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# Measuring the financial risk exposure of the Nigerian commercial banks share prices in the presence of innovation densities

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## Abstract

*Volatility modelling as a tool for measuring financial risk exposure as well as uncertainty is an important tool for many financial and economic applications. Banks and other financial institutions often make volatility assessment as a mean of monitoring their level of financial risk exposure. This study measures the level of financial risk exposure of some selected Nigerian commercial banks stock prices using symmetric and asymmetric GARCH models with non-Gaussian errors. The study utilised daily closing share prices of thirteen selected commercial banks listed on the Nigerian stock exchange (NSE) from 17/02/200 to 24/06/2016. The study employed Ng-Perron modified unit root test, Engle's Lagrange Multiplier test for ARCH effect, GARCH (1,1), GARCH (1,1)-M, EGARCH (1,1) and TARCH (1,1) models with student's-t and Generalized Error Distribution (GED) as methods of analysis. Result showed that the banking stock returns were stationary with non-normality behaviour and the residuals of returns were found to be heteroskedastic. All the estimated GARCH models were found to be stable, stationary and mean reverting. The volatility shocks were quite persistence and the news impact on the conditional variance was asymmetric across the banking stock returns. The study found mixed positive and negative tradeoff relationship between risk and the expected return across the banking stocks. Leverage effects were found to exist in seven commercial banks while there were no leverage effects in six commercial banks. The levels of financial risk exposure of the thirteen selected Nigerian commercial banks were found to be minimal and tolerable as each banking stock return mean reverts to its long-run average level. The study recommended some policy implications for both investors and policy makers.*

**Keywords:** Asymmetry, leverage effect, market news, Nigerian banks, risk, volatility.

## Introduction

The Nigerian Banking industry has witnessed significant changes since the last two decades. The growth of internet banking, automated teller machine (ATM) network, electronic transfer of funds as well as quick diffusion of information have been facilitated through innovations and advancement in information and communication technology (ICT). The impact of internet economy and digitalization on the banking industry in Nigeria has increased retail banking and the use of e-banking channels which further improves financial inclusion. The Central Bank of Nigeria (CBN), recently reported that the total value of electronic payment transactions which was N62.7 trillion recorded in 2016 rose by 32.5 percent to N83.1 trillion in 2017.

The 2004 structural reforms in the Nigerian banks have improved the health of the banking industry, raised efficiency and transparency in the banking system. The improvements in the Nigerian banking system especially loan recoveries have helped the industry to record better profits. The effect of these changes and innovations is crucial to the stock prices of the Nigerian commercial banks. In addition, there are large variations in the information content of the bank stock price, measured by the extent to which bank stocks synchronize with the whole markets[1].

Volatility modeling as a measure of financial risk exposure and uncertainty has been gaining attention from scholars, academia, financial analysts and researchers across the globe in recent times due to its significance in many financial and economic applications including options trading, financial risk management, portfolio selection, equity pricing as well as pair trading strategy. The accuracy in the estimated parameters as well as the efficiency in interval forecast can also be improved when the variance of the errors are modeled accurately[2]. The fact that volatility of financial asset cannot be observed directly makes many financial analysts to be keenly interested in obtaining accurate estimates of the conditional variance so as to improve portfolio selection, risk management and valuation of financial derivatives[3]. Banks and other financial institutions often make volatility assessment as part of monitoring their financial risk exposure[4].

An in-depth understanding of stock return behaviour and stock market risk is crucial to emerging stock markets which consists of risk averse investors. This is because investors would always demand for high risk premium due to the high degree of volatility (risk) presence in emerging stock markets. This would create a higher cost of capital, which impedes investment and slows economic growth and development.

The Autoregressive Conditional Heteroskedasticity (ARCH) model which was introduced by Engle R.F.[5], the Generalized ARCH (GARCH) model extended by Bollerslev T.[6], the GARCH-in-mean (GARCH-M) model of Engle R. et al.[7], the exponential GARCH model due to Nelson D.B.[8] and the threshold ARCH (TARCH) model introduced by Glosten L. et al.[9] and Zakoian, J.M.[10] among others are some of the most widely used heteroskedastic models in assessing the level of risk exposure (volatility) of financial stock returns. While the basic ARCH and GARCH models are used in capturing the symmetric properties of returns, the basic GARCH-M model is used for investigating the tradeoff between risk and expected return on investment. The asymmetric EGARCH and TARCH models are employed in capturing asymmetry as well as leverage effects in the stock returns. Several empirical evidences in recent financial literature found support for the GARCH-type models in modeling volatility of financial asset. This study therefore utilizes the lower GARCH family models in measuring the financial risk exposure of the banking stock returns of the daily closing shares prices of thirteen selected commercial banks listed on the Nigerian stock exchange (NSE).

Several documented evidence are found in literature regarding volatility modeling of banking stock returns across the globe. Murari[1] employed ARIMA (1,0,2) model to make short term forecast of volatility in the Indian banking stock returns to assist investors as well as speculators in making their short-run buying and selling decisions for the bank stocks. Ekta and Rajkumar[11] employed GARCH models to study the volatility behaviour of 18 commercial banks in India using their daily share prices from 1st January, 2008 to 10th April, 2012. Results showed that all the banks stock returns exhibited time-varying volatility with evidence of volatility clustering and high shock persistence. Mohit[12] assessed the volatility behaviours of stock returns of the banks in India using GARCH (1,1) model. The empirical findings indicated high shock persistence for the Indian banking stock returns and the lagged bank returns had significant effect on the current period's stock returns. Singh[13] conducted a study to estimate the volatility of the Indian banks stock market returns using symmetric and asymmetric GARCH family models. Results showed high shock persistence and the presence of asymmetry and leverage effects in the banking stock returns. The conditional volatility of the Indian banking sector was found to increase during the global financial crisis of 2007 to 2009.

In Nigeria, published works on volatility modeling of banking stock returns are also well documented in the literature. See for examples, Lawal *et al.* (2013) 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[14]. Emenike and Ani (2014) examined the nature of stock returns volatility in the Nigerian banking sector and the All-share Index (ASI) of the Nigerian Stock Exchange using GARCH models from 3rd January 2006 to 31st December 2012. Results indicated high level of volatility clustering and shock persistence for stock returns of the Nigerian banking sector than the ASI stock returns for the sample period. The results of the study also revealed that stock returns distribution of the banking sector was leptokurtic and the sign of innovations had insignificant influence on the volatility of stock returns of the banks[15].

Onwukwe *et al.*[16] modeled and forecasted daily stock return volatility of 15 commercial Nigerian bank stocks. They used daily closing share prices of the 15 banks for the period 04/01/2005 to 31/08/2012. They employed three symmetric models which are ARCH(1), ARCH(2) and GARCH(1,1) to capture the volatility pattern and two asymmetric models EGARCH(1,1) and TARCH(1,1) to account for leverage effect. EGARCH (1, 1) produced better forecasts compared to other competing GARCH models. Although no evidence of leverage effect was recorded. Gil-Alana *et al.*[17] employed fractional integration and structural break procedures in studying the daily share prices of the Nigerian banking sector between 2001 and 2012. The results obtained through parametric and semi-parametric methods indicated little evidence of mean reversion in the return series. There was evidence of long memory in the absolute and squared return series. The presence of structural breaks was also evident with the number of breaks depending on the bank examined. The breaks which were more noticed in the month of December 2008 relating to the global financial crisis also affected the Nigerian banking sector. The daily stock returns of the first bank Plc in Nigeria was modeled using ARMA (2,2)-ARCH(1) model by Akpan E.A. et al.[18]. Kuhe and Chiawa[19] examined the impact of structural breaks on the conditional variance and mean reversion of eight commercial banks in Nigeria using symmetric and asymmetric GARCH models in the presence of random level shifts. The study employed symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TGARCH (1,1) models. Results showed high volatility shocks persistence in all the estimated models across the banking stocks when structural breaks were ignored. However, the shocks reasonably reduced when level shifts were incorporated in the volatility models and volatility half-lives drastically reduced. TGARCH was found to outperform the other competing GARCH models in terms of shock reduction.

## Materials and methods

**Source of Data and Data Transformation:** The data used in this study are the daily closing share prices of thirteen commercial banks in Nigeria listed on the Nigerian Stock Exchange (NSE) and obtained from www.nse.ng.org for the period 17th February, 2003 to 24th June, 2016. The daily shares prices are transformed to daily stock returns $r_t$ by the formula:

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

Where: $r_t$ denotes the bank stock return series, $\Delta$ is the first difference operator and $P_t$ denotes the closing market index at the current day $(t)$.

**Unit Root and Heteroskedasticity Tests:** In order to check for the presence of unit root in stock prices and returns, Ng and Perron modified unit root[20]. To test for the presence of ARCH effects in the return series, Engle's Lagrange Multiplier test[5]. 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.

**Model Specification:** Due to the presence of ARCH effects in the residuals of the stock return series, the following heteroskedasticity models are specified for this study.

**The generalized autoregressive conditional heteroskedasticity (GARCH) model:** The ARCH model of Engle[5] was extended by Bollerslev[6] to Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model. For the log return series $(r_t)$, the GARCH (1,1) model is specified as:

$$r_t = \mu + \varepsilon_t \tag{2}$$

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

$$h_t = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4}$$

Where: $r_t$ is the return series, $\varepsilon_t$ is the shock at day $t$ which follows heteroskedastic error process, $\mu$ is the conditional mean of $(r_t)$, $h_t$ is the volatility (conditional variance) at day $t$ and $\varepsilon_{t-1}^2$ is the square innovation at day $t-1$ 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 basic GARCH (1,1) model is adequate in capturing all volatility in any financial time series.

**The GARCH-in-mean (GARCH-M) model:** Engle, Lilien and Robins[6] extended the GARCH-in-mean model to relate the level of volatility to the expected return. A simple GARCH (1,1)-in-mean model is specified as:

$$r_t = \mu + \lambda h_t + \varepsilon_t,\ \varepsilon_t = \sigma_t e_t \tag{5}$$

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

Where: $\lambda$ is the risk premium parameter. When $\lambda$ is positive, it means that the return is related positively to its past volatility.

**The exponential GARCH (EGARCH) model:** Nelson[8] extended the EGARCH model to capture asymmetric and leverage effects between positive and negative shocks. The conditional variance equation for EGARCH (1,1) model specification is given as:

$$\ln(h_t) = \omega + \alpha_1\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma\left[\frac{\varepsilon_{t-1}}{h_{t-1}}\right] + \beta_1\ln(h_{t-1}) \tag{7}$$

Where: $\gamma$ represents the asymmetric and leverage effect coefficient in the model, if $\gamma$ is negative, then, there is presence of leverage effect, $\beta_1$ coefficient represents the measure of shock persistence. Asymmetry exists if $\gamma \neq 0$.

**Threshold ARCH (TARCH) model:** The TARCH model was proposed independently by Glosten et al.[9] and Zakoian J.M.[10]. The conditional variance equation for the TARCH (1,1) model specification is given by:

$$h_t = \omega + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma\varepsilon_{t-1}^2\mathbb{I}_{t-1}^- \tag{8}$$

Where: $\mathbb{I}_t^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise. For the threshold ARCH 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 $\alpha_1$, while bad news has an impact of $\alpha_1 + \gamma$. When $\gamma > 0$, bad news produces more volatility than good news which indicates leverage effect. If $\gamma \neq 0$, the impact of news on conditional variance is asymmetric.

**GARCH models estimation and innovation densities:** The estimates of GARCH parameters are obtained by maximizing the log likelihood function:

$$ln(L\theta_t) = -{}^1\!/_2\sum_{t-1}^{T}\left(\ln 2\pi + lnh_t + \frac{\varepsilon_t^2}{h_t}\right) \tag{9}$$

This study employs two innovation densities (heavy-tailed distributions) in the estimation of GARCH parameters.

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

$$f(z) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\sqrt{v\pi}\Gamma\left(\frac{v}{2}\right)}\left(1+\frac{z^2}{v}\right)^{-\left(\frac{v+1}{2}\right)}, -\infty < z < \infty \tag{10}$$

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

$$l_t = \frac{1}{2}\log\left[\frac{\pi(v-2)\Gamma\left({}^v\!/_2\right)^2}{\Gamma\left({}^{(v+1)}\!/_2\right)}\right] - \frac{1}{2}\log h_t - \frac{(v+1)}{2}\log\left[1+\frac{\left(y_t - X_t'\theta\right)^2}{h_t(v-2)}\right] \tag{11}$$

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

The Generalized Error Distribution (GED) is given as:

$$f(z,\mu,\sigma,v) = \frac{\sigma^{-1}ve^{\left(-\frac{1}{2}\left|\frac{\left(\frac{z-\mu}{\sigma}\right)}{\lambda}\right|^v\right)}}{\lambda 2^{(1+(1/v))}\Gamma\left(\frac{1}{v}\right)}, 1 < z < \infty \tag{12}$$

$v > 0$ 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:

$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma(1/v)^3}{\Gamma(3/v)(v/2)^2}\right] - \frac{1}{2}\log h_t - \left[\frac{\Gamma(3/v)(y_t - X_t'\theta)^2}{h_t\Gamma(1/v)}\right]^{\frac{v}{2}} \quad (13)$$

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

## Results and discussion

**Summary Statistics of Daily Banks Stock Returns:** To better understand the distributional characteristics of the daily stock returns, summary statistics for all the daily banks return series are computed and results are presented in Table-1.

The summary statistics shown in Table-1 indicate positive daily means for Access, Guaranty trust, Union, Wema and Zenith banks stock returns which indicate gains in the daily share prices for these banks for the trading period under review. The summary statistics indicate negative means for rest of the banks indicating losses in the daily share prices of these banks for the period under review. The positive standard deviations for the daily stock returns shows the dispersion from the means and high variability of price fluctuations in the stock market during the study period. The summary statistics also show positive asymmetries for Access, UBA, Union, Unity, Skye, Sterling and Wema banks stock returns as their skewness coefficients are positive and negative asymmetries for First bank, FCMB, Fidelity, Guaranty trust and Zenith banks stock returns as their skewness coefficients are all negative. The distributions of all the banks returns are leptokurtic (fat-tailed) as their kurtosis coefficients are all positive and large. The distributions of all the banks stock returns are non-normal as the Jarque-Bera statistics are very large with marginal p-values of 0.0000 in all the series. The above observations from summary statistics suggest that the daily banks stock return series can only be modeled with innovation densities, non-normal or heavy-tails distributions.

**Unit Root Test Result:** To investigate the presence or absence of unit root in the banking stock prices and returns in Nigeria, Ng and Perron modified unit root testing procedure with intercept and linear trend is employed and the result is presented in Table-2.

**Table-1:** Summary Statistics of Bank Returns.

| Return | N | Mean | Std. Dev. | Skewness | Kurtosis | JB | P-value |
|---|---|---|---|---|---|---|---|
| ACBank | 3995 | 0.03790 | 3.60155 | 1.52619 | 197.0286 | 6268221 | 0.0000 |
| Diamond | 2908 | -0.07226 | 3.88104 | 0.37071 | 259.2053 | 7953652 | 0.0000 |
| FBank | 4032 | -0.05068 | 10.9708 | -0.46576 | 902.2827 | 1.36E+08 | 0.0000 |
| FCMB | 3015 | -0.04199 | 2.77460 | -0.10030 | 8.626873 | 3982.556 | 0.0000 |
| Fidelity | 2915 | -0.04788 | 3.36564 | -0.08225 | 129.1525 | 1932946 | 0.0000 |
| GTB | 3996 | 0.044313 | 6.01258 | -0.20869 | 1044.371 | 1.81E+08 | 0.0000 |
| UBA | 3995 | -0.02534 | 7.58016 | 0.20367 | 562.5184 | 5211605 | 0.0000 |
| UBank | 3995 | 0.04099 | 6.2266 | 5.23449 | 379.7132 | 23640817 | 0.0000 |
| Unity | 2756 | -0.04944 | 6.30140 | 19.5789 | 707.824 | 57222566 | 0.0000 |
| Skye | 2754 | -0.07477 | 3.83199 | 3.02411 | 142.7676 | 2245835 | 0.0000 |
| Sterling | 2573 | -0.06611 | 7.59075 | 8.66767 | 807.3690 | 69397033 | 0.0000 |
| Wema | 3996 | 3.60422 | 3.90107 | 1.87175 | 5.741113 | 3584.339 | 0.0000 |
| Zenith | 3050 | 0.00777 | 2.76749 | -1.26249 | 33.6141 | 11915.8 | 0.0000 |

**Table-2:** Ng and Perron (NP) Modified Unit Root Test for Daily Prices and Returns.

| Variable | Option | Ng-Perron test statistics | | | |
|---|---|---|---|---|---|
| | | $MZ\alpha$ | $MZ_t$ | MSB | $MP_T$ |
| ACBank Prices | Intercept & trend | -4.99776 | -1.53921 | 0.30798 | 18.0392 |
| ACBank Returns* | Intercept & trend | -37.54940 | -11.94286 | 0.02735 | 1.02705 |
| Diamond Prices | Intercept & trend | -5.67666 | -1.65317 | 0.29122 | 15.9948 |
| Diamond Returns* | Intercept & trend | -73.7606 | -12.60221 | 0.08911 | 0.74664 |
| FBank Prices | Intercept & trend | -12.5607 | -2.47992 | 0.19743 | 7.40509 |
| FBank Returns* | Intercept & trend | -177.893 | -9.43108 | 0.05302 | 0.51244 |
| FCMB Prices | Intercept & trend | -2.58255 | -1.09552 | 0.42420 | 33.8180 |
| FCMB Returns* | Intercept & trend | -31.1702 | -9.25009 | 0.05352 | 1.32561 |
| Fidelity Prices | Intercept & trend | -2.77354 | -1.16398 | 0.41967 | 32.4325 |
| Fidelity Returns* | Intercept & trend | -1451.74 | -26.9419 | 0.01856 | 0.06277 |
| GTB Prices | Intercept & trend | -14.9688 | -2.72525 | 0.18206 | 6.15214 |
| GTBReturns* | Intercept & trend | -51.51361 | -10.84422 | 0.05775 | 2.52405 |
| UBA Prices | Intercept & trend | -7.30101 | -1.90648 | 0.26113 | 12.4899 |
| UBA Returns* | Intercept & trend | -34.22743 | -11.43880 | 0.04035 | 1.41016 |
| UBank Prices | Intercept & trend | -8.91858 | -2.11159 | 0.23676 | 10.2179 |
| UBank Returns* | Intercept & trend | -1880.63 | -30.6631 | 0.01630 | 0.04980 |
| UnityBank Prices | Intercept & trend | -10.1771 | -2.25563 | 0.22164 | 8.95467 |
| UnityBank Returns* | Intercept & trend | -39.0221 | -4.41483 | 0.11314 | 2.34791 |
| SkyeBank Prices | Intercept & trend | -4.13063 | -1.40030 | 0.33900 | 21.6781 |
| SkyeBank Returns* | Intercept & trend | -42.03479 | -8.63831 | 0.01684 | 2.4262 |
| SterBank Prices | Intercept & trend | -8.99239 | -2.11899 | 0.23564 | 10.1395 |
| SterBank Returns* | Intercept & trend | 30.24311 | -8.75962 | 0.00459 | 0.18626 |
| WemaBank Prices | Intercept & trend | -4.04342 | -1.39966 | 0.34616 | 22.2874 |
| WemaBank Returns* | Intercept & trend | -28.5147 | -13.76883 | 0.03217 | 3.23792 |
| ZenBank Prices | Intercept & trend | -4.92454 | -1.54846 | 0.31444 | 18.3992 |
| ZenBank Returns* | Intercept & trend | -71.52812 | -9.77615 | 0.00791 | 0.08525 |
| Asymptotic Critical Values | 1% | -23.8000 | -3.42000 | 0.14300 | 4.03000 |
| | 5% | -17.3000 | -2.91000 | 0.16800 | 5.48000 |
| | 10% | -14.2000 | -2.62000 | 0.18500 | 6.67000 |

Note: *denotes NP test statistic is significant at the designated test sizes. Asymptotic critical values are taken from Ng and Perron[20] (Table-1).

From the results of Ng and Perron modified unit root test presented in Table-2, we fail to reject the null hypothesis of unit root for all the banking stock prices indicating that the daily prices of the banking sector are contaminated with unit roots. This is shown by their $M$ test statistics being greater than their corresponding asymptotic critical values at the conventional test sizes. However, we reject the null hypothesis of unit root for all the banking stock returns indicating the absence of unit root in all the daily stock returns of the banking sector. This is shown by their $M$ test statistics being less than their corresponding asymptotic critical values at the conventional test sizes. We therefore conclude that the daily stock prices of the banking sector are non-stationary while their log returns are stationary and hence integrated of order one, I(1).

**ARCH LM Heteroskedascity Test Results:** To check for ARCH effects in the residuals of the daily banks stock return series, ARCH LM heteroskedasticity test by Engle is applied, results are presented in Table-2.

The results of the residual test of heteroskedasticity for ARCH effects presented in Table-3 gladly rejects the null hypothesis of no ARCH effects in the residuals of the banks stock returns as the p-values of the ARCH LM test statistics are highly statistically significance. This indicates the presence of ARCH effects in the residuals of the banking stock returns indicating that the errors are non-constant, time varying and should be modeled using heteroskedastic ARCH family models.

**Innovation Densities:** Two innovation densities (error distributions) are utilized in estimating volatility via GARCH variants in this study: The Generalized Error Distribution (GED) and Student's-t Distribution (STD). The innovation densities are optimally selected using information criteria and the log likelihood. For the standard GARCH models, all the banking stock returns volatility are estimated using GED, for the GARCH-M models, Diamond and Fidelity banks stocks are estimated using STD while the rest of the banks stocks are estimated using GED. The estimation of asymmetric EGARCH models utilized STD for Diamond, FCMB, Fidelity, UBA, Unity, Skye, Sterling and Zenith banks stock returns while the remaining five banking stocks are estimated using GED. For the asymmetric TARCH models, UBA and Sterling banks stocks are estimated using STD while the remaining eleven banks stock returns were estimated using GED. The detailed results for the selection of innovation densities are however omitted in this study.

**Estimation Results for Symmetric GARCH Models:** To investigate the symmetric volatility behaviour of the banking stock returns, symmetric GARCH (1,1) and GARCH (1,1)-in-mean models are employed for this purpose. Results of the standard GARCH (1,1) models are presented in Table-4 while that of basic GARCH (1,1)-M models are reported in Table-5.

**Table-3:** Heteroskedasticity Test for ARCH Effests.

| Return | F-Statistic | P-value | $nR^2$ | P-value |
|---|---|---|---|---|
| AC Bank Returns | 759.2878 | 0.0000 | 638.2426 | 0.0000 |
| Diamond Returns | 854.9641 | 0.0000 | 796.0752 | 0.0000 |
| FBank Returns | 148.0775 | 0.0000 | 142.8978 | 0.0000 |
| FCMB Returns | 608.5683 | 0.0000 | 506.5843 | 0.0000 |
| Fidelity Returns | 937.7315 | 0.0000 | 709.7434 | 0.0000 |
| GTB Returns | 694.6738 | 0.0000 | 592.0034 | 0.0000 |
| UBA Returns | 410.8463 | 0.0000 | 372.6869 | 0.0000 |
| U Bank Returns | 311.7821 | 0.0000 | 289.3354 | 0.0000 |
| Unity Bank Returns | 812.3503 | 0.0000 | 803.3852 | 0.0000 |
| Skye Bank Returns | 201.4915 | 0.0000 | 157.8727 | 0.0000 |
| Ster Bank Returns | 8003.712 | 0.0000 | 1946.288 | 0.0000 |
| Wema Bank Returns | 1239.913 | 0.0000 | 946.4832 | 0.0000 |
| Zen Bank Returns | 219.9698 | 0.0000 | 205.2890 | 0.0000 |

**Table-4:** Parameter Estimates of Symmetric GARCH (1,1) Models for Bank Returns.

| Return | $\mu$ | $\omega$ | $\alpha_1$ | $\beta_1$ | $\alpha_1+\beta_1$ | $v$ | ARCH LM Test | |
|---|---|---|---|---|---|---|---|---|
| ACBank | 0.0003* | 1.8408 | 0.3960 | 0.4648 | 0.8608 | 1.5000 | 0.0023 | 0.9616 |
| Diamond | -0.0003* | 0.1291 | 0.2598 | 0.6613 | 0.9211 | 1.1380 | 0.0059 | 0.9386 |
| FBank | -0.3261* | 0.4969 | 0.1233 | 0.4678 | 0.5911 | 1.0562 | 0.0088 | 0.9251 |
| FCMB | 0.0002* | 0.6787 | 0.5157 | 0.4809 | 0.9966 | 0.9156 | 0.1014 | 0.7502 |
| Fidelity | -0.0004* | 2.1891 | 0.6121 | 0.2750 | 0.8871 | 0.9341 | 0.0081 | 0.9285 |
| GTB | 0.0005* | 0.8144 | 0.5178 | 0.4812 | 0.9990 | 0.9228 | 0.0003 | 0.9852 |
| UBA | 0.0005* | 2.6067 | 0.6675 | 0.3097 | 0.9772 | 1.0850 | 0.0094 | 0.9184 |
| UBank | -0.0005* | 0.3496 | 0.3443 | 0.5596 | 0.9039 | 1.0924 | 0.0034 | 0.9532 |
| Unity | -0.0015* | 1.7494 | 0.4421 | 0.5543 | 0.9964 | 1.1170 | 0.0063 | 0.9276 |
| Skye | 0.0001* | 1.7771 | 0.4378 | 0.4239 | 0.8617 | 1.0696 | 0.0041 | 0.9489 |
| Sterling | -0.0002* | 0.7388 | 0.4832 | 0.5145 | 0.9977 | 1.0939 | 0.0174 | 0.8951 |
| Wema | -0.0002* | 0.0744 | 0.4308 | 0.5628 | 0.9936 | 1.1935 | 0.1092 | 0.7793 |
| Zenith | -0.0003* | 0.4424 | 0.3716 | 0.6074 | 0.9790 | 0.9393 | 0.0043 | 0.9487 |

Note: * denotes non-significant parameter.

From the results of symmetric GARCH (1,1) models for the banking stock returns presented in Tables-4 and 5, all the parameters in the variance equations of the models are statistically significant at the 5% significance levels and satisfied the non-negativity constraints of the models. The positive and significant coefficients of the ARCH terms ($\alpha_1$) indicated how the stock market news about past volatilities had explanatory powers on the current volatilities across the banking stock returns. The estimated models clearly showed evidence of high volatility shock persistence, volatility clustering and leptokurtosis (fat-tails) among the Nigerian banking stock returns. The sums of ARCH ($\alpha_1$) and GARCH ($\beta_1$) terms are less than unity in all the estimated symmetric GARCH (1,1) models (i.e., $\alpha_1+\beta_1<1$) indicating faster reactions of volatility to market changes. This also indicates that the conditional variance processes of the banking stock returns are very stable, stationarity, predictable and mean revert to their long-run average levels after deviation from it. Stationary, predictable and mean reverting stocks offered good and long-term investment opportunities for both local and foreign investors.

The risk premium parameter ($\lambda$) of the GARCH (1,1)-in-mean model presented in Table-5 which measures the tradeoff relationship between risk and the expected return has produced mixed findings of positive and negative relationships across the banking stocks. While there are positive risk-return tradeoffs in Access bank, First bank, Fidelity and GTB stock returns, there exist negative relationships between risk and expected returns in the Diamond, FCMB, UBA, Union, Unity, Skye, Sterling, Wema and Zenith banking stock returns. When a positive risk-return relationship exists, it means that the conditional variance used as proxy for the risk of returns is related to the level of returns positively and the investors holding such stocks should be compensated for holding risky assets.

**Estimation Results for Asymmetric GARCH Models:** To examine the asymmetric volatility behaviour of the banking stocks, asymmetric EGARCH (1,1) and TARCH (1,1) models are employed for this purpose. Results of the EGARCH (1,1) models are presented in Table-6 while that of asymmetric TARCH (1,1) models are reported in Table-7.

**Table-5:** Parameter Estimates of Symmetric GARCH (1,1)-M Models for Bank Returns.

| Return | $\mu$ | $\lambda$ | $\omega$ | $\alpha_1$ | $\beta_1$ | $\alpha_1+\beta_1$ | $v$ | ARCH LM |
|---|---|---|---|---|---|---|---|---|
| ACBank | -0.0907* | 0.0463 | 1.4539 | 0.4178 | 0.4983 | 0.9161 | 1.5182 | 0.9583 |
| Diamond | 0.0001* | -0.0246 | 0.0001 | 0.1888 | 0.5682 | 0.7570 | 2.9030 | 0.9654 |
| FBank | -0.9648 | 0.8131 | 0.8379 | 0.7968 | 0.1055 | 0.9023 | 1.0961 | 0.7312 |
| FCMB | 0.0001* | -0.0002 | 0.0005 | 0.2627 | 0.7098 | 0.9725 | 1.4829 | 0.9827 |
| Fidelity | -0.0002* | 0.0006 | 0.0009 | 0.3636 | 0.6270 | 0.9906 | 5.2812 | 0.9792 |
| GTB | -0.0074* | 0.0061 | 0.8853 | 0.5832 | 0.4029 | 0.9861 | 1.0042 | 0.9845 |
| UBA | 0.0014* | -0.0008 | 2.3796 | 0.7176 | 0.2579 | 0.9755 | 1.0025 | 0.7895 |
| UBank | 0.1983 | -0.0949 | 4.0375 | 0.3143 | 0.6174 | 0.9317 | 0.9592 | 0.9550 |
| Unity | 0.6418 | -0.3185 | 1.8322 | 0.3185 | 0.5482 | 0.8667 | 1.1264 | 0.7592 |
| Skye | 0.2211* | -0.1269 | 1.3710 | 0.4028 | 0.5475 | 0.9503 | 1.0198 | 0.9566 |
| Sterling | 0.0003* | -0.0002 | 1.5272 | 0.5136 | 0.3948 | 0.9084 | 1.0898 | 0.8967 |
| Wema | 0.0496* | -0.0968 | 0.0804 | 0.3248 | 0.6745 | 0.9993 | 1.1334 | 0.8719 |
| Zenith | 0.0024* | -0.0034 | 0.1705 | 0.2995 | 0.6470 | 0.9465 | 0.7592 | 0.9175 |

Note: * denotes non-significant parameter.

**Table-6:** Parameter Estimates of Asymmetric EGARCH (1,1) Models for Bank Returns.

| Return | $\mu$ | $\omega$ | $\alpha_1$ | $\beta_1$ | $\gamma$ | $\phi$ | $v$ | ARCH LM |
|---|---|---|---|---|---|---|---|---|
| ACBank | 0.0001 | 0.0297 | 0.1030 | 0.8546 | -0.0351 | 0.9576 | 0.8151 | 0.9887 |
| Diamond | -0.0002* | -0.1480 | 0.3659 | 0.5445 | -0.0188* | 0.9104 | 4.1109 | 0.8184 |
| FBank | 0.0001* | 0.6420 | 0.4723 | 0.5276 | -0.9012 | 0.9999 | 0.9245 | 0.9643 |
| FCMB | -0.0001* | -0.1962 | 0.2410 | 0.7495 | 0.0601 | 0.9905 | 5.0149 | 0.8275 |
| Fidelity | -0.0056 | -0.2012 | 0.4252 | 0.5745 | 0.3091 | 0.9997 | 2.6287 | 0.3619 |
| GTB | 0.0002* | 0.0953 | 0.0782 | 0.8162 | 0.0790 | 0.8944 | 1.0662 | 0.8989 |
| UBA | -0.0007* | 3.9672 | 0.0050 | 0.8749 | 0.0075 | 0.8799 | 2.6899 | 0.7361 |
| UBank | -0.0012* | 2.3790 | 0.5821 | 0.1761 | 0.1508 | 0.7582 | 0.8389 | 0.8763 |
| Unity | -0.0002* | -0.0915 | 0.1330 | 0.8057 | -0.2040 | 0.9387 | 4.9210 | 0.1798 |
| Skye | -0.0001* | -0.0398 | 0.2506 | 0.7249 | -0.0856 | 0.9755 | 5.9471 | 0.4718 |
| Sterling | -0.0009* | -0.1311 | 0.3078 | 0.6914 | 0.0603 | 0.9992 | 6.2297 | 0.9877 |
| Wema | -0.0001 | 0.0148 | 0.2474 | 0.7252 | -0.0405 | 0.9726 | 1.5112 | 0.6936 |
| Zenith | -0.0002* | -0.2041 | 0.3518 | 0.6478 | -0.0981 | 0.9996 | 2.6899 | 0.7381 |

Note: * denotes non-significant parameter; $\phi = \alpha_1 + \beta_2$ measures shock persistence in volatility.

The results of asymmetric EGARCH (1,1) and TARCH (1,1) models presented in Table-6 and 7 reveal that all the parameters of the models in the variance equations are statistically significant at the 5% significance level. The coefficients of the asymmetric and leverage effect parameter ($\gamma$) for Access, Diamond, First, Unity, Skye, Wema and Zenith banks are negative and statistically significant for the EGARCH model but positive and statistically significant for TARCH model. This indicates that market retreats (bad news) produce more volatility than market advances (good news) of the same magnitude in these banking stock returns.

On the other hand, results of the asymmetric EGARCH (1,1) and TARCH (1,1) models presented in Table-6 and 7 show that the parameters of the models in the variance equations are all statistically significant at the 5% significance level. The coefficients of the asymmetric and leverage effect parameter ($\gamma$) for FCMB, Fidelity, GTB, UBA, Union and Sterling banks are positive and statistically significant for the EGARCH model but negative and statistically significant for TARCH model. This indicates that market advances (good news) generate more volatility than market retreats (bad news) of the same magnitude in these banking stock returns.

The volatility shocks are quite persistence for both EGARCH (1,1) and TARCH (1,1) models across the banking stocks. The sums of ARCH and GARCH terms are less than unity in all the returns ($\alpha_1 + \beta_1 < 1$). This shows that the conditional volatility for the banking stocks are stationary, mean reverting as well as predictable. From the estimated symmetric and asymmetric GARCH models, all the banking stock returns retain the fat tails behaviour typical of financial data as the shape parameter ($v$) of the estimated models is greater than two ($v > 2$) for student-t distribution and less than two ($v < 2$) for GED.

The post-estimation Engle's LM tests for ARCH effects presented in the last columns of Table-4, 5, 6 and 7 failed to reject the null hypotheses of no ARCH effects in the residuals of the banking stock returns indicating that the estimated GARCH family models have captured all the remaining ARCH effects in the residuals of returns. These showed that our estimated GARCH models are good-fits for the banking stock data.

**The Magnitude of News Impact on the Conditional Variances of the Banking Stock Returns:** To investigate the magnitude of good or bad news impact on the conditional variances of the banking stock returns and indeed confirm the existence or otherwise of leverage effects in the returns, we compute the asymmetry for each return and present the result in Table-8.

**Table-7:** Parameter Estimates of Asymmetric TARCH (1,1) Models for Bank Returns.

| Return | $\mu$ | $\omega$ | $\alpha_1$ | $\beta_1$ | $\gamma$ | $\varphi$ | $v$ | ARCH LM |
|---|---|---|---|---|---|---|---|---|
| ACBank | -0.0003* | 0.9608 | 0.4087 | 0.4672 | 0.0797* | 0.9158 | 1.1178 | 0.9265 |
| Diamond | -0.0003* | 0.2297 | 0.3780 | 0.5307 | 0.0377* | 0.9276 | 1.1112 | 0.9681 |
| FBank | -0.5133* | 0.8051 | 0.2193 | 0.5688 | 0.1344 | 0.8553 | 1.1262 | 0.8837 |
| FCMB | -0.0098 | 0.0984 | 0.2614 | 0.6343 | -0.0739 | 0.8588 | 1.500 | 0.4817 |
| Fidelity | -0.0003* | 0.4563 | 0.3431 | 0.6410 | -0.0558* | 0.9562 | 1.1393 | 0.7916 |
| GTB | 0.0005* | 0.9498 | 0.5545 | 0.4256 | -0.0329* | 0.9637 | 1.0277 | 0.8748 |
| UBA | -0.0234* | 1.4225 | 0.0923 | 0.6621 | -0.0422* | 0.7333 | 12.4679 | 0.7119 |
| UBank | -0.0005* | 2.9714 | 0.4531 | 0.4348 | -0.2009 | 0.7075 | 1.0737 | 0.1927 |
| Unity | -0.0008* | 1.2647 | 0.1868 | 0.6838 | 0.2021 | 0.9717 | 1.1643 | 0.9471 |
| Skye | -0.0004* | 0.1184 | 0.2493 | 0.5479 | 0.2307 | 0.9126 | 0.9996 | 0.8845 |
| Sterling | -0.1289 | 1.6569 | 0.4073 | 0.5730 | -0.0789 | 0.9409 | 5.9814 | 0.7318 |
| Wema | -0.0361* | 0.1259 | 0.2564 | 0.6327 | 0.2059 | 0.9921 | 1.1832 | 0.5692 |
| Zenith | -0.0002* | 0.3698 | 0.2518 | 0.6441 | 0.0478* | 0.9198 | 0.8547 | 0.4585 |

Note: * denotes non-significant parameter; $\varphi = \alpha_1 + \beta_2 + \gamma/2$ measures shock persistence in volatility.

**Table-8:** The Magnitude of News Impact on Conditional Variance.

| Return | EGARCH (1,1) Model | TARCH (1,1) Model | EGARCH (1,1) Model | TARCH (1,1) Model |
|---|---|---|---|---|
| | Good news | Bad news | Good news | Bad news |
| ACBank | 0.9649 | 1.0351 | 0.4087 | 0.4884 |
| Diamond | 0.9812 | 1.0188 | 0.3780 | 0.4157 |
| FBank | 0.0988 | 1.9012 | 0.2193 | 0.3537 |
| FCMB | 1.0601 | 0.9399 | 0.2614 | 0.1075 |
| Fidelity | 1.3091 | 0.6909 | 0.3431 | 0.2073 |
| GTB | 1.0790 | 0.9210 | 0.5545 | 0.5216 |
| UBA | 1.0075 | 0.9925 | 0.0923 | 0.0501 |
| UBank | 1.1508 | 0.8492 | 0.4531 | 0.2522 |
| Unity | 0.7960 | 1.2040 | 0.1868 | 0.3889 |
| Skye | 0.9144 | 1.0856 | 0.2493 | 0.4800 |
| Sterling | 1.0603 | 0.9397 | 0.4073 | 0.3284 |
| Wema | 0.9595 | 1.0405 | 0.2564 | 0.4623 |
| Zenith | 0.9019 | 1.0981 | 0.2518 | 0.2996 |

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, the denominator represents good news impact on volatility.

The results of asymmetry presented in Table-8 clearly show that bad news (negative shocks) generate more volatility in Access bank, Diamond bank, First bank, Unity bank, Skye bank, Wema bank and Zenith bank returns than good news (positive shocks) of similar magnitude. In these banking stocks, there is evidence that asymmetry and leverage effects exist. The implication is that changes in stock prices for these banks are negatively correlated with changes in volatility. For these banking stocks, an unexpected drop in price will increase volatility more than a similar unexpected price increase. On the other hand, good news (market advances) produce more volatility in FCMB, Fidelity, GTB, UBA, Union bank and Sterling bank returns than bad news (market retreats) of the same modulus. In these banking stocks, there is evidence that asymmetry exist but no leverage effects. This implies that changes in stock prices for these banks are positively correlated with changes in volatility. For these banking stocks, an unexpected price increase will increase volatility more than a similar unexpected price decrease.

**Results of Volatility Mean Reversion and Half-Life:** The volatility means reversion rates and the speed of mean reversion (volatility half-life) for the banking stocks are computed and presented in Table-9.

The results of Table-9 show that the sums of ARCH and GARCH coefficients are less than one ($\alpha_1 + \beta_1 < 1$) for all the estimated GARCH models across the banking stock returns. The results indeed indicated the mean reverting behaviour of the banking stock prices and that the stock prices come back to their long-run average values after deviating from it. It is observed that the higher the mean reversion rate ($\alpha_1 + \beta_1$), the higher the volatility shock persistence and the slower the mean reversion process. The speed of mean reversion (volatility half-life) as computed by different GARCH models yields different speed depending on the model used. For instance, Union bank (U Bank) demonstrated the lowest sums of ARCH and GARCH terms across the models, thus it takes Union bank stock prices about 7, 10, 3 and 2 days according to GARCH (1,1), GARCH (1,1)-M, EGARCH (1,1) and TARCH (1,1) models respectively to revert back to half of its distance (mean) after deviating from it, which are the shortest periods as compared to other banking stocks. Access bank (AC Bank), Diamond, UBA and Skye banks stocks demonstrate similar characteristics. All the banking stock prices, no matter how short or long it takes mean revert back to their historical long-run averages.

From the results of the study so far presented, it can be said that the volatility shocks of the thirteen selected commercial banks in Nigeria are quite persistence and their conditional variances are stable, stationary, and predictable and mean reverting. This poses minimal and tolerable risk levels as well as long-term investment horizon to investors as mean reverting asset are less risky.

**Table-9:** Volatility Mean Reversion and Half-life (in days) for the Banking Stocks.

| Bank | GARCH (1,1) | GARCH (1,1)-M | EGARCH (1,1) | TGARCH (1,1) | GARCH (1,1) | GARCH (1,1)-M | EGARCH (1,1) | TGARCH (1,1) |
|---|---|---|---|---|---|---|---|---|
| | $\alpha_1+\beta_1$ | Half-life | $\alpha_1+\beta_1$ | Half-life | $\alpha_1+\beta_1$ | Half-life | $\alpha_1+\beta_1$ | Half-life |
| ACBank | 0.8608 | 5 | 0.9161 | 8 | 0.9576 | 16 | 0.9158 | 8 |
| Diamond | 0.9211 | 8 | 0.7570 | 3 | 0.9104 | 7 | 0.9276 | 9 |
| FBank | 0.5911 | 1 | 0.9023 | 7 | 0.9999 | 6931 | 0.8553 | 5 |
| FCMB | 0.9966 | 204 | 0.9725 | 25 | 0.9905 | 73 | 0.8588 | 5 |
| Fidelity | 0.8871 | 6 | 0.9906 | 73 | 0.9997 | 2310 | 0.9562 | 16 |
| GTB | 0.9990 | 693 | 0.9861 | 50 | 0.8944 | 6 | 0.9637 | 19 |
| UBA | 0.9772 | 30 | 0.9755 | 28 | 0.8799 | 6 | 0.7333 | 2 |
| UBank | 0.9039 | 7 | 0.9317 | 10 | 0.7582 | 3 | 0.7075 | 2 |
| Unity | 0.9964 | 192 | 0.8667 | 5 | 0.9387 | 11 | 0.9717 | 24 |
| Skye | 0.8617 | 5 | 0.9503 | 14 | 0.9755 | 28 | 0.9126 | 8 |
| Sterling | 0.9977 | 301 | 0.9084 | 7 | 0.9992 | 866 | 0.9409 | 11 |
| Wema | 0.9936 | 108 | 0.9993 | 990 | 0.9726 | 25 | 0.9921 | 87 |
| Zenith | 0.9790 | 33 | 0.9465 | 13 | 0.9996 | 1733 | 0.9198 | 8 |

## Conclusion

This study investigated the volatility behaviour as a measure of financial risk exposure of thirteen selected Nigerian commercial banks stock prices using GARCH variants in the presence of non-Gaussian errors. The study utilised daily closing share prices of thirteen commercial banks listed on the Nigerian stock exchange (NSE) for the period 17/02/200 to 24/06/2016. The study investigated the stationarity properties of stock prices and returns using Ng and Perron modified unit root test, while heteroskedasticity test for ARCH effect as investigated using Engle's Lagrange Multiplier test. Symmetric GARCH (1,1) and GARCH (1,1)-M models were employed to study the symmetric characteristics of stock returns as well as the risk-return tradeoff while the asymmetric EGARCH (1,1) and TARCH (1,1) models were employed to study the asymmetric and leverage effect properties of returns. All the models were estimated using either student-t or Generalized Error Distribution (GED).

Results of the analysis showed that all the banking stock returns were stationary with non-normality behaviour and the residuals of returns were found to be heteroskedastic. All the estimated GARCH models were found to be stable, stationary, and predictable and mean reverting. The volatility shocks were quite persistence and the news impact on the conditional variance was asymmetric across the banking stock returns. There were mixed findings of positive and negative tradeoff relationships between risk and the expected return across the banking stocks. There were also mixed findings regarding the existence of leverage effects across the commercial banking stock returns. The levels of financial risk exposure of the thirteen selected Nigerian commercial banks were found to be minimal and tolerable as each banking stock return mean reverts to its long-run average level. As a policy implication, stationary and mean reverting stocks pose minimal risk and therefore offer good opportunities for long term investment for both local and foreign investors.

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