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Modelling Volatility of Asset Returns in Nigerian Stock Market: Applications of Random Level Shifts Models

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Authors' contributions

This work was carried out in collaboration between both authors. Author DAK designed the entire study, performed the statistical analysis, wrote the abstract and wrote the first draft of the manuscript. Author MAC proof read, made and effected all the necessary corrections of the study and managed the literature reviews. Both authors read and approved the final manuscript.

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Abstract

This study examines the impact of structural breaks on conditional variance and mean reversion in symmetric and asymmetric GARCH models. A multiple breakpoint testing procedure was used to identify structural break points in conditional variance of daily stock returns of 8 commercial banks in Nigerian stock market for the period 17th February, 2003 to 31st September, 2016. Standard GARCH, EGARCH and TGARCH models with and without break points were applied to evaluate variance persistence, mean reversion rates and leverage effects while estimating conditional volatility. Results showed high persistence in conditional volatility for the banking stocks, but when the random level shifts were incorporated into the models, there was reduction in the conditional volatility of these models. The half-lives of volatility shocks also reduce in the presence of these regime shifts. TGARCH was found to be the best fitting model among the standard GARCH and EGARCH models. The study recommends estimation of volatility models to incorporate structural breaks in order to avoid over estimation of shock persistence in the conditional variance.

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1 Introduction

Volatility modeling of stock returns using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) type models has become topical among financial researchers in recent years after its first introduction by [1] and [2]. This is partly because GARCH type models are more successful in capturing most of the volatility features or stylized facts of financial data such as volatility clustering, volatility shock persistence, volatility mean reversion, leverage effect and risk premium among others; and partly because volatility is an important concept for many economic and financial applications such as risk management, option trading, portfolio optimization and asset pricing. The prices of stocks and other assets depend on the covariance structure (expected volatility) of returns. Banks and other financial institutions make volatility assessments as a part of monitoring their risk exposure [3].

Recent studies have shown that volatility of stock returns is considerably affected by sudden structural break points or sudden regime shifts which occur as a result of local, international or global financial, political and economic crises or recession. In studies conducted by Perron [4,5], results showed that the sum of autoregressive parameters are always biased to unity when stationary processes are contaminated with sudden regime shifts. It is therefore, more reasonable to incorporate these sudden shifts in variance when modeling and estimating parameters of volatility models.

Several researchers have conducted studies that are related to sudden shifts in variance across the globe. [6] found that ignoring structural break points in volatility increases persistence in conditional variance of stock returns whereas incorporating these sudden shifts in volatility reduces the persistence in conditional variance using heteroskedastic models. [7] conducted a study on the Canadian stock data using GARCH type models and found that persistence in volatility shocks reduced drastically when the sudden break points were considered while estimating conditional volatility. [8], while predicting volatility in Gulf Arab countries stock markets also found significant reduction in volatility shock persistence when valid sudden shifts in variance were incorporated. [9] examined the impact of structural breaks in conditional volatility on variance persistence of asymmetric GARCH models using Bai and Perron multiple breaks testing procedure to detect structural break points in conditional variance of daily stock returns of seven emerging markets from 1977 to 2014. They estimated EGARCH (1,1) and TGARCH (1,1) with and without breaks and found that persistency in variance significantly reduced when regime shifts were considered in the conditional volatility of these models. The half-lives to volatility shocks were also found to decline significantly in the presence of these sudden break points. See [10,11,12,13] for similar contributions.

In Nigeria, studies relating to sudden shifts in conditional variance of stock return volatility are very scarce. However, [14] modeled abrupt shift in time series using indicator variable by employing symmetric and asymmetric GARCH models with and without sudden shifts in variance. They used daily closing share prices of 10 insurance stocks of the Nigerian stock exchange from 02/01/2006 to 26/05/2014. They found that the highly persistence in volatility of most insurance stock return rates were reduced when the regime shifts were incorporated into the models. In this paper, we extend the existing literature by investigating the impacts of sudden regime shifts on the conditional variance of eight banking returns in Nigerian stock market using both symmetric and asymmetric GARCH type models with and without structural break points.

2 Materials and Methods

2.1 Data source and integration

The data used in this study comprise of 2628 daily closing share prices from ACCESS Bank covering the period 04/11/2005 to 31/09/2016; 1645 daily closing share prices from ECOBANK covering the period 01/08/2010 to 31/09/2016; 2693 daily closing share prices from DIAMOND Bank covering the period

29/07/2005 to 31/09/2016; 3295 daily closing share prices of FIRST Bank Holding covering the period 19/02/2003 to 31/09/2016; 3297 daily closing share prices from GUARRANTY TRUST Bank covering the period 17/02/2003 to 31/09/2016; 3292 daily closing share prices from UNITED BANK FOR AFRICA covering the period 25/02/2003 to 31/09/2016; 3228 daily closing share prices from UNION Bank covering the period 06/06/2003 to 31/09/2016 and 2882 daily closing share prices from ZENITH Bank covering the period 21/10/2004 to 31/09/2016 taken from www.nse.com. All the banks are commercial banks in Nigeria and all the share prices are in Nigerian naira. The daily returns r_t were calculated as the continuously compounded returns corresponding to the first differences in logarithms of closing prices of successive days.

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \times 100 = [\log(P_t) - \log(P_{t-1})] \times 100 \tag{2.1}$$

where P_t denotes the closing market index at the current day (t) and P_{t-1} denotes the closing market index at the previous day $(t-1)$.

2.2 Bai and Perron test procedure for multiple level shifts

Bai and Perron [15] proposed a test for multiple structural break points which predict persistently several shifts in variance. The power of the test was strengthened by [16] which made the test more efficient. In the model they consider m breaks or $m+1$ regimes as a multiple linear model.

$$y = x_i^T \beta + u_t \tag{2.2}$$

$$y_i = x_i^T \beta_i + z_i^T \delta + u_t \tag{2.3}$$

where $u_i \sim iid(0, \sigma^2)$, $i = 1, 2, 3, \dots, n$ and y_i is the response variable at time i and $x_i = [1, x_{i2}, x_{i3}, \dots, x_{ik}]^T$ is a vector of order $k \times 1$ of independent variables one as its initial value and β_i is also $k \times 1$ vector of coefficients. The hypothesis for random level shift is:

H_0: $\beta_i = \beta_0$ for $i = 1, 2, 3, \dots, n$ (i.e., there is no random level shift in the series) versus alternative that with the random level shift in time the vector of coefficients also changes, also assuming that they have no stochastic behaviour as a departure from the null hypothesis. i.e.,

$$\|x_i\| = \boldsymbol{O}(1) \text{ and that } \quad \frac{1}{n}\sum_{i=1}^{n} x_i x_i^T \to Z$$

where Z represents a finite matrix. This expression permits the detection of multiple breakpoints in data. We implement this same procedure in E-views version 8.0 to detect multiple break points in the given commercial banks in this study before moving forwards.

2.3 The basic GARCH model with and without shifts in variance

After getting date wise breaks in variance, we try to estimate persistency in variance in order to determine the impact of structural breaks on the conditional variance. We start with the basic GARCH model without incorporating dummy variable for volatility shifts. The basic Generalized Autoregressive Conditional Heteroskedasticity or GARCH model was first introduced by [2]. The basic GARCH specification without dummy variable is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2.4}$$

The requirements for stationarity in basic GARCH model are that $\alpha_i + \beta_j < 1$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\omega > 0$. The GARCH model with dummy variable in the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{l=1}^{n_c} \phi_c DUM_{c,j,t} \tag{2.5}$$

where ε_t is the innovation/shock at day t and it follows heteroskedastic error process, σ_t^2 is the volatility at day t (conditional variance), ε_{t-i}^2 is squared innovation at day $t-i$, ω is a constant term, p is the order of the autoregressive GARCH term; q is the order of the moving average ARCH term, n_c denotes the total numbers of date wise changes in market c, DUM is the dummy variables added to the conditional variance which takes value 1 as the sudden shift comes out in conditional volatility and elsewhere it takes value zero.

2.4 EGARCH model with and without dummy variable

The EGARCH model is an asymmetric GARCH model first proposed by [17] to overcome some weaknesses of the basic GARCH model in handling financial time series, particularly to allow for asymmetric effects between positive and negative asset returns. EGARCH without level shifts in variance can be expressed as:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right\} + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \left[\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right] \tag{2.6}$$

where γ represents the asymmetric coefficient in the model. If the relationship between variance and returns is negative then the value of γ must be negative and significant. The difference between α_i and γ_k is expressed as impact of shocks on conditional volatility. β coefficient represents the measure of volatility persistence, which is usually less than one but as its value approaches unity the persistence of shock increases. The sufficient condition for the stationarity of the EGARCH model is that $|\beta| < 1$. The model equation (2.6) also implies that the leverage effect is exponential rather than quadratic and the forecasts of the conditional variance are guaranteed to be non-negative. However, the value of the intercepts, ω, varies according to the distributional assumptions.

To facilitate the sudden shifts in variance we introduce dummy variable in the specification of the above model as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right\} + \sum_{j=1}^{q} \beta_j \ln\left(\sigma_{t-j}^2\right) + \sum_{k=1}^{r} \gamma_k \left[\frac{\varepsilon_{t-k}}{\sigma_{t-k}} \right] + \sum_{l=1}^{n_c} \phi_{c,l} DUM_{c,l,t} \tag{2.7}$$

where n_c represents total numbers of date wise shifts in market c, DUM indicates dummy variable added to the conditional variance model which takes value 1 as the sudden shift appears in conditional volatility onwards and otherwise it takes value 0.

2.5 TGARCH model with and without level shifts in variance

After detecting the date wise breakpoint, we apply yet another asymmetric model called threshold GARCH or TGARCH introduced independently by Zokian [18] and Glosten et al. [19]. The generalized specification of TGARCH for the conditional variance without dummy variable for level shifts is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-i}^2 + \sum_{k=1}^{v} \gamma_k \varepsilon_{t-k}^2 \, S_{t-k}^- \tag{2.8}$$

where $S_t^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance; good news has impact on α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility, and we say that there is a leverage effect for the $i - th$ order. If $\gamma \neq 0$, the news impact is asymmetric.

The TGARCH model with dummy variable for structural break points is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-i}^2 + \sum_{k=1}^{v} \gamma_k \varepsilon_{t-k}^2 S_{t-k}^- + \sum_{l=1}^{n_c} \phi_c DUM_{c,j,l} \tag{2.9}$$

Where n_c are total numbers of date wise changes, DUM denotes dummy variables taking value 1 as the sudden shift comes out in conditional volatility and elsewhere it takes value zero.

2.6 Innovation densities

In assessing the essential parameters of GARCH-type models, error distribution has significant role to play. [1] and [2] contributed the Gaussian distribution in ARCH and GARCH models respectively. The Gaussian distribution has great contribution in assessing the parameters of GARCH-type models but due to high kurtosis in the financial data, it is unsuccessful in capturing the fat tails of stock returns. To address this issue we use Generalized Error Distribution (GED) proposed by [17] in the basic GARCH model and student-t distribution in the asymmetric GARCH models to overcome this problem as anticipated by Bollerslev [2].

The Generalized Error Distribution introduced by [17], where the parameter is degree of freedom models the heavy tails of returns is given as:

$$f(\eta_t) = \frac{v e^{-\frac{1}{2}|x/\lambda|^v}}{\lambda 2^{\left(v+\frac{1}{2}\right)} \Gamma\left(\frac{1}{v}\right)} \tag{2.10}$$

$$\text{where } \lambda = \left[\frac{2^{-\frac{2}{v}} \Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)}\right]^{1/2}$$

Here v is the heavy tail parameter if $v = 2$, σ_t^2 follows a standard normal distribution, but if $v < 2$, σ_t^2 has thicker tails and if $v > 2$, σ_t^2 has thinner tails. The student-t distribution is given by:

$$f(\eta_t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi(v-2)}\left(1 + \frac{\eta_t^2}{v-2}\right)^{v+\frac{1}{2}}} \tag{2.11}$$

Where $\Gamma(.)$ is the gamma function. The value of v, degree of freedom indicate the number of parameters to be estimated. If $v > 4$ the conditional kurtosis approximates to $3(v-2)(v-4)^{-1}$ and is different from the normal value of 3, but if $v \to \infty$ it approaches the standard normal distribution. Many studies used several distributions for innovation but in this paper we employed GED for basic GARCH and student-t innovation for asymmetric GARCH due to their fat tails capturing ability and better estimation results.

2.7 Volatility half-life

For any stationary GARCH-type model, the mean reverting rate implied by most fitted models is given by the sum of ARCH and GARCH parameters $(\alpha_1 + \beta_1)$ which is usually very close to 1. The magnitude of $(\alpha_1 + \beta_1)$ controls the speed of mean reversion. The half life of a volatility shocks with and without sudden shifts in variance is given by the formula:

$$\boldsymbol{L}_{half} = 1 - \left\{\frac{\log(2)}{\log(\alpha_1 + \beta_1)}\right\} \tag{2.12}$$

Where $\boldsymbol{L}_{half}$ stands for half life shock to volatility. The half life measures the average time it takes for $|\varepsilon_t^2 - \hat{\sigma}^2|$ to decrease by one half. The closer $(\alpha_1 + \beta_1)$ is to one the longer the half life of a volatility stock. If $(\alpha_1 + \beta_1) > 1$, the GARCH model is non-stationary and the volatility explodes to infinity.

2.8 Volatility forecast evaluation

In this paper three different accuracy measures are used for evaluating the performance of volatility forecasts from different GARCH models. Suppose the forecast sample is $j = T + 1, T + 2, \dots, T + h$ and denote the actual and forecasted value in period t as σ_t^2 and $\hat{\sigma}_t^2$, respectively. The reported forecast error statistics are computed as follows:

The Root Mean Square Error (RMSE): The RMSE is calculated as

$$\text{RMSE} = \sqrt{\frac{1}{h}\sum_{t=T+1}^{T+h}[\hat{\sigma}_t^2 - \sigma_t^2]^2}$$

The Mean Absolute Error (MAE): The MAE is calculated as

$$\text{MAE} = \frac{1}{h}\sum_{t=T+1}^{T+h}|\hat{\sigma}_t^2 - \sigma_t^2|$$

Mean Absolute Percentage Error (MAPE): The MAPE is computed as

$$\text{MAPE} = \frac{1}{h}\sum_{t=T+1}^{T+h}\left|\frac{\hat{\sigma}_t^2 - \sigma_t^2}{\sigma_t^2}\right| \times 100$$

RMSE and MAE depend on the scale of the dependent variable. These should be used as relative measures to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion. The MAPE is scale invariant.

3 Results and Discussion

3.1 Descriptive statistics of daily returns

A descriptive analysis of daily return series $\{r_t\}$ for the eight commercial banks are displayed in Table 1. The summary statistics shows that the mean of returns for ACCESS Bank, GTB and ZENITH Bank are positive while the mean of returns for ECO, DIAMOND, FBANK, UBA and UNION Banks are negative. These negative mean returns indicate that the banks incurred loss during the study period. The daily standard deviations of all the returns are quite high reflecting high levels of dispersions from the average daily returns in the market over the period under review. The wide gaps between the maximum and minimum returns give supportive evidence to the high level of variability of price changes in Nigerian stock market. The return series for ACCESS, ECO, UBA and UNION Banks display positive skewness whereas the DIAMOND, FBANK, GTB and ZENITH Banks returns exhibit negative skewness. All returns exhibit excess kurtosis. All the return series have non-normal distributions with high kurtosis and skewness values. The Jarque-Bera test rejects the null hypothesis of normality in all the returns with highly significant p-values.

Table 1. Summary statistics of banking returns in Nigeria

Bank	Mean	Max.	Min.	S.D	Skew.	Kurt.	J-Bera	P-value	N
ACCESS	0.031	69.65	-21.25	3.2095	4.3700	100.38	925654	0.0000	2628
ECO	-0.097	109.86	-70.15	4.6764	7.1154	266.76	389865	0.0000	1645
DIAMOND	-0.021	30.01	-29.64	3.1827	-0.123	16.14	17191	0.0000	2693
FBANK	-0.041	14.66	-70.70	3.0032	-5.189	112.67	151232	0.0000	3295
GTB	0.048	14.85	-32.43	2.8248	-2.304	27.07	74929	0.0000	3297
UBA	-0.017	60.26	-53.99	3.7788	0.4233	68.19	52921	0.0000	3292
UNION	-0.038	167.43	-33.94	4.6625	15.339	576.17	401404	0.0000	3228
ZENITH	0.022	9.72	-40.58	2.6906	-2.175	31.33	88266	0.0000	2882

3.2 Unit root and heteroskedasticity test results

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests presented in Table 2 shows that the return series are all stationary. This means that there is no unit root found in the return series. Because ADF and PP unit root tests suffer from severe size distortions and low power problems depending on the sample size, we also perform the Ng-Perron unit root test in order to cross-check the results given by the ADF and the PP tests. The Ng-Perron unit root test results which is presented in Table 3 interestingly confirms the results given by the ADF and PP unit root tests that the return series are indeed stationary. To test for ARCH effect in the return series, the Lagrange Multiplier (LM) test procedure introduced by Engle (1982) was employed. The result is reported in Table 4. The p-values of the F-statistics as well as nR^2 are all highly statistically significant at 1% marginal significance levels. This means that all the eight commercial banks stock returns exhibit heteroskedasticity and can be modeled using ARCH or GARCH models.

Table 2. ADF and PP unit root test results

Returns	ADF test statistic	PP test statistic	P-value	5% critical value
ACCESS	-41.97	-41.97	0.0000	-3.41
ECO	-33.31	-33.34	0.0000	-3.41
DIAMOND	-41.44	-41.26	0.0000	-3.41
FBANK	-48.25	-47.99	0.0000	-3.41
GTB	-47.34	-46.88	0.0000	-3.41
UBA	-28.84	-55.21	0.0000	-3.41
UNION	-50.97	-50.94	0.0000	-3.41
ZENITH	-42.05	-41.56	0.0000	-3.41

Table 3. NG & Perron unit root test results

Ng-Perron test statistics	MZa	MZt	MSB	MPT
Asymptotic 5% critical values*	-17.3000	-2.91000	0.16800	5.48000
ACCESS	-1139.53	-23.8697	0.02095	0.07997
ECO	-56.5142	-5.28715	0.09355	1.75060
DIAMOND	-29.3487	-3.93862	0.01939	2.29394
FBANK	-23.1781	-4.56597	0.01472	0.92044
GTB	-1445.46	-26.8836	0.01860	0.06312
UBA	-39.6506	-4.44762	0.11217	2.32523
UNION	-1449.48	-26.9210	0.01857	0.06287
ZENITH	-22.2140	-6.42294	0.01837	0.73292

*Note: *denotes Ng-Perron (2001, Table 1)*

Table 4. Heteroskedasticity test results

Returns	F-statistic	P-value	nR^2	P-value
ACCESS	9.985869	0.0009	9.98630	0.0006
ECO	11.125789	0.0029	10.125965	0.0027
DIAMOND	347.6080	0.0000	303.6446	0.0000
FBANK	7.032574	0.0080	7.020754	0.0081
GTB	15.81881	0.0001	15.74606	0.0001
UBA	901.3974	0.0000	692.7406	0.0000
UNION	8.193377	0.0002	8.193497	0.0004
ZENITH	9.497262	0.0021	9.469701	0.0021

3.3 Bai and Perron multiple breakpoints test results

With the application of Bai and Perron methodology to the return series, we obtained different break points and dates for different commercial banks in Nigerian stock market. We detect maximum of 5 break points for ZENITH bank, 4 break points for ECO, DIAMOND and UBA banks and minimum of 3 break points for ACCESS, FBANK, GTB and UNION banks. The structural break points in volatility with time periods are presented in Table 5.

Table 5. Structural breakpoints in volatility with time periods

Banks	Break points	Time periods
ACCESS	3	23rd May 2007-4th February 2009
		31st August 2010-18th January 2011
		2nd February 2012-24th February 2012
		25th February 2012-16th July 2013
ECO	4	7th June 2007-7th September 2007
		18th April 2008-27th August 2008
		3rd March 2009-8th September 2009
		19th February 2010-12th July 2010
		13th July 2010-24th February 2011
DIAMOND	4	28th June 2007-18th January 2008
		2nd February 2009-10th September 2009
		10th January 2011-25th January 2011
		28th June 2012-11th July 2012
		8th July 2013-8th January 2014
FBANK	3	17th August 2005-15th August 2006
		14th August 2007-23rd January 2008
		2nd February 2009- 25th August 2009
		8th April 2013-25th July 2013
GTB	3	6th June 2005-3rd March 2006
		16th April 2007-21st February 2008
		17th February 2009-27th August 2009
		25th February 2011-12th August 2011
UBA	4	2nd August 2005-27th March 2006
		19th July 2007-9th August 2007
		21st May 2008-21st August 2008
		15th January 2009-25th August 2009
		16th February 2010-29th September 2011
UNION	3	23rd March 2005-19th February 2006
		6th August 2007-8th October 2008
		6th February 2009- 25th June 2009
		15th June 2011-24th September 2011
ZENITH	5	20th August 2007-28th December 2007
		17th April 2008-27th August 2008
		28th August 2008-15th December 2008
		4th January 2009- 28th July 2009
		23rd September 2011-17th October 2011
		11th January 2013-3rd June 2013

The major reason for these structural break points is the global financial crises of 2007-2009 which affected the Nigerian stock market particularly. The economic recession in 2004 and the prices of oil problems in the country was another cause, also in 2005-2006 the economic recovery in Nigeria commonly affect the banking sector. The terrorist attacks of Niger Delta militants in 2011-2012 and Boko Haram in 2013 were also a contributing factor. The other breaks detected are as a result of local or domestic individual political and economic crises in the country. The date wise break points vary from bank to bank due to individual factors and politics internally affecting these banks.

3.4 Symmetric and asymmetric GARCH models without breaks

After obtaining sudden level shifts in variance we first applied symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TGARCH (1,1) without dummy variables to the eight bank returns. The results are presented in Table 6 and Table 7. In the symmetric GARCH (1,1) model all the parameters in the conditional variance equations are highly statistically significant. The shock persistence parameter (β_1) is quite high in all the eight banks with UNION bank having the highest value of $\beta_1 = 0.9253$ and ACCESS bank having the least value of $\beta_1 = 0.5648$. The mean reverting rates of volatility shocks are all stationary as the sum of ARCH and GARCH terms ($\alpha_1 + \beta_1$) are strictly less than unity in all the banking stocks. For the EGARCH (1,1) and TGARCH (1,1) models all the parameters in the conditional variance equations are statistically significant at 5% significance levels except for the leverage effect parameters in ECO, DIAMOND and UBA banks. For ACCESS, FBANK, GTB, UNION and ZENITH banks the impact of shocks on conditional volatility are asymmetric which indicates the presence of leverage effects. The leverage effect parameters are negative and significant indicating that market retreats (bad news) produces more volatility than market advances (good news) of the same modulus. The shock persistence parameters (β_1) are also very high for both EGARCH (1,1) and TGARCH (1,1) in all the eight banks with UNION bank having the highest value of $\beta_1 = 0.846$ for EGARCH (1,1) and $\beta_1 = 0.801$ for TGARCH (1,1) while ZENITH bank has the least value of $\beta_1 = 0.538$ for EGARCH (1,1) and DIAMOND bank has the least value of $\beta_1 = 0.505$ for TGARCH (1,1). The mean reverting rates of volatility shocks are quite high but very stable as the sum of ARCH and GARCH terms ($\alpha_1 + \beta_1$) are strictly less than unity in all the banking stocks. While using GED innovation for symmetric GARCH (1,1) and student-t innovations for asymmetric EGARCH (1,1) and TGARCH (1,1), it is glaring to know that all the estimated models detain the fat tails behaviour typical of financial time series data.

Table 6. Symmetric GARCH (1,1) result without structural breaks with GED innovations

Bank	Symmetric GARCH models without breaks					
	μ	ω	α_1	β_1	$\alpha_1 + \beta_1$	v
ACCESS	0.0002	1.0592*	0.3882*	0.5648*	0.9680	1.0244*
ECO	-0.0912*	0.0436*	0.3528*	0.6471*	0.9999	1.0524*
DIAMOND	0.0004	0.1327*	0.2933*	0.6802*	0.9735	0.9424*
FBANK	0.0003	0.0360*	0.2746*	0.6928*	0.9674	0.9641*
GTB	-0.0001	0.9655*	0.2993*	0.6910*	0.9903	0.7783*
UBA	-0.0002	3.4855*	0.1520*	0.8465*	0.9985	0.8881*
UNION	0.0001	3.1113*	0.0260*	0.9253*	0.9513	1.1235*
ZENITH	-0.0000	0.2120*	0.2808*	0.7073*	0.9881	0.8843*

Note: **denotes the statistical significant result at 1% marginal significance level*

3.5 Symmetric and asymmetric GARCH models with structural breaks

We considered the detected break points by incorporating dummy variables in the conditional variance equations of the estimated GARCH-type models. We first consider symmetric GARCH (1,1) and then asymmetric EGARCH (1,1) and TGARCH (1,1) models. The results are presented in Table 8 and Table 9. The estimated results show significant decrease in the shock persistence parameter β_1 for all the estimated models due to incorporating these sudden level shifts. The mean reverting rates ($\alpha_1 + \beta_1$) also declined significantly for all the stock returns as a result of including these level shifts in the conditional variance equations. Apart from GTB and ZENITH banks where the indicator variable $\boldsymbol{\phi}$ is positive and significant in case of symmetric GARCH (1,1) model and positive and insignificant in case of asymmetric EGARCH (1,1) and TGARCH (1,1) models indicating that the global financial crises did not affect them, the shift variable $\boldsymbol{\phi}$ is negative and significant in ACCESS, ECO, DIAMOND, FBANK, UBA and UNION banks for symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TGARCH (1,1) models indicating that the global financial meltdown affected them negatively.

Table 7. Asymmetric GARCH results without structural breaks with t innovations

Bank	EGARCH models results without dummy						
	$\boldsymbol{\mu}$	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\alpha_1+\beta_1}$	$\boldsymbol{\gamma}$	$\boldsymbol{v}$
ACCESS	-0.000	-0.088*	0.351*	0.634*	0.985	-0.144*	3.170*
ECO	-0.000	0.442*	0.429*	0.563*	0.992	-0.038	3.728*
DIAMOND	-0.002	-0.192*	0.385*	0.559*	0.944	0.014	3.668*
FBANK	0.001	-0.154*	0.336*	0.641*	0.977	-0.228*	2.094*
GTB	0.000	-0.197*	0.267*	0.726*	0.993	-0.137*	2.811*
UBA	-0.009	-0.196*	0.245*	0.752*	0.997	0.019	3.305*
UNION	0.000	0.020*	0.047*	0.846*	0.993	-0.121*	4.540*
ZENITH	0.001*	-0.203*	0.461*	0.538*	0.999	-0.450*	2.184*
	TGARCH models results without dummy						
ACCESS	0.000	0.000*	0.310*	0.685*	0.995	-0.304*	2.816*
ECO	0.000	0.586*	0.373*	0.625*	0.998	0.032	2.718*
DIAMOND	0.000	0.001*	0.491*	0.505*	0.996	0.341	2.269*
FBANK	-0.000	0.000*	0.292*	0.664*	0.956	-0.177*	2.306*
GTB	0.000	0.000*	0.375*	0.589*	0.964	-0.376*	2.318*
UBA	-0.000	0.000*	0.420*	0.564*	0.984	-0.183	2.717*
UNION	0.000	0.000*	0.178*	0.801*	0.979	-0.856*	2.083*
ZENITH	0.000	0.000	0.425*	0.574*	0.999	-2.923*	2.044*

Table 8. Symmetric GARCH (1,1) result with structural breaks in GED innovations

Bank	Symmetric GARCH models with breaks							
	$\boldsymbol{\mu}$	$\boldsymbol{\omega}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\alpha_1+\beta_1}$	$\boldsymbol{v}$	$\boldsymbol{\phi}$	**ARCH**
ACCESS	0.000	0.000	0.273*	0.495*	0.768	2.567*	-0.002*	0.9816
ECO	-0.001	0.001*	0.327*	0.466*	0.793	2.274*	-0.000*	0.9741
DIAMOND	-0.000	0.000	0.343*	0.456*	0.799	3.115*	-0.006*	0.9674
FBANK	0.000	0.000	0.227*	0.519*	0.746	2.262*	-0.007*	0.9584
GTB	0.000	0.000	0.364*	0.525*	0.889	2.183*	0.001*	0.9800
UBA	0.000	0.000*	0.395*	0.581*	0.976	2.743*	-0.008*	0.9816
UNION	0.000	0.000	0.239*	0.496*	0.735	2.459*	-0.003*	0.9852
ZENITH	0.000	0.000*	0.285*	0.609*	0.894	2.582*	0.018*	0.9710

3.6 Half-life shocks to volatility with and without structural breaks

We also estimated the half-lives of volatility shocks for the symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TGARCH (1,1) for the eight stock returns. The results are presented in Table 10. The volatility half life measures the average number of days it takes a volatility shock to decrease by 0.5 to its size. For all the models without structural breaks, the volatility half-lives are quite high. However, half-lives of volatility shocks decline significantly when the random level shifts are included in these models.

3.7 Model selection criteria and diagnostic checks

From the three competing GARCH-type models for the eight banking stock returns, the selection of the model that gives the best fit in each bank return was carried out using the Log likelihood (LogL), Akaike information criterion (AIC), Schertz information criterion (BIC) and Hannan Quinn criterion (HQC). The model with the highest LogL and minimum information criteria produces the best fit. From the results of our model selection presented in Table 11, TGARCH (1,1) produced the best fit for ACCESS, DIAMOND, FBANK, GTB, UBA, UNION and ZENITH banks while EGARCH (1,1) produced the best fit for ECObank. This clearly indicates that asymmetric GARCH models produce better fits in volatility models. All the estimated GARCH models passed the diagnostic checks as the p-values of the ARCH LM test statistics are highly statistically insignificant in all cases.

Table 9. Asymmetric GARCH results with structural breaks in t innovations

Bank	**EGARCH models with breaks**								
	μ	ω	α_1	β_1	λ	γ	v	ϕ	**ARCH**
ACCESS	0.000	0.087*	0.324*	0.575*	0.899	-0.053*	1.251	-0.000*	0.9338
ECO	0.001	1.820*	0.430*	0.539*	0.969	0.059*	1.152*	-0.008*	0.9453
DIAMOND	0.000	-0.219*	0.403*	0.493*	0.896	0.003	0.744*	-0.005*	0.8898
FBANK	0.000	-0.169*	0.414*	0.485*	0.899	0.043*	0.886*	-0.003*	0.9774
GTB	0.000	-0.069*	0.417*	0.552*	0.969	0.075*	0.906*	0.009	0.8648
UBA	-0.001	3.453*	0.399*	0.597*	0.986	0.042*	1.042*	-0.004*	0.4692
UNION	0.000	0.542*	0.424*	0.555*	0.979	-0.024	1.112*	-0.007*	0.9713
ZENITH	-0.000	-0.125*	0.482*	0.506*	0.988	0.007	0.851*	0.004	0.9975
	TGARCH models with breaks								
ACCESS	0.003	0.843*	0.357*	0.627*	0.984	-0.060	0.910*	-0.007*	0.9425
ECO	-0.000	0.859*	0.563*	0.429*	0.992	-0.163	0.944*	-0.000*	0.9501
DIAMOND	0.000	0.144*	0.532*	0.455*	0.987	-0.032	0.948*	-0.003*	0.5005
FBANK	-0.000	0.045*	0.334*	0.543*	0.877	0.134*	1.048*	-0.005*	0.8048
GTB	-0.000	0.593*	0.358*	0.521*	0.879	-0.129	0.815*	0.003	0.8029
UBA	0.000	0.297*	0.505*	0.474*	0.979	0.018	0.775*	-0.008*	0.9203
UNION	0.003	1.097*	0.407*	0.532*	0.939	-0.145*	1.491*	-0.007*	0.9772
ZENITH	-0.000	0.080*	0.449*	0.542*	0.991	0.038	0.677*	0.006	0.6856

Note: $\lambda = \alpha_1 + \beta_1$

Table 10. Half-life shocks to volatility with and without structural breaks

Bank	**Basic GARCH (1,1)**		**EGARCH (1,1)**		**TGARCH (1,1)**	
	Without breaks	**With breaks**	**Without breaks**	**With breaks**	**Without breaks**	**With breaks**
ACCESS	22	4	47	8	139	44
ECO	7	4	87	23	347	87
DIAMOND	27	4	13	7	174	54
FBANK	22	4	31	8	16	6
GTB	72	3	100	23	20	6
UBA	463	30	232	50	44	34
UNION	15	3	100	34	34	12
ZENITH	59	7	694	54	694	78

3.8 Models forecast performance evaluation

To select the best forecast performance model among the three competing GARCH models for the eight banking stock returns, we employed model accuracy measures, namely: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results are presented in Table 12. The smaller the accuracy measure, the better the forecast performance according to our criterion, TGARCH (1,1) produced better forecasts in ACCESS, DIAMOND, UBA and ZENITH banks while EGARCH (1,1) provided better forecasts for ECO, FBANK, GTB and UNION banks. It is important to mention that in terms of comparing the best fitting GARCH model and the best forecast performance GARCH model, the evidence provided by this study shows that the best fitted models are not necessarily the best forecast performance models. However, all the three competing GARCH models can be used for forecasting purposes since the differences between the accuracy measures are quite small.

Table 11. Model selection criteria and diagnostics of the estimated GARCH-type models

Banks	Model	Model selection criteria				ARCH LM test	
		LogL	**AIC**	**SIC**	**HQC**	**F-stat.**	**P-value**
ACCESS	GARCH (1,1)	-5393	4.6450	4.6574	4.6495	0.0054	0.9416
	EGARCH (1,1)	-5302	4.5677	4.5826	4.5731	0.0025	0.9604
	TGARCH (1,1)*	**-4952**	**4.2669**	**4.2817**	**4.2722**	0.0006	0.9807
ECO	GARCH (1,1)	-3299	4.9277	4.9471	4.9350	0.0041	0.9491
	EGARCH (1,1)*	**-3214**	**4.8021**	**4.8254**	**4.8108**	0.0048	0.9446
	TGARCH (1,1)	-5327	4.8225	4.8458	4.8312	0.0039	0.9501
DIAMOND	GARCH (1,1)	-5327	4.4637	4.4758	4.4681	0.5434	0.4611
	EGARCH (1,1)	-5188	4.3484	4.3629	4.3537	0.0050	0.9439
	TGARCH (1,1)*	**-4630**	**3.8812**	**3.8957**	**3.8865**	0.0017	0.9670
FBANK	GARCH (1,1)	-6147	4.1138	4.1238	4.1174	0.0314	0.8593
	EGARCH (1,1)	-6025	4.0327	4.0447	4.0370	0.0144	0.9044
	TGARCH (1,1)*	**-4018**	**2.6941**	**2.7030**	**2.6953**	0.0028	0.9580
GTB	GARCH (1,1)	-6414	4.2891	4.2991	4.2976	0.0847	0.7711
	EGARCH (1,1)	-6356	4.2515	4.2635	4.2558	0.0658	0.7976
	TGARCH (1,1)*	**-5297**	**3.5432**	**3.5553**	**3.5476**	0.0006	0.9800
UBA	GARCH (1,1)	-7141	4.7831	4.7931	4.7867	0.1364	0.7120
	EGARCH (1,1)	-6993	4.6850	4.6971	4.6894	0.0170	0.8963
	TGARCH (1,1)*	**-5862**	**3.9275**	**3.9396**	**3.9319**	0.0012	0.9723
UNION	GARCH (1,1)	-7234	4.9514	4.9617	4.9551	0.0012	0.9699
	EGARCH (1,1)	-7060	4.8328	4.8451	4.8372	0.0006	0.9808
	TGARCH (1,1)*	**-4357**	**2.9842**	**2.9965**	**2.9886**	0.0003	0.9852
ZENITH	GARCH (1,1)	-15276	4.0973	4.1087	4.1015	0.0452	0.8317
	EGARCH (1,1)	-5051	3.9230	3.9367	3.9280	0.0012	0.9728
	TGARCH (1,1)*	**-4734**	**3.6774**	**3.6910**	**3.6823**	0.0023	0.9618

*Note: *denotes optimal Model selected by the information criteria*

Table 12. Forecast performance evaluation of estimated GARCH-type models

Bank	Model	Accuracy measures		
		RMSE	**MAE**	**MAPE**
ACCESS	GARCH (1,1)	3.2090	2.0124	85.3699
	EGARCH (1,1)	3.2090	2.0124	85.3703
	TGARCH (1,1)*	**3.2090**	**2.0124**	**85.3668**
ECO	GARCH (1,1)	4.6756	2.1856	62.9366
	EGARCH (1,1)*	**4.6755**	**2.1854**	**62.9364**
	TGARCH (1,1)	4.7091	3.4898	63.6042
DIAMOND	GARCH (1,1)	3.1821	2.1171	80.0376
	EGARCH (1,1)	3.1821	2.1174	80.0133
	TGARCH (1,1)*	**3.1820**	**2.1170**	**79.8898**
FBANK	GARCH (1,1)	3.0030	1.7508	85.2540
	EGARCH (1,1)*	**3.0030**	**1.7507**	**85.2514**
	TGARCH (1,1)	3.0030	1.7508	85.2558
GTB	GARCH (1,1)	2.8247	1.7721	87.2375
	EGARCH (1,1)*	**2.8247**	**1.7721**	**87.2365**
	TGARCH (1,1)	2.8247	1.7721	87.2369
UBA	GARCH (1,1)	3.7782	2.2272	85.9417
	EGARCH (1,1)	3.7782	2.2282	85.9627
	TGARCH (1,1)*	**3.7780**	**2.2271**	**85.8437**
UNION	GARCH (1,1)	4.6619	2.2731	79.8998
	EGARCH (1,1)*	**4.6618**	**2.2729**	**79.8806**
	TGARCH (1,1)	4.6619	2.2760	80.0040
ZENITH	GARCH (1,1)	2.6708	1.6735	85.7489
	EGARCH (1,1)	2.6908	1.6771	87.4037
	TGARCH (1,1)*	**2.6701**	**1.6712**	**85.1429**

*Note: *denotes the best forecasting model selected by accuracy measures*

4 Conclusion

This study examines the impact of structural breaks on conditional volatility and mean reversion in symmetric and asymmetric GARCH models by applying Bai and Perron multiple breakpoint testing procedure to detect structural break points in conditional variance of daily stock returns of 8 commercial banks in Nigerian stock market for the period 17th February, 2003 to 31st September, 2016. These sudden shifts in volatility are due to the global financial crises, Niger Delta militant/Boko Haram attacks as well as local or domestic political and economic events. Having identified logical date wise structural breaks, we employed standard GARCH, EGARCH and TGARCH models with and without break points to evaluate variance persistence, mean reversion rates and leverage effects while estimating conditional volatility. The log likelihoods and information criteria were used in selecting the best fitting models while the forecast performances of these estimated GARCH models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The results showed high persistence in conditional volatility for the banking stocks, but when the random level shifts were incorporated into the models, there was reduction in the conditional volatility of these models. The half-lives of volatility shocks also reduce in the presence of these regime shifts. TGARCH was found to be the best fitting model among the standard GARCH and EGARCH models. However, the best fitting models were not necessarily found to be the best forecasting models. This study recommends estimation of volatility using asymmetric GARCH models by incorporating structural breaks which is necessary to avoid over estimation of shock persistence in the conditional variance and to allow free flow of market information and wide range of aggressive trading of securities so as to increase market depth and make the Nigerian stock market less volatile.

Competing Interests

Authors have declared that no competing interests exist.

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