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STOCK VOLATILITY IN THE EYES OF TURBULENCE: EVIDENCE FROM NIGERIAN BANKS

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Abstract: In this paper, effects of the crises and the financial reforms introduced in the Nigerian financial market by the Central Bank of Nigeria (CBN) on the volatility of stock prices of some selected banks in the Nigerian Stock Market (NSM) using ARCH/GARCH family models, are investigated. Daily closing stock prices of four prominent banks in Nigeria from 2004-2014 covering periods of the indicated scenarios are considered; and based on the Nigerian experience four (sub)periods are identified. Hence for us to satisfy some vital underlining assumptions of volatility models, stationarity and heteroscedasticity are examined using appropriate test statistics. It was found that in times of crises, different GARCH candidate models were fitted for the four banks compared to before and after the crises and reforms, the situation that could be attributed to the observed varying level of persistence in the volatility of the returns for these banks occasioned by the indicated scenarios.

Keywords: financial reforms; global financial crisis; Nigerian Stock Market (NSM); heteroscedasticity; volatility.

2010 AMS Subject Classification: 91B84, 62M10.

1. Introduction

The financial meltdown experienced worldwide which had its origin from the sub-prime lending crises in the United State of America had affected both developed and developing economies markets leading to global financial crises between 2007 and 2008. Theses crises triggered unexpected change in the expectations, speculative bubbles, declining prices and regular insolvencies (Sanusi, 2010, 2011). As the crises unfold, there was major restriction to development and growth in most nations, aggravated by banking system crisis, currency crisis as

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well as a foreign debt crisis. Financial institutions such as banks, or assets, e.g. stocks, bonds and currencies instantly lose most of their values, during such crisis.

The Nigerian economy was however insulated from the first round effects of these crises and not until its second round effects. This became possible as the nation was not a significant player in the international market. The banking industry was partially integrated into the global market coupled with strong macroeconomic policies implemented by the country. However, at the instance of the second round effects, there was near total collapse of confidence in the banking system, de-leveraging as well as banks inability to maintain capital adequacy, poor consumers demand and drop in global output which impacted the country financial and real sectors negatively (Sanusi, 2010).

Nigerian Stock Market that recorded about 14.45% increase in its All share index(ASI) between December 31st, 2007 and March, 2008(the peak of the bull-run), suddenly experienced a sharp decline of near 45.8% in ASI and 32.4% decrease in the market capitalization by the end of 2008 (Sanusi, 2011). The growth witnessed in the Nigerian stock market through its market capitalization, which stood at over 100% between 2007 and 2008 is indeed a proof of the strength of the market and that of the economy (Atoi, 2014). Suddenly, there was significant rise in the risks of doing business or investing in the stock market as a result of speculations, occasioned by high volatility such that many banks and firms are distressed and are near total collapse, except for the quick intervention by the government. Thus the risk-averse investors both local and foreign are concerned about the future of their investment.

Given the above, the need to develop appropriate model to underpin the volatility's behaviour of assets, especially those of the Nigerian banks is germane towards protecting depositors from incurring undue risks. Besides, building a good volatility model is fundamental to identifying data generating process for a return series (Hongyu and Zhichao, 2006). Obtaining reliable estimates of stock market volatility can suggest how robust the economy is and also point at the direction of fiscal and monetary policies of the government (Onwukwe, Bassey and Isaac, 2011). Sustainable financial decisions cannot be made except with ability to identify appropriate model that best capture the stylized facts of returns volatility, and that will engender good forecast for future investment. Understanding volatility could guide investors on how to manage inherent risks associated with holding an asset or the value of an option, and also provides reasonable forecasting confidence interval (Engle et al, 2005).

According to Gujarati (2003: 856), understanding stock volatility is important to market participants in determining the level of fluctuations in the returns and the likely risks associated with their investments. Also market regulators need to know what degree of stock volatility is being experienced in the market since high volatility generates panics among the investors, leading to high transaction cost and loss of confidence in the market (Emenike and Ani, 2014).

Hence, vital questions to ask include to what extent were 2007-2009 global financial crises impacted on the Nigerian Financial market's volatility? How significant were the effects of the 2004/2005 and 2009 financial reforms of the Central Bank of Nigeria (CBN) on the banks stock volatility? Studies such as those of Adamu (2010) and Ali & Afzal (2012) have shown that volatility in stock markets across the world had increased after global financial crisis (Verma & Mahajan, 2012). Thus the underline objective of this research is to examine the effect of different financial scenarios (2007-2009 global financial crises and financial reforms) have shaped the Nigerian banks stock behaviour in term of returns and volatility at different identified periods.

The remaining part of this paper is organised such that section 2 reviews some selected literature found relevant to the research; there after which methodology on the intended ARCH/GARCH family models are briefly discussed in section 3. Section 4 has the presentation and brief discussion on the results of the study. And finally section 5 presents the summary and conclusion of the overall findings of the research.

2. Literature Review

Financial data generally possess some vital characteristics called stylized facts as against the conventional time series data, whereby fitting popular time series models such as Autoregressive (AR), Autoregressive moving average (ARMA) models etc. to capture these features becomes inappropriate. Thus in empirical finance, attempts at capturing these common stylized facts such as time- varying variance behaviour, fat-tail, volatility clustering and leverage effect of financial data has led to development of heteroscedastic models that best capture most of the stylized facts of asset returns.

Right from the time heteroscedastic friendly models, that is autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982), its generalization (GARCH) by Bollerslev (1986) and their other extensions were launched, many financial time series analyst and other researchers using econometric methods have applied these models to capture the second and higher moments of stock volatility. Besides, of all the volatility models previously applied in literature, the most popular and widely accepted that have gained prominence among experts across divides still remain these ARCH/GARCH family models. Apparently, this is so given their ability to capture some dynamics of individual stock returns mentioned earlier (Zhang and Wirjanto, 2009).

Meanwhile, several studies have identified volatility clustering as a major stylized fact of asset returns which according to Mandlebrot (1963) and Fama (1965) represent a phenomenon whereby changes in stock returns of equal magnitude trail one another. This feature simply indicates that shocks to volatility today will significantly impact possible shocks to volatility in some times in the future (Engle and Paton, 2001). Franses and Djik (2000) and Bollerslev (1986) present excellent glossary of the conditional heteroscedasticity models. Studies such as Akgiray (1989), Engle and Mustafa (1992), Schwert (1990), Baillie and Bollerslev (1989), Diebold (1989), and several others have established the presence of ARCH effects, a pointer to identifying volatility clustering in high frequency (daily and weekly) stock data especially; unlike with low frequency (such as monthly and yearly) return series where the effect gradually disappears due to aggregation gaussianity property of stock returns. Presence of ARCH effects in high frequency data according to Diebold and Nerlove (1989) could be attributed to the amount and quality of information reaching the market in clusters or time intervals between the arrival and incorporation of such information into the price by the market participants.

Another important stylized fact characterising asset returns, which has greatly been researched and confirmed across various assets and markets of the developed and emerging economies is the asymmetry or leverage effect. By this effect, negative and positive shocks of equal magnitude impact stock volatility with varying degree; for instance, negative shocks or bad news to the returns lead to increase in volatility; whereas positive shocks or good news induce low volatility in stock returns (see Black, 1976; Christie, 1982; Nelson, 1991; Glosten, Jagannathan and Runkle, 1993). There are different versions of the GARCH class models with each successive one designed to capture the stylized facts, especially asymmetric and long memory phenomenon that standard GARCH could not cater for. Bollerslev (1986) fits ARMA and GARCH models to stock prices in the US stock from 1889 to 1990 to examine the volatility.

Further, $GARCH\ (1,1)$ model has been found to be appropriate for most financial time series (Egert and Koubaa, 2004; Engle and Sheppard, 2001), across various stock markets of developed and emerging economies; and has been subjected to several applications as the benchmark for modelling stock volatility (Engle and Patton, 2000; Engle and Sheppard, 2001; Hansen and Lunde, 2005). Franses, Neele and Djik (1998) compare volatility forecasts of QGARCH (1, 1), GJR-GARCH (1, 1), GARCH (1, 1) and Random Walk Models for stock indices across Germany, Spain, Netherland, Italy, and Sweden. A study by Akigray (1989) used a GARCH (1,1) model to investigate the time series properties of the stock returns and reported that the GARCH models are the best model in describing and forecasting S and P-500 stock index volatility. Haque et al (2004) compare the stock volatility of ten Middle East and African emerging markets by fitting random-walk model, ARMA models and GARCH-M model to their respective stock indexes.

However, the standard GARCH (p, q) and indeed GARCH $(1, 1)$ model has some limitations. The model is not flexible due to non-negativity constraint conditions imposed on its parameters (Wagle, 2008). Secondly, the GARCH model fails to capture asymmetric (or leverage) response of the market as it lacks the power to distinguish between different impacts of respective positive and negative shocks to volatility. This is contrary to known empirical evidence where current volatility is negatively correlated with past stock return; the phenomenon otherwise known as leverage effect. Of significant note is that this leverage effect (which is a negative correlation between past returns and future volatility of returns), could sometimes be defined as the ratio of debt to equity of a firm; and the higher the leverage, the greater the risk or volatility of a company. Meanwhile, high leverage occurs due to negative returns resulting from drop in stock prices, thereby leading to higher debt-equity ratio of a firm; meaning with high volatility in returns of a company, the risk of sustaining the business goes up, the risk averse investors are therefore left with no option than moving their investment (or funds) to less risky assets

In the meantime, while fitting GARCH models to return series, it is often found that GARCH residuals still tend to be heavy tailed. To accommodate this, rather than to use normal distribution the Student's t and GED distribution used to employ ARCH/GARCH type models (Mittnik et al. 2002:98).

Jayasuriya (2002) applies asymmetric GARCH model to determine the impact of stock market liberalization on the returns generated from the Nigeria and other fourteen emerging market data obtained from December, 1984 to March, 2000. The findings show that across the markets investigated, negative (positive) returns have been followed by positive (negative) returns;

indicating there was no significant sign of asymmetry.

Ogum *et al.* (2005) while fitting EGARCH model to describe the volatility in stock prices of both Kenya and Nigeria emerging market observe that their findings even though contradict that of Jayasuriya (2002), reveal that persistence was prevalence in the two markets; but while Nigerian market's volatility responds more to bad news, the volatility in the Kenya tilts towards good news. Okpara and Nwezeaku (2009) in their study of the effect of the idiosyncratic risk and beta risk on stock returns of 41 companies drawn from the Nigerian capital market from 1996 to 2005, found that the persistence in the volatility across these companies was low but confirms the presence of leverage effect fitting EGARCH (1, 3) models. Thereby conclude that the Nigerian market volatility is more susceptible to negative news than the positive ones. Hamadu and Ibiwoye (2010) while fitting ARCH/GARCH family models to daily stock data of 26 insurance companies covering periods from December, 2000 to June 2008 in the Nigerian stock market, notice that of the ARCH(1), GARCH $(1,1)$, TARCH$(1,1)$ and $EGARCH\,(1,1)$ models applied, EGARCH $(1,1)$ performs best even at the out-of-sample forecast level.

3. Data Presentation and Methodology

This section is dedicated to briefly discuss the data used in this research, the procedures followed in the analysis and the various models applied including relevant test to ascertain the adequacy of the choice model for each sub-period.

3.1 Data Presentation

The data consist of daily closing stock prices of the five banks (comprises of two old generations banks and three new generations bank that have) from August 2004 to May, 2014; covering the periods of financial crises and reforms in the industry. These banks are: Access, United Bank for Africa (UBA), Guaranty Trust and First bank. Thus the periods considered in this research are subdivided into five (5) sub-periods and the overall period such as: **(1)** August, 2004-Dec., 2005-Banks Consolidation; **(2)** Jan, 2006- Dec, 2007- Post Consolidation; **(3)** Jan, 2008-May, 2009- Periods of Crises;**(4)** June, 2009- Dec,2010- Banks Reform; **(5)** Jan, 2011- May 2014- Post Reform; and finally, **(6)** August, 2004-May, 2014

The returns are generated from the stock prices using the formula:

$$\mathbf{r_t = \log(R_t) = \log(P_t) - \log(P_{t-1}) = p_t - p_{t-1}} \qquad \textbf{(3.1)}$$

Where r_t is called geometric or compounded return; commonly used in the analysis of stock data, $\mathbf{P_t}$ is the log of price at time "t" and $\mathbf{P_{t-1}}$ is the log of price at time "$t-1$" period preceding time "t"

In this research having generated returns from the daily closing prices of the stocks for each bank, both price and returns series are produced; thereafter which descriptive statistics of the series are obtained. Then stationarity test is obtained, followed by fitting AR model to examine the residuals for the presence of ARCH effect (or heteroscedasticity), via appropriate tests and production of the residual plots. Once the ARCH effect is confirmed, an appropriate ARCH/ GARCH family model is fitted to each of the series across different epoch indicated in this research.

Stationary/Non-Stationary/ Unit Root Test

The following are the proposed possible tests as contained in the literature:

Dickey and Fuller (1979): Dickey-Fuller (DF) test

Said and Dickey (1984): Augmented Dickey-Fuller (ADF) test

Phillips and Perron (1988): Phillips-Perron (PP) Unit root tests

Elliot, Rothenberg, and Stock (2001): Efficient unit root (ERS) test statistic

However, for the Augmented -Dickey-Fuller (ADF) that we shall be adopting, given its popularity and robustness, the following procedures are followed

Fit AR (1) model by least squares;

$y_t = \varphi y_{t-1} + \varepsilon_t$ (RW without drift) **(3.2)**

OR

$y_t = \varphi y_{t-1} + \delta + \varepsilon_t$ (RW with drift,δ); **(3.3)**

$where\ \varepsilon_t \sim WN(0, \sigma^2)$

Set the hypotheses:

$H_0: \varphi = 1\ (unit\ root, nonstationarity\ in\ \varphi(x) = 0\ ) \Rightarrow\ y_t \sim I(1)$

$versus\ H_1: |\varphi| < 1 \Rightarrow y_t \sim I(0)$ (stationarity)

Define the test statistic, called Dickey-Fuller test as:

$$t_{(\varphi=1)} = \frac{\hat{\varphi} - 1}{SE(\hat{\varphi})} \sim \chi_1^2$$ **(3.4)**

We reject the null hypothesis if the generated p-value is less than significant level ($\alpha = 5\%\ or\ 1\%$); and if we do reject then it means the series is stationary. This mean we can continue to work with the original series without differencing.

3.2 Methodology

Most of the commonly referenced volatility forecast models are members of the GARCH family of models with the leading member being autoregressive conditional heteroscedasticity (ARCH) model proposed by Engle (1982). The generalized ARCH (GARCH) model of Bollerslev (1986) has however formed the base model for most volatility models; thereafter which quite a number of its extensions have emerged purposely to correct some noticeable limitations of the standard GARCH model.

GARCH family models are conditional volatility models that are based on using optimal exponential weighting of historical returns to obtain a volatility forecast. Returns on a period (t) are a function of returns on previous periods ($t-1$), where older returns are assigned a lower weight than more recent returns. The model parameters are then estimated by maximum likelihood estimation method.

Four different types of GARCH models- ARCH, GARCH, GJR-GARCH (known to be very similar with TGARCH) and EGARCH are to be explored, considering the distributions of errors, which may follow any of the following distributions- Normal distribution, Student-t-distribution or Generalized error distribution.

Some Stylized Facts of Volatility

(1) Squared Returns are positively correlated- meaning, a slight increase in today's asset returns may be followed by a slightly increase in such returns tomorrow; **(2)** Volatility spikes up during crises but falls back to approximately same level it was before the crisis immediately the crisis disappears; **(3)** Returns exhibit excess kurtosis (or fatter) tails, relative to a normal distribution; and that **(4)** r_t are uncorrelated variables but are not identically and independently distributed (iid)

ARCH EFFECT TEST

This test is essential to ascertain the returns series is characterised by volatility clustering, a stylized fact establishing the presence of time -varying component of any financial time series data before fitting ARCH/GARCH family MODELS.

To confirm this however, the use of Lagrange Multiplier (LM) test proposed by Engle (1982) has mostly been explored. The procedures involved are presented as follows:

We run Ordinary Least Squares (OLS)/Autoregressive (AR) regression on the returns series, and then obtain the residuals, $\varepsilon_t = (r_t - \mu)$ and corresponding square the residuals, $\varepsilon_t^2 = (r_t - \mu)^2$

Autoregressive (AR) model of the squared residual is then run, that is: $\varepsilon_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \varepsilon_{t-2}^2 + \cdots + \omega_p \varepsilon_{t-p}^2 + \eta_t$

The following hypothesis is set:

$H_0: \omega_0 = \omega_1 = \omega_2 = \cdots = \omega_p = 0$

versus

$H_1: Atleast\ one\ of\ parameters\ is\ different\ from\ zero$

We estimate the model parameters and obtain the R^2

The LM test statistic is thus computed, LM= T*R^2 $\sim\chi_p^2$, where T is the total number of observations. The generated p-value is then observed to make a decision.

However, in general, other popular heteroscedasticity tests that have widely been explored in the literature in case Engle's LM fails in capturing the inherent clustering in the data include: White (1980) general test, Breusch-Pagan (BP) test of 1979, and Harvey test

Also to complement the test, the residual plot is observed for possible sign of volatility clustering in the returns

$ARCH$ (p)

Suppose the return on a period "t" is expressed as:

$$r_t = \mu + a_t \qquad \textbf{(3.5)}$$

Re- writing **(3.5)**, called mean equation as:

$r_t = \mu + \sigma_t \varepsilon_t$

Where "μ" stands for average (or mean) return for period "t"

Thus, $a_t = (r_t - \mu)$, the shock of an asset return is serially uncorrelated, but dependent and that the dependence of a_t can be defined by a quadratic function of its lagged values **(Tsay, 2014 p.185)**

Assumptions of a Mean Equation

(1) The expected (or mean) return μ is a constant;

(2) The "risk" to the returns, σ_t is a positive random variable having more than one possible realized value;

(3) The stochastic process (σ_t) is stationary, E[σ_t^4] is finite and all the autocorrelations of $\{\sigma_t^2\}$ are positive;

(4) the innovations, ε_t is a standardized normal variable such that $\varepsilon_t \sim N(0,1)$ and that $\varepsilon_{t's}$ are independently and identically distributed (iid) variables; and **(5)** The processes ε_t and σ_t are stochastically independent

Then an ARCH (p) assumes that

$$a_t = \sigma_t \varepsilon_t \qquad \textbf{(3.6)}$$

Such that

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \dots + \alpha_p a_{t-p}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 \qquad \textbf{(3.7)}$$

Where $\{\varepsilon_t\}$ stands for sequence of independent and identically distributed (iid) random variables with mean $[E(\varepsilon_t) = 0]$ and variance $[V(\varepsilon_t) = 1]$ equals to zero and one respectively, with coefficients satisfying the conditions as specified: $\alpha_0 > 0$, and $\alpha_i \geq 0 \; \forall \; i > 0$.

***ARCH* (1)**

It states that the distribution of the returns for period t, conditional on all previous returns, is normal with constant mean μ and time-varying conditional variance σ_t^2, defined by**:**

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 \qquad \textbf{(3.8)}$$

Given that the parameters $\alpha_0 > 0$ and $0 < \alpha_1 < 1$, then (3.8) is said to be positive and stationary. The implication of (**3.8**) is that volatility of the return in period t solely depends on the immediate previous period ($t-1$)'s squared residuals.

NB:

In ARCH(1) model, if the residual a_t is large in magnitude, the forecast for the next period's conditional volatility σ_{t+1} will also be large

Either large positive (+) or negative (-) return at time $(t-1)$, implies that higher than average volatility in the next period when α_1 is positive

That the returns near the mean level μ imply lower than average future volatility

The unconditional volatility for ARCH (1) can then be obtained by taking the expectation of the conditional volatility of (**3.8**):

$$\sigma^2 = \frac{\alpha_0}{1-\alpha_1} \tag{3.9}$$

Where α_0 is termed to be long run volatility, α_1 is the coefficient of heteroscedastic term (or measure of ARCH effect)

Unconditional Kurtosis for (3.8)

$$k_4 = \frac{3(1-\alpha_1^2)}{1-3\alpha_1^2} > 3 \;\; iff \;\; 3\alpha_1^2 < 1 \tag{3.10}$$

The major limitation of the model is that it fails to describe the return process successfully simply because the squared residuals have autocorrelations that cannot be approximated by the autocorrelation function, $\rho_k = \alpha^{|k|}$. The autocorrelations are defined when the squared residual at time t, a_t^2 has a finite variance requiring that $3\alpha_1^2 < 1$

Weaknesses of ARCH models

The model assumes that positive and negative shocks have the same effects on volatility because it depends on the square of the previous shocks. In practice, it is well known that price of a financial asset responds differently to positive and negative shocks.

The ARCH model is rather restrictive. The constraint becomes complicated for higher order ARCH models. In practice, it limits the ability of ARCH models with Gaussian innovations to capture excess kurtosis.

The ARCH model does not provide any new insight for understanding the source of variations of a financial time series. It merely provides a mechanical way to describe the behaviour of the conditional variance. It gives no indication about what causes such behaviour to occur.

ARCH models are likely to over predict the volatility because they respond slowly to large isolated shocks to the return series.

One of the weaknesses of the ARCH model is that it often requires many parameters and a high order q to capture the volatility process (Dima, Haim and Rami; 2008)

$GARCH$ (p, q)

Suppose the expected returns and its corresponding variance are obtained as $\mu = E[r_t/I_{t-1}]$ and

$\sigma_t^2 = Var(r_t / I_{t-1})$ such that I_{t-1} is information set available at time $(t-1)$; then the unexpected shock (or news) to the returns is $r_t - \mu = \varepsilon_t$. An unexpected increase in the returns due to positive value of ε_t, could be attributed to the arrival of good news (Engle and Ng, 1993); this is so because the returns (r_t) at time (t) is higher than expected (μ). However, when the value of ε_t is less than zero (0), it could be an indication of bad news since the return falls below the expectation.

GARCH model which could be written as an ARCH (∞) process is the conditional variance at time t, which is defined as the weighted sum of past squared residuals and the weighted past squared volatilities; the weights which decrease as time progresses. Thus according to Bollerslev (1986), the generalized ARCH model of the conditional volatility to GARCH (p, q) model is given as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_p a_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_q \sigma_{t-q}^2$$

$$= \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad \textbf{(3.11)}$$

Where $a_t = \sigma_t \varepsilon_t$; with **(3.11)** satisfying the conditions the parameters:

$$\alpha_i > 0, \beta_j > 0 \ and \ \sum_{i,j}^{pq} (\alpha_i + \beta_j) < 1; \ \forall \ i = 0,1,..,p \ and \ j = 1,2,..,q$$

According to Leeves (2007), GARCH $(1,1)$ process is the mostly applied in the empirical studies, and assumes the shock impacts on the volatility decline geometrically with time.

***GARCH* (1,1)**

The distribution of the returns for period t, conditional on all the previous returns, is defined as: $r_t \vdots r_2, r_3, \ldots \sim N(\mu, \sigma_t^2)$ such that its conditional variance is expressed as**:**

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad \textbf{(3.12)}$$

With its four parameters (μ, α_0, α_1 and β_1 subject to the constraints $\alpha_0 > 0$ $\alpha_1 \geq 0$ $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$ leaves (3.11) to be both positive and covariance stationary .The necessary and sufficient condition for the existence of the volatility equation, with the normality assumption is however that $\alpha_1 + \beta_1 < 1$ and for its fourth moment, kurtosis to exist, $(3\alpha_1^2 + 2\alpha_1\beta_1 + \beta_1^2) < 1$ (Ling and Li, 1997; Leeves, 2007). The model is the most popular ARCH family model especially when modelling daily returns. It is an extension of ARCH (1) model by adding a lagged variance term to the conditional variance equation. It is popular because its four parameters (μ, α_0, α_1 and β_1), are easy to estimate; it also captures major stylized facts of daily returns; and that the volatility forecasts produced by the model have similar accuracy to forecasts from more complicated ARCH family models.

Unconditional Variance for GARCH ($1, 1$)

This could also be derived by taking the unconditional expectation of (**3.12**) as:

$$\sigma^2 = \frac{\alpha_0}{1-(\alpha_1+\beta_1)} \qquad \textbf{(3.13)}$$

Unconditional Kurtosis for (**3.12**) is given as:

$$k_4 = \frac{3(1-(\alpha_1+\beta_1)^2)}{1-(3\alpha_1^2+2\alpha_1\beta_1+\beta_1^2)} > 3 \quad iff \quad 3\alpha_1^2 + 2\alpha_1\beta_1 + \beta_1^2 < 1 \qquad \textbf{(3.14)}$$

β_1 is the coefficient of the lagged conditional volatility term, α_1 is the parameter for ARCH effect while the sum $(\alpha_1 + \beta_1)$ is the measure of volatility persistence, which is the rate of mean (or volatility) reverting towards the unconditional variance. So, when

$(\alpha_1 + \beta_1) = 1$, there is presence of unit root in the GARCH process there by resulting into a new process called Integrated Generalized Autoregressive Conditional heteroscedastic (IGARCH$(1,1)$) model, where in the GARCH(1,1) automatically becomes:

$\sigma_t^2 = \alpha_0 + (1-\beta_1)a_{t-1}^2 + \beta_1\sigma_{t-1}^2.$

In this case, squared shocks are persistent such that the variance follows a random walk with drift α_0

GJR GARCH(p, q)

The GJR- GARCH model is an extension of GARCH with a leverage parameter which allows for leverage effects in the returns and was developed by Glosten, Jagananthan and Runkle (1993) to correct the limitation of the standard GARCH model, which is the imposition of symmetry on the conditional variance equation leading to its inability to respond to past negative and positive innovations differently. The GJR model therefore includes an additional term for negative lagged residuals in the standard GARCH model

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i\, a_{t-i}^2 + \gamma_i a_{t-i}^2 I_{t-1}\ \sum_{j=1}^{q} \beta_j\, \sigma_{t-j}^2 \qquad \textbf{(3.15)}$$

GJR-GARCH (1,1)

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \gamma_1 a_{t-1}^2 I_{t-1} + \beta_1 \sigma_{t-1}^2 \qquad \textbf{(3.16)}$$

Where I_{t-1} is the leverage effect indicator parameter and could be defined as:

$$I_{t-1} = \begin{cases} 1, & if\, a_{t-1} < 0 \ indicating\ bad\ news \\ 0,\ if & a_{t-1} \geq 0\ indicating\ \ good\ news \end{cases}$$

From the model, impact of good news is measured by α_i, whereas bad news impact is determined by ($\alpha + \gamma$). News impact is asymmetric if and only if $\gamma \neq 0$, but when $\gamma > 0$ it indicates leverage effect is present. To satisfy non-negativity condition coefficients should be $\alpha_0 > 0$ $\alpha_1 > 0$ $\beta_1 > 0$ and ($\alpha_1 + \gamma_1$)≥ 0. However, according to Brooks (2008:406), this model will still be good even if $\gamma < 0$ given that ($\alpha_1 + \gamma_1$)≥ 0.

The necessary conditions for the second and fourth moments of the model to exist as established by Ling and McAleer (2002), are respectively $(\alpha_1 + \beta_1 + \frac{\gamma_1}{2}) < 1$ and

$$\left(\beta_1^2 + 2\alpha_1\beta_1 + 3\alpha_1^2 + \beta_1\gamma_1 + 3\alpha_1\gamma_1 + \frac{3}{2}\gamma_1^2\right) < 1$$

especially under the assumption that the error $\varepsilon_t \approx N(0,1)$. Meanwhile, suppose it is assumed that the error $\varepsilon_t \approx t(\nu)\ \forall\ \nu \geq 5$, the fourth moment's stationarity condition becomes $(\beta_1^2 + 2\alpha_1\beta_1 + s\alpha_1^2 + \beta_1\gamma_1 + \frac{s}{2}(2\alpha_1\gamma_1 + \gamma_1^2)) < 1$, with $s = {}^{3(\nu-2)}/_{(\nu-4)}$ and when the degree of freedom, $\nu \to \infty$ the stationary condition for the fourth moment reduces to that of a normal error (**see** Ling and McAleer, 2002)

EGARCH(p,q): Exponential GARCH

Exponential GARCH (EGARCH) proposed by Nelson (1991) is another widely GARCH extension which considers leverage effects in the returns series. In this model, volatility depends on the sign of the lagged residuals and may be written as:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \left| \frac{a_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \sum_{k=1}^{r} \gamma_k \frac{a_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-1}^2) \qquad \textbf{(3.17)}$$

Alternatively (**3.13**) may be written as, especially for EGARCH(1,1):

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1(\varepsilon_{t-1}) + \beta_1 \ln(\sigma_{t-1}^2) + \delta(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) \quad \textbf{(3.18)}$$

Where δ (or γ_k) is the leverage parameter that would be computed along with α_1 and β_1. Equation (3.14) has in its last term the difference between absolute residuals and its expectation which produces leverage effects (effects which distinguishes the impacts of positive shocks from negative shocks to the stock returns). Note that δ (or γ_k) is that parameter that accounts for the asymmetry in the model where in negative shock or bad news, $\varepsilon_{t-1} < 0$, generates more volatility than good news; this serves an advantage of EGARCH over the standard GARCH model. Another significant advantage of this model is that by modelling $\ln(\sigma_t^2)$ instead of σ_t^2; Volatility's estimate is certainly going to be positive. This view according to Thomas and Mitchell (2005:16), in standard GARCH model, while there is need for model restrictions, EGARCH is however unrestricted in the course of model estimation to ensure the volatility is positive. According to Malmsten and Teräsvirta (2004), while the term $\delta(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)$ determines the magnitude effects of negative and positive news, the term $\alpha_1(\varepsilon_{t-1})$ measures asymetry. The existence conditions for the moments of EGARCH (1, 1) as derived by Nelson (1991), saying with β_1, given that the error process (ε_t) assumes all moments, then EGARCH (1, 1) exists if and only if $|\beta_1| < 1$ (Malmsten and Teräsvirta , 2004). In the term $\delta(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)$, the $E(|\varepsilon_{t-1}|)$, the expectation of absolute residuals, equals to $\sqrt{2}/\pi$ when the residual ε_{t-1} has a normal distribution; but when ε_{t-1} follows student t-distribution with v degree of freedom, the $E(|\varepsilon_{t-1}|) = \frac{2\sqrt{v-2}\,\Gamma[\frac{v+1}{2}]}{\sqrt{\pi}(v-1)\Gamma[\frac{v}{2}]}$; and finanlly, when ε_{t-1} is distributed as generalized error distribution(GED), with thickness parameter η , the $E(|\varepsilon_{t-1}|) = \Gamma(2\eta^{-1})/\{\Gamma(\eta^{-1})\Gamma(3\eta^{-1})\}^{1/2}$ (see: **Taylor, 2011**)

Model selection

Statistical model selection criteria are used to select the orders (p, q) of an ARMA process.

Procedures

Fit an ARMA (p, q) models with $0 \leq p \leq p_{max}$ and $0 \leq q \leq q_{max}$ for the chosen value of maximal orders

Let $\hat{\sigma}^2\ (p,q)$ be the MLE of the $\sigma^2 = Var(\varepsilon_t)$, the variance of ARMA innovations under GAUSSIAN or Normal assumption.

Choose (p,q) to maximise one of the following

Akaike Information Criterion, **AIC** (p,q)= $\log\left(\hat{\sigma}^2\ (p,q)\right) + 2(\frac{p+q}{n})$

Bayesian Information Criterion, **BIC** $(p,q) = \log\left(\hat{\sigma}^2\ (p,q)\right) + \log(n)(\frac{p+q}{n})$

Hannan-Quinn Criterion, **HQ** (p,q)= $\log\left(\hat{\sigma}^2\ (p,q)\right) + 2(\log(n))\left(\frac{p+q}{n}\right)$

Meanwhile, according to Danielsson (2011), for models with equal number of parameters, one could consider the model with maximum value of likelihood (LL) functions as the best; whereas for models with unequal number of parameters, parsimony is favoured such that either AIC or BIC criterion (Malmsten and Teräsvirta, 2004), which is an adjusted form of likelihood function should be preferred. Another model selection choice is premised on settling for model with the best forecast ability by choosing the one with least error measure; and finally model could be chosen by considering the one that best passed misspecification tests. In this research however, the use of least AIC would be preferred in selecting the best model considering other underlined respective models' assumptions.

News Impact Curve (NIC)

Holding constant, all information in time, $t-2, t-3, \dots \dots$; according to Engle and Ng(1993), the relationship between information available in the next period $(t-1)$, summarised by ε_{t-1} and the conditional variance σ_t^2 is termed to be news impact curve (NIC). The NIC is a useful tool used in describing the asymmetric responses of stock returns to volatility (Leeves, 2007). All lagged conditional variances are estimated at the unconditional variance of the stock returns, with NIC measuring how new information is factored into the volatility estimates. That is, NIC helps to determine how much impact shocks have on the conditional volatility. According to Henry (1998), the NIC of GARCH $(1,1)$ is both centred and symmetric at the point where ε_{t-1} = 0, and those of EGARCH $(1,1)$ and GJR models also centred at $\varepsilon_{t-1} = 0$. However, while EGARCH (1, 1) has a steeper slope for $\varepsilon_{t-1} < 0$, given that $\delta_1 < 0$, the GJR generates different slopes for both its negative and negative parts.

Table 1 below contains the relevant NICs, for various lagged conditional variance σ_t^2, at its unconditional level σ^2 for different ARCH/GARCH family models as presented in Henry (1998) and (Leeves, 2007).

Table 1: News Impact Curves for the Selected Models

Model	**News Impact Curves**
ARCH(1)	$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2$ OR $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$; i.e. $a_{t-1}^2 = \varepsilon_{t-1}^2$
GARCH (1, 1)	$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma^2$ OR $\sigma_t^2 =$ A+ $\alpha_1 a_{t-1}^2$ ($\forall A = \alpha_0 + \beta_1 \sigma^2$)
EGARCH (1,1)	$\sigma_t^2 = Dexp\left[\frac{(\delta_1+\alpha_1)}{\sigma} a_{t-1}\right] \forall a_{t-1} > 0$ and $\sigma_t^2 = Dexp\left[\frac{(\delta_1-\alpha_1)}{\sigma} a_{t-1}\right] \forall a_{t-1} < 0$, where D= $\sigma^{2\beta} \exp[\alpha_0 - \alpha_1\sqrt{\frac{2}{\pi}}]$
GJR	$\sigma_t^2 = A + \alpha_1 a_{t-1}^2$, $\forall a_{t-1} > 0$; $\sigma_t^2 = A + (\alpha_1+\delta_1) a_{t-1}^2, \forall a_{t-1} < 0$, where $A = \alpha_0 + \beta_1 \sigma^2$

4. Results and Discussions

Series Plots Interpretation

Figures 1 to 4 are the price series while figures 5 to 8 are the returns series for the four banks at the overall. From the price series it is obvious that the plots look differently but across the four banks, right from the consolidation period, there is steady increase in the stock prices of the banks till the beginning of 2008 when a sharp decline started to set in and reached its lowest point close to the end of 2008 across the four banks series. While First bank and UBA continue on the low trend and fail to recover till the end of the 2014, GTB and Access bank struggle to recover and rise again but could not rise at a rate it was before the decline. In the returns series there are spikes due to volatility in price, but with the spikes rate in GTB less pronounced compared to other banks. Thus, the varying levels in both series especially the price, across the four banks serves a significant justification for the sub-division into sub-periods as adopted in this research, such that in-depth examination with respect to the effects of the identified scenarios on the bank stock could be appreciated.

Figure 1: First Bank Price Series 2004-2014

Figure 2: Guaranty Trust Price Series 2004-2014

Figure 3: UBA Price Series 2004-2014

Figure 4: Access Bank Series 2004-2014

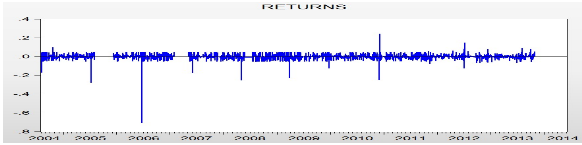

Figure 5: First Bank Returns Series 2004-2014

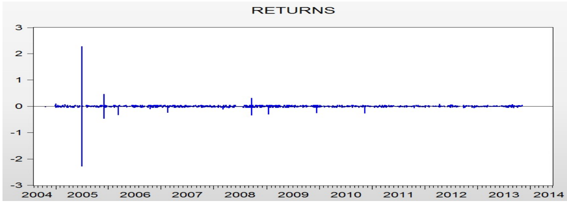

Figure 6: GTB Returns Series 2004-2014

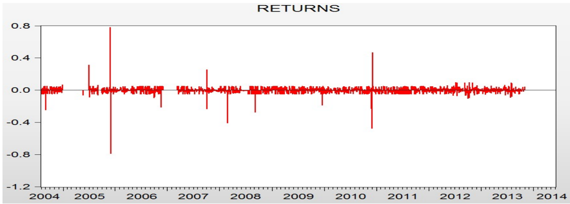

Figure 7: UBA Returns Series 2004-2014

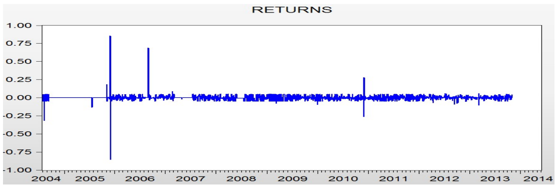

Figure 8: Access Bank Returns Series 2004-2014

Summary Statistics

In order to determine the distribution of the stock returns of these banks, we compute the relevant descriptive statistics and the results are presented in tables 2, 3, 4 &5 below. It is found that the sample sizes for the four banks across the periods investigated are approximately the same, except for GTB which traded 23 days more than other banks during consolidation. The mean returns of the four banks though either negative or positive, are approximately zeros, while the median are all zeros except for the financial crisis period when negative values are obtained across the four banks. Of the significant note however is that both the mean and median returns are consistently negative during the crisis across the four banks. Also observed is that the returns series for the four banks, across all the period could be said to be negatively skewed with very high kurtoses; with first bank being mostly negatively skewed(-10.7967) during post-consolidation period, and GTB appears to be mostly leptokurtic (799.992), at the overall period.

Table 2: ACCESS BANK DESCRIPTIVE STATISTICS

Period	Sample size(T)	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
Consolidation	343	-0.0006	0.0000	0.1829	-0.3192	0.02566	-4.9381	80.5186
Post-Consolidation	486	0.0042	0.0000	0.8540	-0.8540	0.06688	2.1010	132.6981
Financial Crisis	350	-0.0023	-0.0037	0.0488	-0.0513	0.03269	0.0901	1.9137
Bank Reforms	394	-0.0002	0.0000	0.0488	-0.0959	0.03144	-0.1057	2.3178
Post-Reforms	844	0.0000726	0.0000	0.2799	-0.2626	0.02767	0.0762	24.1811
Overall	2417	0.0004	0.0000	0.8540	-0.8540	0.0397	1.9603	218.8464

Table 3: UBA Summary Statistics

Period	Sample size	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
Consolidation	343	0.000368	0.0000	0.3126	-0.2446	0.03088	1.4997	43.4973
Post-Consolidation	486	0.0022	0.0000	0.78097	-0.7888	0.0580	-0.4789	139.5274
Financial Crisis	350	-0.0024	-0.0039	0.2563	-0.4099	0.0424	-2.5773	33.8739
Bank Reforms	394	-0.0015	0.0000	0.04879	-0.1891	0.0301	-0.6340	5.7236
Post-Reforms	844	-0.000209	0.0000	0.46898	-0.4775	0.0384	-0.3260	57.2936
Overall	2417	-0.00017	0.0000	0.7810	-0.7888	0.0417	-0.6569	127.0956

Table 4: GTB Summary Statistics

Period	Sample size	Mean	Median	Max.	Min.	Std Dev.	Skewness	Kurtosis
Consolidation	370	0.0001	0.0000	2.8278	-2.2828	0.1708	0.03264	173.6019
Post-Consolidation	486	0.0021	0.0007	0.4655	-0.4695	0.0432	-1.4204	66.2166
Financial Crisis	350	-0.0027	-0.0038	0.3179	-0.3444	0.0441	-1.1385	25.5236
Bank Reforms	394	0.0007	0.0000	0.0488	-0.2561	0.0282	-1.8421	19.2456
Post-Reforms	844	0.0006	0.0000	0.0913	-0.2619	0.0211	-2.1259	31.9421
Overall	2418	0.0004	0.0000	2.2828	-2.2828	0.0729	-0.1438	799.9332

Table 5: First Bank Summary Statistics

Period	Sample size	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
Consolidation	343	0.0003	0.0000	0.0970	-0.2772	0.0273	-3.5099	37.4236
Post-Consolidation	486	0.0007	0.0000	0.0488	-0.7070	0.0409	-10.7967	186.4636
Financial Crisis	350	-0.0018	-0.0049	0.0488	-0.2538	0.0335	-1.0183	10.7367
Bank Reforms	394	-0.0014	0.0000	0.0488	-0.2282	0.0286	-1.4306	12.6642
Post-Reforms	841	0.00013	0.0000	0.2438	-0.2490	0.0263	0.1063	22.5086
Overall	2414	-0.0003	0.0000	0.2438	-0.7070	0.0313	-5.5001	119.0459

Normality Tests

To examine how close to normality are the return series of the four banks, we conducted student-t tests around the mean, skewness and kurtosis of each of the banks across the six periods of investigation; the results of which are presented in tables 6,7, 8 & 9 below. From the findings, mean returns are all approximately equal to zero, simply because the computed t-statistic values are all less than the critical value of 1.96, this is in line with the standard Random Walk (RW) assumption.

The test around skewness reveals that UBA and first bank series are all highly skewed across the six periods of investigation; whereas for Access the we could not reject hypothesis of symmetry during financial crisis (0.6883<1.96) and bank reforms period (-0.8566> -1.96), and for GTB, the only period the hypothesis of symmetry could not be rejected is during consolidation (0.2563<1.96).

Also for kurtosis and Jarque Bera tests, it is obvious the kurtosis are all above the value accommodated by a normal distribution; the same goes to the normality tests across all the periods, the p-value shows that all are significant, meaning the distributions of the stock prices across the six periods are non-normal.

Table 6: ACCESS BANK Normality Tests

Period	Mean (t)	Skewness test(t)	Kurtosis test(t)	Jarque -Bera	p-value
Consolidation	-0.4329	-37.339	293.053	87274.44	0.0000
Post-Consolidation	0.1385	18.9109	583.6415	340994.8	0.0000
Financial Crisis	-1.3165	0.6883	-4.1484	17.6809	0.0001
Bank Reforms	-0.1266	-0.8566	-2.7642	8.3747	0.0152
Post-Reforms	0.0763	10.7324	125.6293	15778.02	0.0000
Overall	0.0000495	39.3477	2166.0951	74508912	0.0000

Table 7: UBA Normality Tests

Period	Mean (t)	Skewness test(t)	Kurtosis test(t)	Jarque -Bera	p-value
Consolidation	0.2208	11.339	153.0973	23567.29	0.0000
Post-Consolidation	0.8362	-4.3101	614.3733	377473.1	0.0000
Financial Crisis	-1.0590	-19.6844	117.9017	14288.31	0.0000
Bank Reforms	-0.9892	-5.1376	11.0353	148.1760	0.0000
Post-Reforms	-0.2017	-3.8665	321.9691	103679.2	0.0000
Overall	-0.2004	-13.1844	1245.3433	1551054	0.0000

Table 8: GTB Normality Tests

Period	Mean (t)	Skewness test(t)	Kurtosis test(t)	Jarque -Bera	p-value
Consolidation	0.0108	0.2563	667.4891	448702	0.0000
Post-Consolidation	1.0717	-12.7836	284.4747	81089.34	0.0000
Financial Crisis	-1.1454	-8.6954	172.0268	7473.922	0.0000
Bank Reforms	0.4927	-14.9275	65.8231	4555.524	0.0000
Post-Reforms	0.8261	-25.2138	171.6310	30092.99	0.0000
Overall	0.2698	-2.8868	7999.1612	63986585	0.0000

Table 9: First Bank Normality Tests

Period	Mean (t)	Skewness test(t)	Kurtosis test(t)	Jarque -Bera	p-value
Consolidation	0.2035	-26.5379	130.1361	17639.65	0.0000
Post-Consolidation	0.3773	-97.1703	825.5862	691035	0.0000
Financial Crisis	-1.0052	-7.7774	29.5450	933.3943	0.0000
Bank Reforms	-1.2492	-11.5929	39.1569	1667.666	0.0000
Post-Reforms	0.1433	1.2585	115.4831	13337.92	0.0000
Overall	-0.4709	-110.3224	1163.8388	1366693	0.0000

Normal and Q-Q Plots

To further examine the normality of the series, figures **9-12** present the both the histogram and normal plot of the banks series at the overall level. From our observation, we note that the series not only are leptokurtic, are also skewed and fat tailed at both ends. The Q-Q plots presented in figures **13-16** further establish the non-normality of the series and even tell us more about how fat the tails are for the banks. For instance, in all the cases presented, there are outliers, that is some points slightly far away from the straight line, an indication of fat tail.

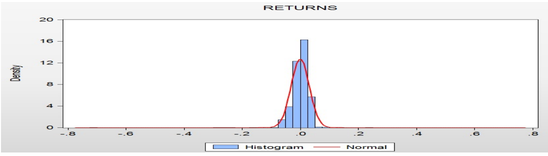

Figure 9: First Bank Normal Plot 2004-2014

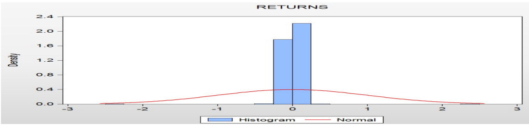

Figure 10: GTB Normal Plot 2004-2014

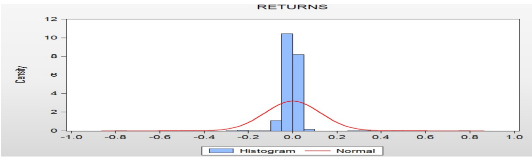

Figure 11: UBA Normal Plot 2004-2014

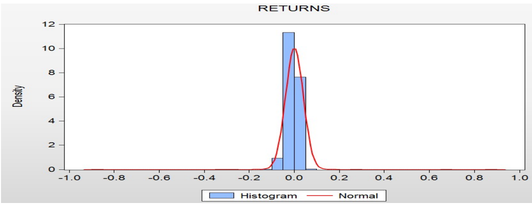

Figure 12: Access Bank Normal Plot 2004-2014

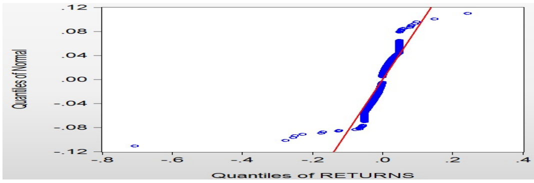

Figure 13: Q-Q Plot First Bank 2004-2014

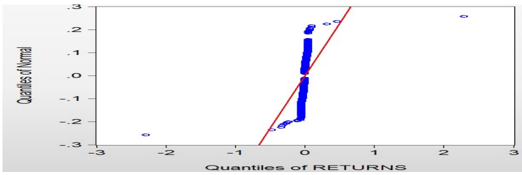

Figure 14: Q-Q Plot for GTB 2004-2014

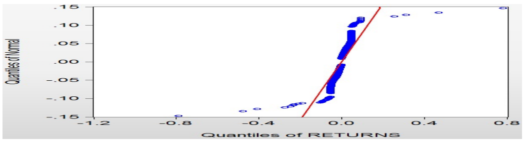

Figure 15: Q-Q Plot for UBA 2004-2014

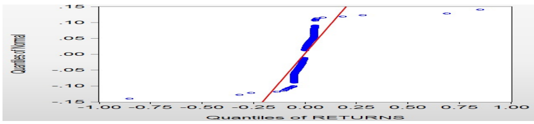

Figure 16: Q-Q Plot for Access Bank 2004-2014

Unit Root (Stationary) Tests

Having determined the normality status of the series we proceed on to test for the presence of unit root in the series, which is a measure for stationarity. To achieve this, Augmented-Dickey Fuller (ADF), commonly used for this purpose is explored and the results are as displayed in tables 10-113. From the results first we observe that ADF test at only level of the returns series is sufficient for achieving required results. Our findings show that the series are all stationary for the four banks and across the six periods of our investigation.

Table 10: Unit Root (Stationarity) Tests for UBA

Period	t-test	p-value	Decision
Consolidation	-17.298	0.0000	Stationary
Post-Consolidation	-31.457	0.0000	Stationary
Financial Crisis	-14.973	0.0000	Stationary
Bank Reforms	-15.028	0.0000	Stationary
Post-Reforms	-25.045	0.0000	Stationary
Overall	-53.466	0.0001	Stationary

Table 11: Unit Root (Stationarity) Tests for GTB

Period	t-test	p-value	Decision
Consolidation	-15.227	0.0000	Stationary
Post-Consolidation	-26.296	0.0000	Stationary
Financial Crisis	-18.695	0.0000	Stationary
Bank Reforms	-15.669	0.0000	Stationary
Post-Reforms	-28.657	0.0000	Stationary
Overall	-33.089	0.0001	Stationary

Table 12: Unit Root (Stationarity) Tests for First Bank

Period	t-test	p-value	Decision
Consolidation	-17.637	0.0000	Stationary
Post-Consolidation	-21.411	0.0000	Stationary
Financial Crisis	-12.228	0.0000	Stationary
Bank Reforms	-13.534	0.0000	Stationary
Post-Reforms	-30.431	0.0000	Stationary
Overall	-44.589	0.0001	Stationary

Table 13: Unit Root (Stationarity) Tests for Access Bank

Period	t-test	p-value	Decision
Consolidation	-19.299	0.0000	Stationary
Post-Consolidation	-29.885	0.0000	Stationary
Financial Crisis	-12.539	0.0000	Stationary
Bank Reforms	-14.324	0.0000	Stationary
Post-Reforms	-30.092	0.0000	Stationary
Overall	-54.796	0.0001	Stationary

Heteroscedasticity Tests

Subject to fitting appropriate ARCH/GARCH family models to the banks returns, we conducted test to confirm the presence of ARCH effect/volatility clustering in the returns. To achieve this Lagrange Multiplier (LM) proposed by Engle is explored; where this fails, we double check using Breusch-Pagan Godfrey (**BP**) test instead. The results of these tests are obtained in tables 14-17 below. From the results we find that there is presence of ARCH effects across the four banks and periods. Note that where LM fails, the BP is enclosed in the bracket.

Table 14: ARCH Effect Test for Access Bank's Returns at Lag 1

Period	t-test-Engle(BP)	p-value	Decision
Consolidation	-12.28(**BP**)	0.0000	Significant
Post-Consolidation	9.89	0.0000	Significant
Financial Crisis	9.69	0.0000	Significant
Bank Reforms	7.44	0.0000	Significant
Post-Reforms	15.97	0.0000	Significant
Overall	21.99	0.0000	Stationary

Table 15: ARCH Effect Test of First bank's Returns at Lag 1

Period	t-test-Engle(BP)	p-value	Decision
Consolidation	-13.20(**BP**)	0.0000	Significant
Post-Consolidation	-28.62(**BP**)	0.0000	Significant
Financial Crisis	-6.44(**BP**)	0.0000	Significant
Bank Reforms	-9.13(**BP**)	0.0000	Significant
Post-Reforms	14.39	0.0000	Significant
Overall	-28.83(**BP**)	0.0000	Stationary

Table 16: ARCH Effect Test for GTB Returns at Lag1

Period	t-test-Engle(BP)	p-value	Decision
Consolidation	10.97	0.000	Significant
Post-Consolidation	10.27	0.0000	Significant
Financial Crisis	7.18	0.0000	Significant
Bank Reforms	-9.46(**BP**)	0.0000	Significant
Post-Reforms	-12.00(**BP**)	0.0000	Significant
Overall	28.30	0.0000	Stationary

Table 17: ARCH Effect Test for UBA' Returns at Lag 1

Period	t-test-Engle(BP)	p-value	Decision
Consolidation	4.37(**BP**)	0.000	Significant
Post-Consolidation	12.49	0.0000	Significant
Financial Crisis	-9.39(**BP**)	0.0000	Significant
Bank Reforms	2.88	0.0042	Significant
Post-Reforms	16.11	0.0000	Significant
Overall	26.12	0.0000	Stationary

Fitting Appropriate ARCH/GARCH Model

Having ascertained that the returns series of all the banks are heteroscedastic using appropriate test statistic, we proceed on to fitting the indicated models: ARCH (1), GARCH (1, 1), GJR-GARCH (1, 1) and EGARCH (1, 1); with the assumptions that the innovations (or errors) are distributed as: (i) Normal; (ii) Student-t; and (iii) Generalized error distributions. Thereafter which model with the least Akaike Information Criterion (AIC) (or the highest log-likelihood) in each case, is chosen as our favoured one with the results of the selected models displayed in tables 18-21 below.

Table 18: Selected Models for Access Bank's Returns across Different Periods

Period	Models	Error Distribution	α_0	α_1	$\gamma_1(\delta)$	β_1	AIC	Persistence
Consolidation	ARCH(1)	T-Distribution	6.49E-14(6.7478)	0.348(9.314)	N/A	N/A	-22.998	0.3476
Post-Consolidation	GARCH(1,1)	T-Distribution	2.34e-13 (2.461)	0.774 (13.386)	N/A	0.482(84.237)	-6.3739	1.256>1
Financial Crisis	GARCH(1,1)	T-Distribution	7.60E-09 (0.309)	0.8709 (7.1224)	N/A	0.4304 (13.117)	-4.445	1.2013>1
Bank Reforms	GARCH(1,1)	GED	6.62E-05(2.14)	0.1416(2.912)	N/A	0.7808(10.476)	-4.244	0.9224
Post-Reforms	GARCH(1,1)	GED	0.000195	0.3375(3.126)	N/A	0.436(3.515)	-4.648	0.7730
Overall	**GARCH(1,1)**	**T-Distribution**	**4.07E-14(1.947)**	**0.5283(23.571)**	**N/A**	**0.6079(180.632)**	**-7.0034**	**1.1362>1**

Table 19: Selected Models for First Bank's Returns across Different Periods

Period	Models	Error Distribution	α_0	α_1	$\gamma_1(\delta)$	β_1	AIC	Persistence
Consolidation	GARCH(1,1)	GED	2.62E-13(0.028)	0.9697(4.865)	N/A	0.5225(31.41)	-8.8174	1.4922>1
Post-Consolidation	GARCH(1,1)	T-Distribution	7.03E-12(1.64)	0.6498(13.18)	N/A	0.5798(84.35)	-6.260	1.2296>1
Financial Crisis	GARCH(1,1)	T-Distribution	7.91E-09(0.655)	1.045(6.179)	N/A	0.4382(14.166)	-4.569	1.4831>1
Bank Reforms	GARCH(1,1)	GED	0.00012(2.755)	0.5025(2.755)	N/A	0.4662(4.1745)	-4.607	0.9690
Post-Reforms	GARCH(1,1)	GED	0.000123(4.350)	0.4639(3.972)	N/A	0.4454(5.986)	-4.902	0.9093
Overall	**GARCH(1,1)**	**T-Distribution**	**3.16E-14(0.748)**	**0.979(7.399)**	**N/A**	**0.6343(143.97)**	**-5.056**	**1.613>1**

Table 20: Selected Models for GTB's Returns across Different Periods

Period	Models	Error Distribution	α_0	α_1	$\gamma_1(\delta)$	β_1	AIC	Persistence
Consolidation	EGARCH (1,1)	T-Distribution	-0.3926(-20.64)	0.1584(18.044)	0.1201(14.105)	0.9659(612.2601)	-6.246	0.9659
Post-Consolidation	GARCH(1)	GED	0.00057(8.95)	0.4802(3.47)	N/A	0.5145(13.34)	-4.4129	0.9947
Financial Crisis	EGARCH (1,1)	T-Distribution	-1.315(-5.149)	0.8389(6.491)	0.1954(2.092)	0.8969(29.264)	-4.1496	0.8969
Bank Reforms	GARCH(1,1)	GED	0.000118(2.78)	0.515(3.6081)	N/A	0.430(3.839)	-4.6715	0.9452
Post-Reforms	GARCH(1,1)	GED	0.000139(3.968)	0.5069(3.2752)	N/A	0.2879(2.487)	-5.321	0.7948
Overall	**EGARCH(1,1)**	**GED**	**-0.326(-19.096)**	**0.213(12.43)**	**0.145(8.97)**	**0.971(748.532)**	**-5.1445**	**0.9710**

Table 21: Selected Models for UBA's Returns across Different Periods

Period	Models	Error Distribution	α_0	α_1	$\gamma_1(\delta)$	β_1	AIC	Persistence
Consolidation	GARCH(1,1)	GED	5.76E-05(5.851)	0.216(3.0856)	N/A	0.4908(6.922)	-5.427	0.7068
Post-Consolidation	GARCH(1,1)	T-Distribution	1.93E-13(0.392)	0.941(10.28)	N/A	0.4203(39.92)	-6.710	1.3608 >1
Financial Crisis	GARCH(1,1)	T-Distribution	1.09E-08(0.712)	1.4688(6.2999)	N/A	0.3136(9.675)	-4.557	1.7824 >1
Bank Reforms	GARCH(1,1)	T-Distribution	0.000221(1.958)	0.287(2.538)	N/A	0.4603(2.2621)	-4.288	0.7471
Post-Reforms	GARCH(1,1)	GED	0.000239(5.508)	0.465(4.422)	N/A	0.4007(6.212)	-4.235	0.8657
Overall	**GJR-GARCH(1,1)**	**T-Distribution**	**7.35E-12(1.045)**	**0.345(14.286)**	**0.1106(2.706)**	**0.6399(118.82)**	**-5.052**	**1.0404 >1**

Brief Discussion on the Fitted Model

In all situation or scenario and across the four banks considered in this research, we observe none of the selected models accommodate Gaussian Error Distribution (GED), of course this is apparent given the leptokurtic nature of the return series of each of the banks as presented earlier. Further critical look at the results also reveals that Student-T distribution was the only distribution found appropriate as the distribution of errors for the selected GARCH-family model especially during the financial crisis, and across the four banks studied. While generally, the persistence level in volatility could said to be very high across the four banks and across the six scenarios examined, there still differences in its rates across the banks and scenarios of interest. Also for Access and First banks in particular, none of the asymmetric GARCH models is accommodated by their respective fitted GARCH-family model across the six scenarios investigated, despite very high levels of persistence noted in volatilities. Discussing further about the volatility persistence for each of the banks, we present the following

For **Access bank**

It is noticed that at the overall period, August 2004 to May, 2014, the persistence level is far above one, the same goes to post consolidation and financial crisis periods witnessed by the bank, phenomenon known to be periods of infinite or extreme prolonged shocks to the respective volatility. This implies that outside the consolidation period, the bank's stock was extremely risky to trade in because no one would be able to quantify the depth of or knew when the bank could recover in event of any shock during the periods of study, especially post consolidation and financial crisis periods.

Another useful observation was that the deep shock experienced by the bank during the financial crisis persisted through to the second reforms initiated by the central bank; aftermath of which there was significant drop in the persistence. Looking inward, one notices that while the causes of the persistence for post consolidated and financial crisis periods could be traced more to shocks due to historical market news especially that of the immediate previous trading period ($t-1$); the persistence during second reform could be more attributed to the previous level of risk suffered or loss experienced by investing in the bank's stocks, that is historic volatility

For **First bank**

The persistence level observed in volatility was the highest, at the overall period when compared to other banks within the same period; the rate that was about 61% higher than one(1). Critical examination shows that right from the consolidation period through to the financial crisis period, the persistence rate has been far above one, the phenomenon that could be traced to over subscription since no notice of leverage effects of either negative or positive shock is observed.

Further examination reveals that the contributions of shocks due to market news, in the previous trading days, were more responsible for the overall persistence observed in volatility, especially the periods of consolidation and financial crisis experienced by the bank. The second reform witnessed though could not bring the persistence level down, significant reductions recorded post reform compared to prior the reform.

For **GTB**

In terms of persistence, the rates though expectedly fall below one across all the periods of interest, they are considered to be very high, for being very close to one except for post-reform period which is relatively lower compared to any other period. Also observed is that at the periods of consolidation, financial crisis and overall period where EGARCH (1, 1) model is fitted, asymmetric effect of positive shock (good news) characterises the respective volatility as against negative shock (bad news) since the leverage effect parameter (δ) is positive in each case.

For **UBA**

No asymmetric GARCH model is fitted at any of the sub-periods except at the overall period where GJR-GARCH (1, 1) is accommodated with leverage parameter ($\gamma = 0.11$) , which indicates that the returns series is characterised by negative (or bad) news, with persistence rate of 1.0404, slightly above 1. News impact on the volatility persistence during financial crisis was very high, and was responsible for the extremely high persistence (1.7824) recorded in volatility at the period, the same goes to post-consolidation periods.

Meanwhile besides GTB, the volatility persistence noted during financial crisis and at the overall level across the three other banks (Access, First and UBA) is far above one; and that historic news impact shocks have been more responsible for the rise in volatility across the various periods examined and across the four banks. Thus with this observation, one could conclude that impacts of the financial crisis on the volatility across the four banks were highly significant.

Table 22: Estimate News Impact Curves Values during Financial Crisis

a_{t-1}	Access-GARCH(1,1)	First-GARCH (1, 1)	GTB-EGARCH (1, 1)	UBA-GARCH(1,1)
-10	87.09	104.5	-0.23	146.88
-9	70.54	84.65	-0.27	130.72
-8	55.74	66.88	-0.32	94
-7	42.6	51.21	-0.38	71.97
-6	31.35	37.62	-0.46	52.88
-5	21.77	26.13	-0.55	36.72
-4	13.93	16.72	-0.66	23.5
-3	7.84	9.41	-0.79	13.22
-2	3.48	4.18	-0.94	5.88
-1	0.87	1.05	-1.13	1.47
0	0	0	-1.35	0
1	0.87	1.05	-1.01	1.47
2	3.48	4.18	-0.76	5.88
3	7.84	9.41	-0.57	13.22
4	13.93	16.72	-0.42	23.5
5	21.77	26.13	-0.32	36.72
6	31.35	37.62	-0.24	52.88
7	42.6	51.21	-0.18	71.97
8	55.74	66.88	-0.13	94
9	70.54	84.65	-0.1	130.72
10	87.09	104.5	-0.07	146.88

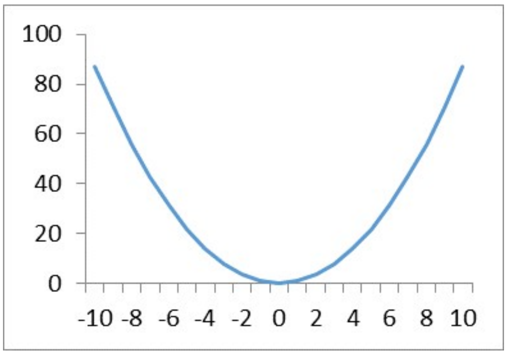

Figure 17: Access Bank NIC in Financial Crisis

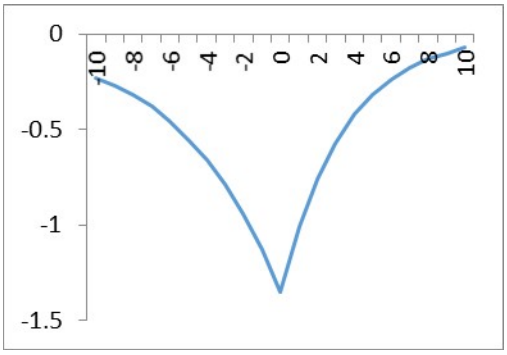

Figure 19: GT Bank NIC in Financial Crisis

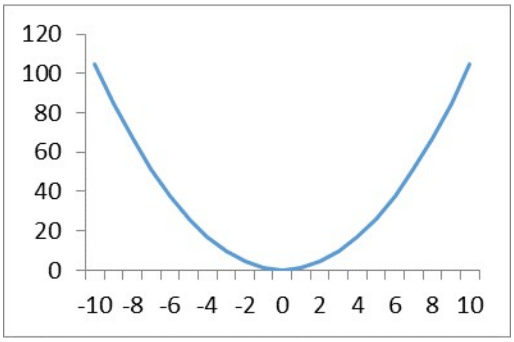

Figure 18: First Bank NIC in Financial Crisis

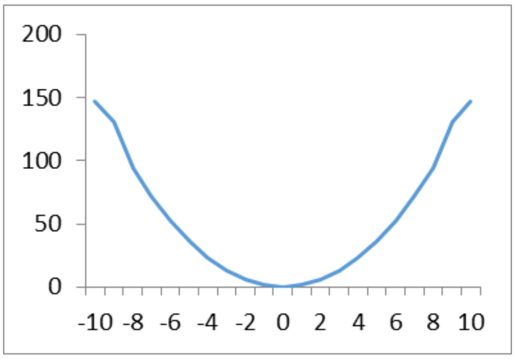

Figure 20: UBA Bank NIC in Financial Crisis

Looking at the NIC plots as presented in figures 17-20 above, regarding the effects of news on the volatility, it could be observed that while the NIC's for Access, First and UBA are symmetric and minimum (or centered) at zero (0), that of the Guaranty Trust Bank falls far below zero (-1.35), during the financial crisis.

5. Summary and Conclusion

So far we have been able to obtain both price and returns series plots at the overall level with respect to the four banks (see figures 1-8). There after which summary statistics are obtained for the four banks across the four scenarios being investigated (see Tables 2-5); we then proceeded on to obtaining tests around the mean, skewness and kurtosis using t-statistic and ended this part with normal tests using Jarque-Bera (JB) statistic (see Tables 6-9 for details). To ascertain the normality tests we went ahead to obtain both the normal and q-q plots for the respective bank, particularly at the overall periods (see figures 9-16).

Testing around the stationarity of the series then followed using Augmented Dickey-Fuller tests (Tables 10-13), thereafter which we obtained heteroscedasticity tests to confirm the presence or otherwise of Arch effects using both Engle and Breusch-Pagan LM tests (Tables 14-17). And finally the models are fitted covering the four scenarios and the models with the least AICs from among the fitted ARCH (1), GARCH (1, 1), EGARCH (1, 1) and GJR-GARCH (1, 1) selected to be appropriate across the six periods/scenarios (see Tables 18-21).Then the news impact curve (NIC) on the effect of news shock on the returns (see figures (see figures 17-20). For the four banks, the volatilities are characterised by the models with non-normal error distributions such as student-T- and GED.

Generally the series are leptokurtic, skewed, thus non-normally distributed. These features are however common across assets and across markets. Also, there is presence of heteroscedasticity in the series, which justifies the fitting ARCH/GARCH family models to the returns. The persistence in volatility across the banks and across the sub-periods are significantly high except for post reforms when significant reduction in persistence was recorded. Thus, one could conclude that the various scenarios experienced so far within the Nigerian financial system, significantly impacted on the volatility persistence of the four banks at varying degree and that in most cases, the historic news announcement was responsible, such that any shock on the volatility persist for a long time.

Conflict of Interests

The authors declare that there is no conflict of interests.

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