Original Research Article

Estimating Stock Return Volatility and the Risk-Return Nexus in the Nigerian Stock Market in the Presence of Shift Dummies

ABSTRACT

Volatility and the trade-off between risk and return in stock markets is an important subject in financial theory which play significant role in investment decision making, portfolio selection, options pricing, financial stability, hedging and pair trading strategy among others. This study estimates stock return volatility and analyzes the risk-return trade-off in the Nigerian stock market using symmetric GARCH (1,1)-in-mean, asymmetric CGARCH (1,1)-in-mean and EGARCH (1,1)-in-mean models with Generalized Error Distribution and Student-t innovation. Data on daily closing all share prices of the Nigerian stock exchange for the period 2nd January, 1998 to 9th January, 2018 are utilized. The data is further divided into three sub-periods of pre-crisis, global financial crisis and post crisis periods to allow volatility behaviour and the risk-return trade-off to be investigated across the sub-periods. Results showed evidence of volatility clustering, leptokurtosis, high persistence of shocks to volatility and asymmetry without leverage effects across the study periods. The persistence of shocks to volatility increased during the global financial crisis period with delayed reactions of volatility to market changes. However, by incorporating the exogenous breaks into the volatility models for the full study period, the shock persistence drastically reduced with faster reactions of volatility to market changes. The results of this study also found supportive evidence for significant positive risk-return relationship in Nigerian stock market across various study sub-periods and model specifications meaning that investors in Nigerian stock market should be compensated for holding risky assets. The empirical findings of this study further suggest 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. The study provides some policy recommendations for investors and policy makers in the Nigerian stock market.

Keywords: Expected Returns, Financial Crisis, GARCH-in-Mean, Risk Premium, Trade-off, Volatility, Nigeria.

1. INTRODUCTION

The relationship between risk and return has become topical among academicians and investors following the early works of Merton [1, 2]. It is expected that risk and return should have a positive relationship since additional risk taken by investors are compensated through higher expected return. The Generalized Autoregressive Conditionally Heteroskedasticity-in-mean (GARCH-M) model proposed by [3] which allows the introduction of the conditional variance, or some function of it, as a regressor in the mean equation is the most commonly used model in evaluating the time-varying risk-return relationship [4, 5, 6].

Most of the previous works that investigated the risk-return tradeoff focused more on developed markets [(7, 8, 4, 5, 6, 9, 10, 11] while little attention has been given to emerging markets [12, 13]. The aim of this paper is to estimate stock return volatility and examine the risk-return nexus in the Nigerian stock market, one of the most active emerging stock market in West Africa. The objectives of the paper are as follows: (i) to examine the nature of shock persistence in Nigerian stock returns (ii) to investigate the nature of relationship that exists between risk and return in Nigerian stock market, and (iii) to investigate the impact of global financial crisis on the risk-return tradeoff in Nigerian stock market. The rest of the paper is organized as follows: Section 2 reviews relevant literature on the subject matter, section 3 presents data and methodology; section 4 focuses on results and discussion while section 5 hinges on conclusion and policy implications.

2. LITERATURE REVIEW

The empirical literature bordering on the risk-return tradeoff in both advanced and emerging stock markets have reported conflicting findings. For instance, [14] examined the intertemporal relationship between risk and return for the aggregate stock market using high-frequency data. They utilized daily realized, GARCH, implied, and range-based volatility estimators to determine the existence and significance of a risk–return trade-off for several stock market indices. The study found a positive and statistically significant relationship between the conditional mean and conditional volatility of market returns at the daily level. By analyzing the risk–return relationship over time using rolling regressions, strong positive relationships between risk and expected return was found to persist throughout the sample period. Jiranyakul [15] investigated the link between risk-return tradeoff in the Thai stock market using AR-GARCH-in-mean model on monthly data from January 1981 to December 2009. The author incorporated dummy variables in the conditional variance equations to capture the impact of the 1987 global stock market crash and the Asian 1997 financial crisis. The study found the existence of a positive risk-return tradeoff in the stock market of Thailand both in the capital gain and dividend excess returns. The shock persistence of excess return volatility also reduced in the presence of shift dummies.

In a similar vein, [16] employed GARCH-in-mean methodology to investigate the risk-return tradeoff of Jordan, Kingdom of Saudi Arabia (KSA), Kuwait and Morocco stock market prices. The tradeoff between expected returns and the conditional variance was found to be positive and significant in all the markets. This empirical finding showed that investors are rewarded for their exposure to more risk in these financial markets. Khan et al. [17] investigated the risk-return trade-off and volatility shock persistence, mean reversion as well as asymmetry and leverage effect on the Pakistani stock market using both aggregate and disaggregate monthly data for the period from 1998 to 2012. The study employed GARCH (1,1), asymmetric EGARCH and GARCH-M for pricing of risk. The study found positive risk-return relationship, high shock persistent, mean reverting and little evidence of asymmetry and leverage effect in both the aggregate and disaggregates data. Abonongo et al. [18] modelled the volatility and investigated the risk-return relationship of some selected stocks on the Ghana Stock Exchange using symmetric and asymmetric GARCH-M (1,1) family models with Normal, Student-t and GED distributions. All the stocks were found to be extremely volatile with evidence of leverage effects. The results also indicated the existence of positive risk premium meaning that investors were compensated for holding risky assets. See also the empirical works of [7, 8, 4, 5, 6] that have also reported positive relationships between risk and return across different stock markets.

On the contrary, other empirical findings have reported a negative relationship between risk and return. For example, Ali et al. [19] investigated the risk-return nexus in the South African stock market using weekly, monthly and quarterly data covering the period from 1973 to 2011. They employed three different GARCH models in conjunction with a plain vanilla time-series approach. Similar to the findings of [10 & 20], their results failed to support a significantly positive risk-return relationship in South Africa across various data frequencies and model specifications. Their results further suggested that the 2007-2009 global financial crises might have altered market dynamics and distorted the risk-return relation in the South African stock market. By employing GARCH (1,1)-M and EGARCH(1,1)-M models on the daily data over the period of January 1, 2006 to December 30, 2011, [21] also found empirical evidence in support of a significant negative relationship between expected returns and conditional volatility for the Sudanese stock market.

Ramadan [22] tested the conditional relationship between risk and expected return in Amman Stock Exchange (ASE) using GARCH model specification, the result of the study did not support the trade-of-theory but concluded that the ASE was not efficient at the semi-strong level of efficiency. By using GARCH family models, [23] similarly found the presence of leverage effect as well as negative risk-return tradeoff in the region of Central and Eastern Europe. Negative relationships between risk and return were also reported by [9, 10 & 11].

In Nigeria, [24] empirically investigated the risk-return dynamics of some selected Nigerian quoted firms using monthly data for the period of January, 2000 to December, 2004. They employed Ordinary Least Squares (OLS) regression in estimating the systematic risk of each of the firm, while market model was used to estimate returns of each firm. Results revealed that the sizes of risks varied positively with the sizes of returns across the firms investigated. This result was similar to the findings of [25 & 26]. Lawal et al. [27] used GARCH-in-mean and EGARCH models to examine the links between mean returns and its volatility on the Nigeria commercial banks portfolio investments. The premium risk parameter estimated from the GARCH-in-mean model showed a positive and significant relationship between commercial bank portfolio return and volatility, whereas the EGARCH model produced a negative relationship.

3.0 MATERIAL AND METHODS

3.1 Data and data transformation

The data utilized 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. The data is further divided into three sub-periods of pre-crisis (1st January, 1998 – 30th December, 2006), global financial crisis (1st January, 2007 – 30th December, 2009) and post crisis (1st January, 2010 – 9th January, 2018) periods to allow volatility behaviour and the risk-return trade-off to be investigated across the sub-periods. The daily 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).

3.2 Unit Root and Heteroskedasticity Tests

This study employs Dickey-Fuller Generalized Least Squares (DF GLS) unit root and Kwaitkowski, Philips, Schmidt and Shin (KPSS) tests to check the unit root and stationarity properties of the daily stock prices and returns across the study periods. Details about these tests are provided by [28 & 29]. To test for heteroskedasticity or ARCH effect, the Lagrange Multiplier test proposed by [30] was employed.

3.3 Model Specification

The following conditional heteroskedasticity models are specified for this study. While the basic GARCH-in-mean model captures the symmetric properties of returns as well as risk-return trade-off, the CGARCH-in-mean and EGARCH-in-mean models capture the asymmetric characteristics of returns as well as risk-return relationship. The choice of lower GARCH models stems from the fact that GARCH (1,1) model is sufficient for capturing all volatilities present in any financial data and also producing the desired relationship between risk and expected returns. For evidence see the works by [31, 32, 33, 34, 35, 36, 37, 38] among others.

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

Engle et al. [3] proposed the GARCH-in-mean model which 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 is specified as:

$$r_t = \mu + \lambda h_t + \varepsilon_t, \qquad \varepsilon_t = \sigma_t e_t \qquad (2)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (3)$$

where r_t is the stock market return at time t, μ and ω are constants, λ is the risk premium parameter. A positive λ indicates that the return is positively related to its past volatility. ε_t is the error term, h_t is the volatility, α_1 and β_1 are the ARCH and GARCH terms respectively. The parameters α_1 and β_1 must satisfy the stationarity conditions such that $\alpha_1 > 0, \beta_1 > 0$ and $(\alpha_1 + \beta_1 < 1)$. When $(\alpha_1 + \beta_1 > 1)$, the GARCH (1,1)-M model explodes indicating non-stationarity and unpredictability of the conditional variance. The symmetric GARCH (1,1)-M model which incorporates structural breaks in the conditional variance is given by:

$$h_t = \omega + \phi_1 D_1 + \cdots + \phi_n D_n + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \qquad (4)$$

where $D_1, \ldots, D_n$ are shift dummies 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.

3.3.2 The Component GARCH (CGARCH) Model

Consider the variance equation of the famous basic GARCH (1,1) model:

$$h_t = \bar{\omega} + \alpha(\varepsilon_{t-1}^2 - \bar{\omega}) + \beta(h_{t-1} - \bar{\omega}) \quad (5)$$

This equation shows mean reversion to a constant, $\bar{\omega}$ at all times. In contrast, the component GARCH model introduced by [40] shows mean reversion to a varying level q_t. The transitory component is specified as:

$$h_t - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) \quad (6)$$

while the long run (permanent) component is specified as:

$$q_t = \omega + \rho(q_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (7)$$

where h_t is volatility and q_t is the time varying long run volatility. The transitory component converges to zero with powers of $(\alpha + \beta)$. The long run component converges to ω with powers of ρ, which lies between 0.99 and 1 so that q_t approaches ω very slowly. The transitory and permanent equations (6) and (7) can be combined to give a two-component GARCH (CGARCH(2)) model as:

$$h_t = (1 - \alpha - \beta)(1 - \rho)\omega + (\alpha + \varphi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha + \beta)\varphi)\varepsilon_{t-2}^2 + (\beta - \varphi)h_{t-1} - (\beta\rho - (\alpha + \beta)\varphi)h_{t-2} \quad (8)$$

Equation (8) shows that the CGARCH(2) model is a nonlinear restricted version of the basic GARCH (2,2) model.

In this work, we utilize an asymmetric CGARCH(2) model by including a threshold term. This model combines the component GARCH model with the asymmetric TARCH model. This specification introduces asymmetric effects in the transitory equation. The model is called Asymmetric Component GARCH model (ACGARCH) and is given by:

$$r_t = x_t'\pi + \varepsilon_t \quad (9)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \varphi(\varepsilon_{t-1}^2 - h_{t-1}) + \theta_1 z_{1t} \quad (10)$$

$$h_t - q_t = \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \gamma(\varepsilon_{t-1}^2 - q_{t-1})D_{t-1} + \beta(h_{t-1} - q_{t-1}) + \theta_2 z_{2t} \quad (11)$$

where z_{1t} and z_{2t} are the exogenous variables and *D* is the dummy variable indicating negative shocks. $\gamma > 0$ indicates the presence of transitory leverage effects in the conditional variance.

3.3.3 The Exponential GARCH (EGARCH) Model

Nelson [41] developed asymmetric EGARCH model to capture asymmetry and leverage effect in financial data. The EGARCH model captures asymmetric responses of the time-varying volatility to shocks and, at the same time, ensures that the variance is always positive. The mean and conditional variance equations of the EGARCH(1,1)-in-mean model are respectively specified as follows:

$$r_t = \mu + \lambda h_t + \varepsilon_t, \qquad \varepsilon_t = \sigma_t e_t \quad (12)$$

$$\ln(h_t) = \omega + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \ln(h_{t-1}) \quad (13)$$

where ω is the mean level, α_1 is the ARCH term, β_1 is the GARCH term which measures persistence and γ is the leverage effect parameter. If γ is negative, then leverage effect exists. If α_1 is positive, then the conditional volatility tends to rise (fall) when the absolute value of the standardized residuals is larger (smaller). The conditional variance of the EGARCH (1,1)-M model with shift dummies is given by:

$$\ln(h_t) = \omega + \phi_1 D_1 + \cdots + \phi_n D_n + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \ln(h_{t-1}) \quad (14)$$

3.4 Estimation and Error Distributions for GARCH family Models

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

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

The two error distributions employed in the estimation of parameters in this work are given by:

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

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

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:

$$f(z,\mu,\sigma,v) = \frac{\sigma^{-1} v e^{\left(-\frac{1}{2}\left|\frac{\left(\frac{z-\mu}{\sigma}\right)}{\lambda}\right|^{v}\right)}}{\lambda 2^{(1+(1/v))}\Gamma\left(\frac{1}{v}\right)}, 1 < z < \infty \quad (17)$$

$v > 0$ is the degrees of freedom or tail -thickness parameter and $\lambda = \sqrt{2^{(-2/v)}\Gamma\left(\frac{1}{v}\right)/\Gamma\left(\frac{3}{v}\right)}$

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

4.0 RESULTS AND DISCUSSION

4.1 Summary Statistics and Normality Test for Return Series

The summary statistics as well as normality measures of returns across the study periods are computed and reported in Table 1.

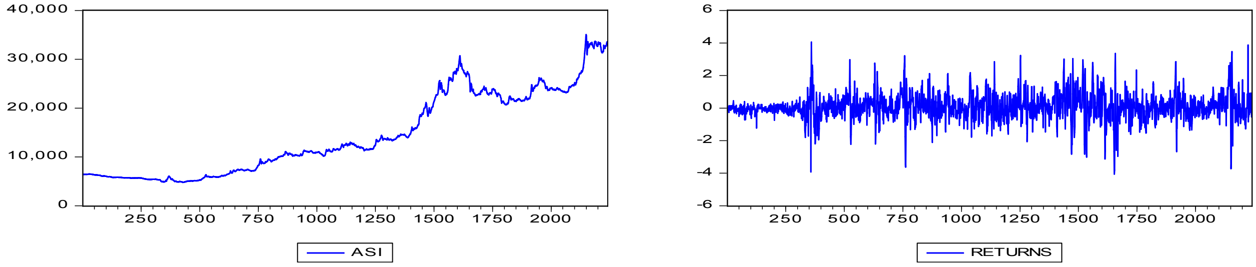
Table 1: Summary Statistics and Normality Test of Returns

Statistic	Pre-Crisis	Crisis Period	Post-Crisis	Full Period
Mean	0.0732	-0.0645	-0.0139	0.0183
Range	8.1133	23.8144	13.1715	23.8144
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

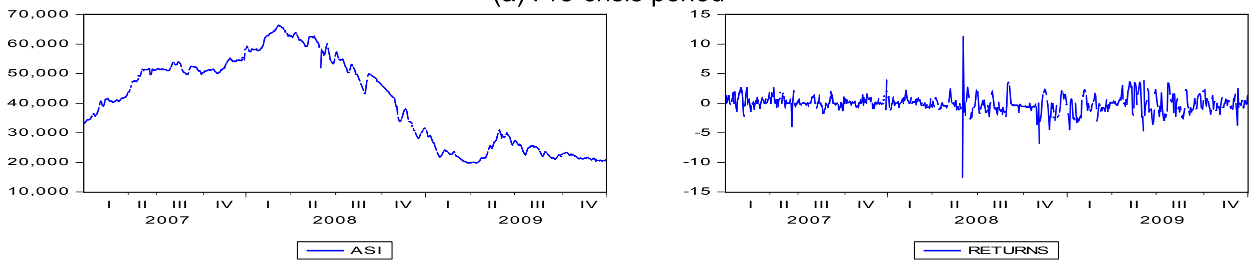
The summary statistics reported in Table 1 showed that the means of daily stock returns during the pre-crisis and the full study periods are positive indicating gains in the stock market for the trading sub-periods under investigation. The daily means of stock returns during the global financial crisis 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. This clearly shows that the stock returns are not normally distributed.

4.2 Graphical Examination of Stock Prices and Returns across Periods

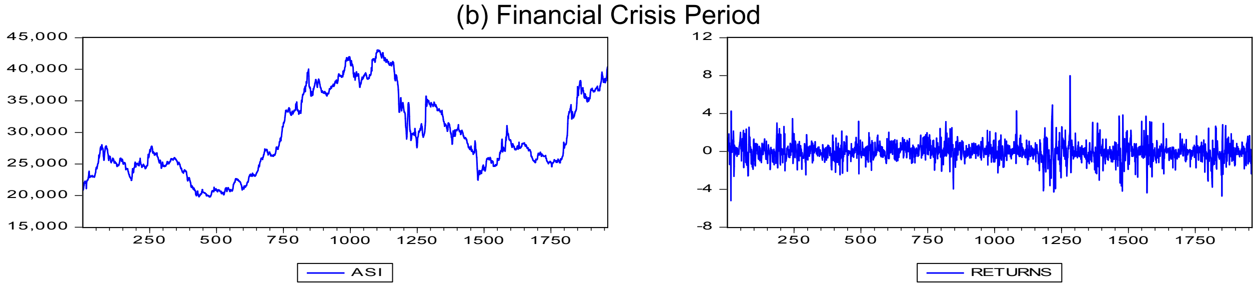
In order to examine the graphical features of the return series, the original daily stock prices and returns are plotted against time. The plots are presented in Figure 1.



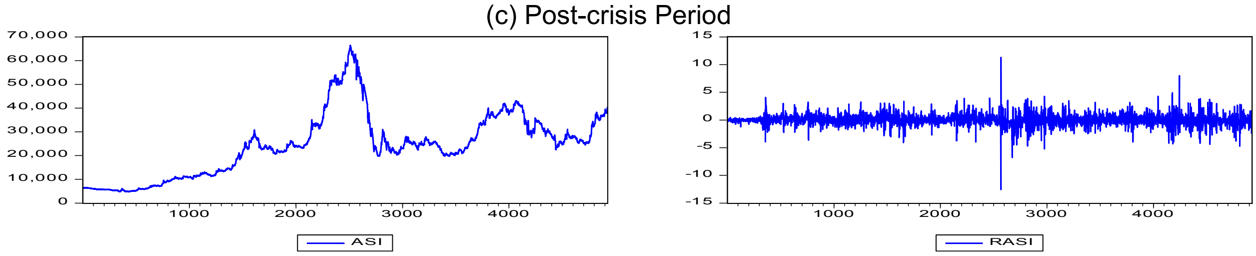
(a) Pre-crisis period



(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 side 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 side 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). We further investigate the stationarity of the series using unit root and stationarity tests.

4.3 Unit Root and Stationarity Test Results

The results of DF GLS unit root and KPSS stationarity tests are presented in Table 2.

Table 2: Unit Root & Stationarity Test Results

Period	Variable	Option	DF GLS Unit Root Test		KPSS Stationarity Test	
			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 and KPSS stationarity tests presented in Table 2 indicate that the daily closing stock 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 test results show evidence of weak stationarity for the daily stock returns across all the study periods 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.

4.4 Heteroskedasticity and Serial Correlation Test Results

Engle's LM heteroskedasticity and Ljung-Box Q-statistic tests are employed to check the presence of ARCH effects and serial correlation in the residuals of returns for the different periods under investigation. The results of the tests are presented in Table 3.

Table 3: Heteroskedasticity and Serial Correlation Test Results

Period	F-statistic	P-value	Q-Statistic	P-value
Pre-crisis	292.1740	0.0000	20.8435	0.0000
Crisis Period	197.2762	0.0000	18.7854	0.0000
Post-Crisis	117.5223	0.0000	23.9732	0.0000
Full Period	1357.541	0.0000	21.0927	0.0000

The Engle's LM and Ljung-Box Q-statistic tests presented in Table 3 gladly reject the null hypotheses of no ARCH effects and no serial correlation in the residuals of stock returns for the different sub-periods in Nigerian stock market. This indicates the presence of ARCH effects and serial correlation in the residuals of stock returns. GARCH family models are therefore the most appropriate models in this situation.

4.5 Models Estimation Results and Diagnostic Checks

We first estimate stock return volatility and the risk-return relationship across the study sub-periods. The results for the pre-crisis period, crisis period, post crisis period and the full study period are reported in Tables 4, 5, 6 and 7 respectively.

Table 4: Estimation Results of Volatility Models and Risk-Return Nexus for the Pre-Crisis Period

Coefficients	GARCH (1,1)-M	CGARCH (1,1)-M	EGARCH (1,1)-M
Conditional Mean Equation			
[illegible]	-0.0433*	-0.0549*	-0.0662*
[illegible]	0.0878*	0.1173*	0.1679*
Conditional Variance Equation			
[illegible]	0.0061*	0.6425*	0.3254*
[illegible]	0.2782*	0.0379*	0.3810*

[illegible]	0.7610*	0.5340*	0.9590*
[illegible]	----	-0.9994*	0.0988*
[illegible]	----	0.3133*	----
[illegible]	1.2789*	1.3998*	1.3277*
[illegible]	1.0392	0.5719	1.3400
ARCH LM Test	0.0969	0.7612	0.8832

231 Observe that from the parameter estimates of volatility models presented in Tables 4, 5, 6, 7 and 8, all the coefficients in the mean and conditional variance equations of the four GARCH models 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 greater than unity (i.e., $\alpha_1 + \beta_1 > 1$) in the symmetric GARCH-in-mean models for the pre-crisis, global financial crisis and full study periods. The asymmetric EGARCH-in-mean model also exhibit this similar characteristics for the pre-crisis and full study periods indicating that the stationarity conditions of GARCH (1,1)-M and EGARCH (1,1)-M models for these study periods are satisfied.

Table 5: Estimation Results of Volatility Models and Risk-Return Nexus for the Crisis Period

Coefficients	GARCH (1,1)-M	CGARCH (1,1)-M	EGARCH (1,1)-M
Conditional Mean Equation			
[illegible]	-0.1445*	-0.0847*	-0.0708*
[illegible]	0.4891*	0.4357*	0.5680*
Conditional Variance Equation			
[illegible]	0.1528*	0.8109*	0.0043*
[illegible]	0.7542*	0.2225*	0.2083*
[illegible]	0.3692*	0.4061*	0.6281*
[illegible]	----	-0.9989*	0.1021*
[illegible]	----	0.4085*	----
[illegible]	6.1600*	6.7833*	2.7104*
[illegible]	1.1234	0.6286	0.8364
ARCH LM Test	0.8891	0.9312	0.7684

When the sums of ARCH and GARCH terms are greater than one, the conditional variances become unstable and eventually explode to infinity. This indicates over persistence of volatility shocks with delayed reactions of volatility to market changes. When this happens, shocks to conditional variances take a longer time to die off (an indication of long memory).

The asymmetric EGARCH (1,1)-M is weakly stationary in the financial crisis sub-period. All the estimated models are stationary in the post crisis sub-period. 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. The CGARCH (1,1) model exhibit stationarity characteristics throughout the study periods with less persistence of shocks to volatility

Table 6: Estimation Results of Volatility Models and Risk-Return Nexus for the Post-Crisis Period

Coefficients	GARCH (1,1)-M	CGARCH (1,1)-M	EGARCH (1,1)-M
Conditional Mean Equation			
[illegible]	-0.1469*	-0.1259*	-0.2096*
[illegible]	0.1383*	0.1141*	0.2093*
Conditional Variance Equation			
[illegible]	0.1246*	1.1505*	0.3250*
[illegible]	0.2658*	0.1361*	0.0177*
[illegible]	0.6272*	0.4314*	0.8749*
[illegible]	----	-0.9491*	0.4132
[illegible]	----	0.1667*	----
[illegible]	1.0994*	1.1137*	1.0960*

$\alpha_1 + \beta_1$	0.8930	0.5675	0.8926
ARCH LM Test	0.7558	0.7707	0.3299

The estimated risk premium coefficients (λ) in the symmetric GARCH (1,1)-M, CGARCH (1,1) and EGARCH (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.

The asymmetric (leverage) effect parameter (γ) captured by CGARCH-M and EGARCH-M models are negative and positive respectively for all the study periods indicating the presence of asymmetry in the stock returns with the absence of leverage effects. This shows that positive and negative shocks generate the same amount of volatility during the study periods under review. Since $\gamma \neq 0$, it shows that the news impact on volatility is asymmetric.

Table 7: Estimation Results of Volatility Models and Risk-Return Nexus for the Full Study Period

Coefficients	GARCH (1,1)-M	CGARCH (1,1)-M	EGARCH (1,1)-M
Conditional Mean Equation			
[illegible]	-0.0506*	-0.0411*	-0.0568*
[illegible]	0.0686*	0.0628*	0.0949*
Conditional Variance Equation			
[illegible]	0.0184*	0.1114*	0.3518*
[illegible]	0.3386*	0.0219*	0.4495*
[illegible]	0.7178*	0.5566*	0.9488*
[illegible]	----	-0.9999*	0.0488
[illegible]	----	0.3251*	----
[illegible]	4.8733*	6.1067*	5.1609*
$\alpha_1 + \beta_1$	1.0564	0.5785	1.3983
ARCH LM Test	0.7665	0.9291	0.5895

4.5.1 Estimation of Volatility for the Full Study Period with Shift Dummies

To investigate the impact of global financial crisis on the risk-return tradeoff in the Nigerian stock market, we introduce shifts dummies in conditional variance of returns during the global financial crisis period (1st January, 2007 – 30th December, 2009) while estimating volatility for the full study period. The result is presented in Table 8.

Table 8: Estimation Results of Volatility Models and Risk-Return Nexus for the Full Study Period with Exogenous Breaks

Coefficients	GARCH (1,1)-M	CGARCH (1,1)-M	EGARCH (1,1)-M
Conditional Mean Equation			
[illegible]	-0.0723*	-0.0503*	-0.0808*
[illegible]	0.1116*	0.0879*	0.1512*
[illegible]	-0.3612*	-0.2755*	-0.3976*
Conditional Variance Equation			
[illegible]	0.0222*	0.4364*	0.3585*
[illegible]	0.2643*	0.0158*	0.2591*
[illegible]	0.6983*	0.5617*	0.7247*
[illegible]	----	-0.9999*	0.0688
[illegible]	----	0.3421*	----
[illegible]	4.6509*	5.8699*	4.8769*
$\alpha_1 + \beta_1$	0.9626	0.5775	0.9838
ARCH LM Test	0.9280	0.9633	0.9384

By introducing shift dummies in the volatility models, the shock persistence parameter (β_1) in all the estimated GARCH-in-mean models have reduced significantly. There are also significant reductions in the values of the mean reversion rates ($\alpha_1 + \beta_1$) in all the estimated models thereby satisfying the stationarity and stability conditions of the models. 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 coefficients of the dummy variable (ϕ) is negative and statistically significant in all the estimated 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 estimated GARCH models retain the positive risk-return trade-off and asymmetric models retain the asymmetric response property without the presence of leverage effects. This result agrees with the empirical findings of [42 & 43]. By comparing the performance of the estimated GARCH-in-mean models, the asymmetric component GARCH (1,1)-M outperformed the symmetric GARCH (1,1)-M and asymmetric EGARCH (1,1)-M models in reducing the volatility shock persistence in Nigerian stock market more gladly. 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.

The Engle's LM test for the remaining ARCH effects in the residuals of returns for the estimated GARCH models across the sub-periods are presented in the lower panels of Tables 4, 5, 6, 7 and 8. The test results failed to reject the null hypotheses of no ARCH effects in the residuals of returns indicating that the estimated GARCH-in-mean models have captured all the remaining ARCH effects.

5. CONCLUSION AND POLICY IMPLICATION

This study has attempted to model volatility and empirically examined the risk-return relationship in the Nigerian stock market using daily closing all share index (ASI) for the period of January 2, 1998 to January 9, 2018. The data was further divided into three sub-periods of pre-crisis, global financial crisis and post crisis periods to allow volatility behaviour and the risk-return trade-off to be investigated across the sub-periods. The paper employed GARCH-M, CGARCH-M as well as the asymmetric EGARCH-M models with and without shift dummies to model volatility and investigate the risk-return nexus in Nigerian stock market. The empirical results of the paper provides strong evidence that the daily returns are well characterized by the GARCH models; the NSE data showed a significant departure from normality and the existence of heteroskedasticity in the residuals returns. Based on the three estimated models, results showed evidence of volatility clustering, leptokurtosis, high persistence of shocks to volatility and asymmetry without leverage effects across the study periods. The persistence of shocks to volatility increased during the global financial period with delayed reactions of volatility to market changes. However, when the exogenous breaks were incorporated into the volatility models for the full study period, the shock persistence drastically reduced with faster reactions of volatility to market changes. The paper also reports a significant positive relationship between conditional volatility (risk) and expected return across the study periods and model specifications, a result which is consistent with the theory of a positive risk premium on stock indices which states that higher returns are expected for assets with higher level of risk. This result indicates that investors in Nigerian stock market are compensated for holding risky assets. The empirical findings of this study further suggest 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. The asymmetric component GARCH-in-Mean model provided superior results among the competing GARCH models with less volatility shock persistence across sub-periods.

Based on the results obtained from this study, it can be concluded that the conflicting results from the previous studies may be due to the type of financial data used or strong linear assumptions when modeling the risk–return trade-off. We argue that these previous evidence can only be viewed as being partial evidence that fails to cover the global behavior of the relation between risk and return. As a policy implication, volatility measures in Nigerian stock market should consider structural breaks caused by the global financial and economic crises in the conditional variance. Stock market operators should consider these regime shifts in their policy design while compensating the investors heavily for holding risky assets.

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