3 Unit Root and Stationarity Tests Results

The results of DF GLS unit root test together with KPSS stationarity test are presented in Table 2.

Table 2: Unit Root & Stationarity Test Results

Period	Variable	Option	DF GLS Unit Root Test		KPSS Test	Stationarity
			Test Stat	5% Critical value	Test Stat	5% Critical value
Pre-Crisis	ASI	Intercept only	2.4144	-1.9409	5.8005	0.4630
		Intercept & Trend	0.8480	-2.8900	1.6186	0.1460
	Returns	Intercept only	-25.3810	-1.9409*	0.0337	0.4630*
		Intercept & Trend	-23.5175	-2.8900*	0.0302	0.1460*
Crisis Period	ASI	Intercept only	0.5653	-1.9412	2.1009	0.4630
		Intercept & Trend	0.6205	-2.8900	0.5756	0.1460
	Returns	Intercept only	-12.4384	-1.9412*	0.0659	0.4630*
		Intercept & Trend	-12.3392	-2.8900*	0.0192	0.1460*
Post-Crisis	ASI	Intercept only	0.6109	-1.9409	1.5448	0.4630
		Intercept & Trend	-1.4936	-2.8900	0.6495	0.1460
	Returns	Intercept only	-31.6761	-1.9409*	0.0666	0.4630*
		Intercept & Trend	-31.4961	-2.8900*	0.0106	0.1460*
Whole Period	ASI	Intercept only	-0.1029	-1.9409	4.2018	0.4630
		Intercept & Trend	-1.5399	-2.8900	0.9106	0.1460
	Returns	Intercept only	-33.7507	-1.9409*	0.0654	0.4630*
		Intercept & Trend	-33.5202	-2.8900*	0.1188	0.1460*

Note: * denotes the significant of DFGLS unit root & KPSS stationarity tests statistics at the 5% significance levels.

The results of DF GLS unit root test and the KPSS stationarity test reported in Table 2 indicate that the daily closing market prices of the Nigerian stock market for the different sub-periods are non-stationary in level (contains unit root). This is shown by the DF GLS and KPSS test statistics being higher than their corresponding asymptotic critical values at the 5% significance levels. However, the DF GLS unit root and KPSS stationarity test results of the daily stock returns for all the sub-periods show evidence of covariance stationarity as the test statistics are all smaller than their corresponding asymptotic critical values at the 5% level of significance for both constant only and for constant and linear trend. Further analyses are therefore performed on the stationary stock return series.

4.4 Heteroskedasticity Test Results

Engle's LM heteroskedasticity test is employed in this study to check the presence of ARCH effects in the residuals of returns for the different periods under investigation. The results of the test are presented in Table 3.

Table 3: Heteroskedasticity Test Results

Period	Lag	F-statistic	P-value	nR^2	P-value
Pre-crisis	1	292.1740	0.0000	258.6261	0.0000
	30	12.9006	0.0000	333.2792	0.0000
Crisis Period	1	197.2762	0.0000	155.1869	0.0000
	30	9.0961	0.0000	202.1281	0.0000
Post-Crisis	1	117.5223	0.0000	110.9779	0.0000
	30	5.6557	0.0000	158.2980	0.0000
Whole Period	1	1357.541	0.0000	1064.307	0.0000
	30	57.6121	0.0000	1283.084	0.0000

The Engle's LM test results presented in Table 3 gladly rejects the null hypothesis of no ARCH effects in the residuals of stock returns for the different sub-periods in Nigerian stock market. This means that the errors are time varying and can only be modeled using heteroskedastic ARCH family models.

4.5 Model Order Selection for Symmetric and Asymmetric GARCH Models

In order to select the best fitting symmetric and asymmetric GARCH models with suitable error distribution, information criteria such as Akaike information criterion (AIC) due to (Akaike, 1974), Schwarz information criterion (SIC) due to (Schwarz, 1979) and Hannan Quinn criterion (HQC) due to (Hannan, 1980) in conjunction with log likelihoods (LogL) were employed. The best fitting model is one with largest log likelihood and minimum information criteria. Results are summarized in Table 4.

Table 4: Model Order Selection Using Information Criteria and Log Likelihood

Period	Model	Distribution	AIC	SIC	HQC	LogL
Pre-Crisis	GARCH (1,1)	GED	1.8709	1.8837	1.8756	-2089.504
	GARCH (1,1) M	GED	1.8680	1.8834	1.8736	-2085.281
	EGARCH (1,1)	GED	1.8566	1.8719	1.8622	-2072.438
	TARCH (1,1)	GED	1.8640	1.8793	1.8695	-2080.695
	GARCH (1,1)	STD	3.0489	3.0806	3.0611	-1095.650

Crisis Period	GARCH (1,1) M	STD	3.0496	3.0876	3.0643	-1094.891
	EGARCH (1,1)	STD	3.0550	3.0931	3.0697	-1096.872
	TARCH (1,1)	STD	3.0501	3.0882	3.0648	-1095.102
Post-Crisis	GARCH (1,1)	GED	2.5294	2.5437	2.5347	-2475.115
	GARCH (1,1) M	GED	2.5282	2.5453	2.5345	-2472.926
	EGARCH (1,1)	GED	2.5325	2.5496	2.5388	-2477.095
	TARCH (1,1)	GED	2.5303	2.5474	2.5366	-2474.979
Whole Period	GARCH (1,1)	STD	2.3310	2.3376	2.3333	-5731.658
	GARCH (1,1) M	STD	2.3302	2.3381	2.3330	-5728.582
	EGARCH (1,1)	STD	2.3193	2.3273	2.3221	-5701.908
	TARCH (1,1)	STD	2.3310	2.3389	2.3337	-5730.504

Table 4 shows results of different symmetric and asymmetric GARCH models with different error distributions selected for modeling volatility in Nigerian stock market for the sub-periods under study. The information criteria together with the log likelihood optimally selects symmetric GARCH (1,1) and GARCH (1,1)-M as well as asymmetric EGARCH (1,1) and TARCH (1,1) all with Generalized Error Distributions (GED) to model volatility in the pre-crisis and post-crisis sub-periods while symmetric GARCH (1,1) and GARCH (1,1)-M as well as asymmetric EGARCH (1,1) and TARCH (1,1) all with Student-t Distributions (STD) are selected to model volatility in Nigerian stock market during the global financial crisis sub-period and the full study period. The choice of lower GARCH models stems from the fact that GARCH (1,1) model is sufficient in capturing all volatility in any financial data. Supportive evidence for the choice of GARCH (1,1) model for measuring volatility are also provided by Hsieh (1989), Taylor (1994), Bekaert and Harvey (1997), Aggarwal et al. (1999), Brook and Burke (2003), Frimpong and Oteng (2006), Olowe (2009) as well as Al-Najjar (2016) among others.

4.5.1 Estimation Results of Volatility Models for the Study Sub-periods

To investigate the behaviour of stock return volatility in Nigerian stock market, we first consider the pre-crisis period (from January 1998 to December 2006) using two symmetric and two asymmetric GARCH models with GED innovation densities with the results presented in Table 5. Secondly, we consider the financial crisis period (from January 2007 to December 2009). Two symmetric and two asymmetric GARCH models with Student-t innovation densities were employed and the results are presented in Table 6. Thirdly, we estimate volatility for the post crisis period (from January 2010 to 9th January 2018), the symmetric and asymmetric GARCH models employed utilized the GED innovations and the results are presented in Table 7. Lastly, we estimate volatility for the full study period from (2nd January 1998 to 9th January 2018) using student-t distributions. The results for the full study period presented in Table 8 ignored structural breaks in the conditional variance while the results presented in Table 9 consider the effect of global financial crisis on Nigerian stock market by incorporating the detected breaks in the volatility models.

Table 5: Parameter Estimates of Volatility Models for Pre-Crisis Period (1998-2006)

Parameter	GARCH (1,1)	GARCH(1,1) M	EGARCH (1,1)	TARCH (1,1)
μ	-0.0028	-0.0433	-0.0017	-0.0009
	(0.0087)	(0.0173)	(0.0087)	(0.0088)
	[0.7449]	[0.0123]	[0.8442]	[0.9139]
ω	0.0063	0.0061	0.3297	0.0063
	(0.0018)	(0.0017)	(0.0265)	(0.0016)
	[0.0003]	[0.0002]	[0.0000]	[0.0001]
$\lambda\lambda$	---	0.0878	----	----
		(0.0375)		
		[0.0193]		
α_1	0.2819	0.2687	0.2634	0.3231
	(0.0307)	(0.0296)	(0.0330)	(0.0375)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\gamma\gamma$	---	----	0.0773	-0.1434
			(0.0176)	(0.0383)
			[0.0000]	[0.0002]
β_1	0.7176	0.7310	0.7563	0.7744
	(0.0184)	(0.0179)	(0.0076)	(0.0177)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
v	1.2608	1.2789	1.3006	1.2795
	(0.0435)	(0.0442)	(0.0405)	(0.0429)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\alpha_1 + \beta_1$	0.9995	0.9997	1.0197	----
$\alpha_1 + \beta_1 + 2/\gamma$	----	----	----	1.0258
ARCH Test	2.5912 [0.1076]	2.7573 [0.0969]	5.3286 [0.0921]	2.5094 [0.1133]
$Q^2(12)$	18.669 [0.0975]	18.836 [0.0932]	18.689 [0.0964]	19.972 [0.0968]

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

From the parameter estimates of volatility models presented in Tables 5, 6, 7, 8 and 9, all the coefficients in the conditional variance equations of the four GARCH models apart from the leverage effect parameters (γ) in the financial crisis period are highly statistically significant and satisfy the non-negativity constraints of the models. The positive and significant coefficients of the ARCH terms (α_1) and GARCH terms (β_1) clearly shows that stock market news about past volatility have explanatory power on current volatility. The models showed evidence of volatility clustering, leptokurtosis (fat-tails) and high shock persistence in Nigerian stock market. The sums of ARCH and GARCH terms are less than unity in the symmetric GARCH models (i.e., $\alpha_1 + \beta_1 < 1$) for the pre-crisis period indicating that the stationarity conditions for symmetric GARCH models are satisfied. Since the coefficients summed up to numbers less than one, which is required to have mean reverting variance processes and since the sums are very close to one, the processes only mean revert slowly and the conditional volatilities are less persistent. However, the sums of ARCH and GARCH terms for the asymmetric EGARCH and TARCH models in the pre-crisis period and for both symmetric and asymmetric models in the global financial crisis period are greater than unity (i.e., $\alpha_1 + \beta_1 > 1$) indicating that the stationarity conditions of the models are not satisfied. Since the sums of ARCH and GARCH terms are greater than one, the conditional variances are unstable and can eventually explode to infinity. The large values of GARCH (1,1) coefficients (β_1) in the four models during the crisis period show that shocks to conditional variances take a longer time to die off (an indication of long memory), so the volatility is highly persistent. Low values of ARCH (1) coefficients (α_1) suggest that large market surprises induce relatively small reversion in future volatility.

Table 6: Parameter Estimates of Volatility Models for the Crisis Period (2007-2009)

Parameter	**GARCH (1,1)**	**GARCH(1,1) M**	**EGARCH (1,1)**	**TARCH (1,1)**
μ	-0.0492	-0.1445	-0.0384	-0.0507
	(0.0312)	(0.0668)	(0.0314)	(0.0325)
	[0.1151]	[0.0306]	[0.2214]	[0.1185]
ω	0.1459	0.1528	0.6451	0.1458
	(0.0340)	(0.0354)	(0.0624)	(0.0340)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
λ	---	0.0891	----	----
		(0.0697)		
		[0.0102]		
α_1	0.7569	0.7542	0.9290	0.6689
	(0.1219)	(0.1231)	(0.0939)	(0.1425)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ	---	----	0.0191	-0.1573
			(0.0604)	(0.1785)
			[0.7518]	[0.3783]
β_1	0.3762	0.3692	0.7595	0.3803
	(0.0535)	(0.0546)	(0.0381)	(0.0533)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
v	6.0765	6.1600	6.5268	6.1381
	(0.7478)	(0.7602)	(0.8371)	(0.7874)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\alpha_1 + \beta_1$	1.1331	1.1234	1.6885	----
$\alpha_1 + \beta_1 + 2/\gamma$	----	----	----	0.9706
ARCH Test	0.0164 [0.8982]	0.0194 [0.8891]	0.1078 [0.7427]	0.0236 [0.8780]
$Q^2(12)$	0.6496 [1.0000]	0.6252 [1.0000]	0.8293 [1.0000]	0.7771 [1.0000]

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

For the post crisis period, the stationarity conditions for both symmetric and asymmetric GARCH models are satisfied. This indicates that the conditional variance of the stock returns during the post crisis period are stationary, stable, mean reverting and the conditional volatility is less persistent indicating faster reactions of volatility to market changes. For the full study period when the exogenous breaks are ignored, the stationarity conditions for all the models are not satisfied indicating that the conditional variance is unstable, unpredictable and the entire process is non-stationary. This indicates over persistence of volatility shocks with delayed reactions of volatility to market changes in Nigerian stock market which can eventually explode to infinity.

Table 7: Parameter Estimates of Volatility Models for Post-Crisis Period

Parameter	GARCH (1,1)	GARCH(1,1) M	EGARCH (1,1)	TARCH (1,1)
μ	-0.0299	-0.1469	-0.0343	-0.0308
	(0.0148)	(0.0569)	(0.0147)	(0.0149)
	[0.0434]	[0.0098]	[0.0198]	[0.0392]
ω	0.1181	0.1246	0.3212	0.1195
	(0.0236)	(0.0246)	(0.0337)	(0.0239)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
λ	---	0.1383	----	----
		(0.0685)		
		[0.0433]		
α_1	0.2560	0.2658	0.2088	0.2453
	(0.0387)	(0.0404)	(0.0455)	(0.0435)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ	---	----	-0.0102	0.0265
			(0.0247)	(0.0553)
			[0.0436]	[0.0326]
β_1	0.6417	0.6272	0.7881	0.6386
	(0.0432)	(0.0445)	(0.0247)	(0.0437)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
v	1.1077	1.0993	1.1043	1.1076
	(0.0429)	(0.0425)	(0.0436)	(0.0429)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\alpha_1 + \beta_1$	0.8977	0.8930	0.9969	----
$\alpha_1 + \beta_1 + 2/\gamma$	----	----	----	0.8707
ARCH Test	0.2312 [0.6308]	0.0967 [0.7558]	1.0301 [0.3103]	0.2084 [0.6481]
$Q^2(12)$	9.7698 [0.6361]	9.8624 [0.6287]	8.6165 [0.7358]	9.7422 [0.6395]

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

The estimated risk premium coefficients (λ) in the symmetric GARCH (1,1)-M models which indicates the risk-return relationship is positive and significant in all the study periods indicating that the conditional variance used as proxy for risk of returns is positively related to the level of returns. An implication of this result is that investors in Nigerian stock market should be compensated for holding risky assets. This result further suggests that the recent global financial crisis have not altered the market dynamics to distort the risk-return trade-off in Nigerian stock market indicating that expected returns are not driven by changes in the stock market volatility.

Table 8: Parameter Estimates of Volatility Models for the Full study Period

Parameter	GARCH (1,1)	GARCH(1,1) M	EGARCH (1,1)	TARCH (1,1)
μ	-0.0133	-0.0485	-0.0128	-0.0117
	(0.0082)	(0.0182)	(0.0081)	(0.0083)
	[0.1038]	[0.0077]	[0.1130]	[0.1577]
ω	0.0195	0.0197	0.3604	0.0184
	(0.0032)	(0.0032)	(0.0176)	(0.0030)
	[0.0000]	[0.0002]	[0.0000]	[0.0000]
λ	---	0.0592	----	----
		(0.0282)		
		[0.0357]		
α_1	0.3397	0.3431	0.4619	0.3532
	(0.0253)	(0.0255)	(0.0245)	(0.0294)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ	---	----	0.0269	-0.0439
			(0.0126)	(0.0308)
			[0.0329]	[0.1546]
β_1	0.7168	0.7143	0.9452	0.7231
	(0.0139)	(0.0140)	(0.0066)	(0.0136)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
v	4.8434	4.8440	5.1012	4.8647
	(0.3086)	(0.3091)	(0.3319)	(0.3095)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\alpha_1 + \beta_1$	1.0555	1.0574	1.4071	----
$\alpha_1 + \beta_1 + 2/\gamma$	----	----	----	1.0983
ARCH Test	0.1520 [0.6966]	0.1062 [0.7446]	0.2846 [0.5937]	0.2144 [0.6433]
$Q^2(12)$	8.2918 [0.7623]	8.4920 [0.7467]	7.1179 [0.8507]	7.6159 [0.8143]

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

The asymmetric (leverage) effect parameter (γ) captured by EGARCH and TARCH models are positive and negative respectively for the pre-crisis, during crisis and in the full study periods indicating the presence of asymmetry in the stock returns without leverage effects. This also shows that positive and negative shocks generate the same amount of volatility during the periods under review. However, the asymmetric (leverage) effect parameter (γ) captured by EGARCH and TARCH models are negative ($\gamma = -0.0102$) and positive ($\gamma = 0.0265$) respectively for the post-crisis study period indicating the presence of asymmetry with leverage effect in the stock returns. Since $\gamma \neq 0$, it shows that the news impact on volatility is asymmetric. This indicates that negative shocks (market retreats) increase the volatility of stock returns more than positive shocks (market advances) of the same magnitude during the post-crisis sub-period. This result is in conformity with the empirical findings of Olowe (2009) and Okpara (2011) that also found asymmetry and leverage effects in Nigerian Stock Market

4.5.2 Volatility Models for the Full Study Period with Dummy Variables

To account for the sudden shifts in variance in the stock returns and to investigate the impact of global financial crisis on Nigerian stock market, Bai and Perron (1998, 2003) multiple breakpoints testing procedure was employed to detect the date-wise breaks during the global financial crisis period. The detected structural breaks (result omitted) are considered in the volatility models by incorporating indicator (dummy) variable in the conditional variance equations. The results are presented in Table 9.

Table 9: Parameter Estimates of Volatility Models for the whole Study Period with Dummy Variables

Parameter	GARCH (1,1)	GARCH(1,1) M	EGARCH (1,1)	TARCH (1,1)
μ	-0.0071	-0.0723	-0.0071	-0.0047
	(0.0084)	(0.0185)	(0.0083)	(0.0085)
	[0.4012]	[0.0001]	[0.3913]	[0.5821]
ϕ	-0.2809	-0.3612	-0.2770	-0.2921
	(0.0386)	(0.0372)	(0.0402)	(0.0388)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
ω	0.0210	0.0222	0.3542	0.0202
	(0.0033)	(0.0035)	(0.0172)	(0.0032)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
λ	---	0.1116	----	----
		(0.0289)		
		[0.0001]		
α_1	0.2510	0.2643	0.2509	0.2742
	(0.0269)	(0.0278)	(0.0240)	(0.0317)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
γ	---	----	0.0402	-0.0676
			(0.0129)	(0.0331)
			[0.0018]	[0.0411]
β_1	0.6073	0.6398	0.6454	0.6135
	(0.0146)	(0.0147)	(0.0065)	(0.0142)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
v	4.7267	4.6509	4.9983	4.7484
	(0.2916)	(0.2817)	(0.3166)	(0.2915)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\alpha_1 + \beta_1$	0.8583	0.9041	0.8963	----

$\alpha_1 + \beta_1 + 2/\gamma$	----	----	----	0.8539
ARCH Test	0.0435 [0.8349]	0.0082 [0.9280]	0.0358 [0.8500]	0.0701 [0.7912]
$Q^2(12)$	3.0369 [0.9952]	2.1772 [0.9995]	3.7658 [0.9872]	2.5635 [0.9987]

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

By incorporating the detected structural breaks in the volatility models, there are significant decreases in the values of volatility shock persistence parameters (β_1) in all the estimated GARCH-type models. There are also significant reductions in the values of mean reversion rates ($\alpha_1 + \beta_1$) in all the estimated models. Also by including the structural breaks in these models, the stationarity and stability conditions of the models are satisfied as the sum of ARCH and GARCH terms are less than one in all the estimated models with breaks. This shows that the conditional variance process is stable and predictable and that the memories of volatility shocks are remembered in Nigerian stock market.

The estimated symmetric GARCH (1,1)-M model retain the positive risk-return trade-off and asymmetric models retain the asymmetric response property without the presence of leverage effects indicating that good and bad news have the same impact on volatility. This result corroborates the findings of Dikko et al. (2015) and Kuhe and Chiawa (2017). By comparing the performance of the estimated GARCH type models, the asymmetric TARCH (1,1) with student-t innovation density outperformed the symmetric GARCH (1,1), GARCH (1,1)-in- mean and asymmetric EGARCH (1,1) models in reducing the volatility shock persistence in Nigerian stock market.

The coefficients of the dummy variable (ϕ) is negative and statistically significant in all the estimated symmetric and asymmetric GARCH models suggesting that the global financial crisis which contaminated the stock return series have negatively affected the Nigerian stock market during the study period. The crash of the Nigerian stock market in 2009 was as a result of the negative impact of market shocks due to this crisis.

4.5.3 Post Estimation Test Results for ARCH Effects and Serial Correlation

To test for the remaining ARCH effects in the residuals of returns for the estimated GARCH models, Engle's LM test is employed; results for each estimated model across the sub-periods are presented in the lower panels of Tables 5, 6, 7, 8 and 9. The tests fail to reject the null hypotheses of no ARCH effects in the residuals of returns. This means that the estimated GARCH-type models are well specified and have captured all the remaining ARCH effects. This is clearly shown by the non-significant p-values of the F-statistics tests associated with the ARCH LM tests. The p-values of the Ljung-Box Q-statistics for squared residuals of returns are highly statistically insignificant across the sub-periods indicating the absence of serial correlations in the residuals of returns. These results also show that the estimated GARCH-type models are good, adequate, valid and accurate in describing the volatility situation in Nigerian stock market.

5. CONCLUSION AND POLICY IMPLICATIONS

This study examined the behaviour of stock returns volatility in the Nigerian stock market using GARCH family models in the context of Global Financial Crisis. The study utilized daily quotations of Nigerian stock exchange for the period from 2nd January 1998 to 9th January 2018. The data was further divided into three sub-periods of pre-crisis; Global Financial Crisis and the post-crisis periods. The study employed symmetric GARCH (1,1), GARCH (1,1)-M as well as asymmetric EGARCH (1,1) and TARCH (1,1) models with heavy-tailed distributions to estimate time varying volatility in the Nigerian stock market.

The empirical findings of the study showed the presence of autoregressive conditional heteroskedasticity (ARCH) effects, volatility clustering, leptokurtosis, high shock persistence and asymmetry across the study periods. The conditional volatility of the Global Financial Crisis sub-period experienced a significant increase as compared to the other sub-periods. The post crisis period showed less persistence to volatility shocks, presence of asymmetry with leverage effects and faster reactions of volatility to market changes. The entire study period also showed high persistence to volatility shocks and presence of asymmetry with absence of leverage effects. The high shock persistence which is associated with the financial crisis also contaminated the return series with structural breaks giving rise to long memory in the stock market. The high volatility persistence levels across the sub-periods means that shocks transmitted through the Nigerian stock market by market news, financial reforms, monetary and fiscal policies as well as financial and economic crises will affect the Nigerian stock market return volatility in the future.

However, when models were estimated with dummy variables for the detected structural breaks, there was significant reduction in shocks persistence and the long memory disappeared. These were indications of more accurate estimates. The coefficient of the dummy variable (ϕ) was negative and significant across all the estimated models indicating that the global financial crisis have affected the Nigerian stock market negatively. This study also found significant positive risk-return trade-off indicating that investors in Nigerian stock market should be highly compensated for holding risky assets.

According to the empirical findings of this study, estimation of volatility in Nigerian stock market should employ symmetric and asymmetric GARCH variants with heavy-tailed distributions while incorporating structural breaks in the conditional variance to avoid overestimation of shock persistence in variance. The findings of this study are very crucial and informative to both investors and traders who might want to invest in Nigerian stocks as well as policy makers in Nigerian stock market and Nigerian stock exchange because structural breaks caused by financial and economic crises can affect investors' decision in a stock market and failute to account for these structural breaks in the stock market may lead to wrong inferences and portfolio decisions by investors. Therefore, policy makers should take into account these regime changes in their financial policy design.

As a policy recommendation, continuous monitoring of volatility and other key characteristics in Nigerian stock market should be intensified and maintained by appropriate monetary policy organizations and research groups such as research departments in the Central Bank of Nigeria (CBN), Nigerian Stock Exchange (NSE), Nigerian Securities and Exchange Commission (SEC), Nigerian Bureau of Statistics, finance and economics research units in Nigerian Universities, financial institutions, stockbrokers, investment and financial analysts, so that signals to possible shifts in the characteristics could be identified and corrected before their full manifestation on the economy.

Inferences on shock persistence in volatility and long memory as revealed by this study are more likely to be episodic and may disguised the short memory property of stock market return series with structural breaks. Hence, caution should be taken when inferences on shock persistence in volatility and long memory are being interpreted in the presence of structural breaks.

The explosive nature of the Nigerian stock market suggests that good news or bad news could have permanent effect on future volatility. The high volatile nature of the Nigerian stock market signals huge threat to both local and foreign investors; hence consistent policy reforms to install investor's confidence in the market should be implemented by government.

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