Modelling Conditional Volatility and Mean Reversion in Nigerian Stock Market using Symmetric and Asymmetric GARCH Models

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***Abstract*—This study attempts to model conditional volatility and mean reversion in Nigerian stock market using symmetric and asymmetric GARCH models. The study utilizes data on daily stock returns of 8 commercial banks in Nigerian stock market for the period 17th February, 2003 to 31st September, 2016 and employ GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models to evaluate variance persistence, mean reversion rates and leverage effects while estimating conditional volatility. The results showed volatility clustering and high persistence of shocks in conditional volatility for the banking stocks. All the estimated models are found to be stable, stationary and mean reverting. Asymmetry and leverage effects are found in ACCESS, FBANK, GTB, UNION and ZENITH while in ECO, DIAMOND and UBA banks the impacts of positive and negative shocks are the same. TGARCH was found to be the best fitting model among the standard GARCH and EGARCH models. All the estimated models detain the fat tails behaviour typical of financial time series data.**

Keywords: *Volatility, Structural Breaks, Conditional Variance, Asymmetric GARCH, Shocks Persistence, Nigeria.*

I. Introduction

Volatility modelling of stock returns using Generalized Autoregressive Conditional Heteroskedascitity (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].

Several documented evidence on volatility modelling using symmetric and asymmetric GARCH models are found in the literature with mixed empirical findings. For example, [4] investigated the forecasting performance of APARCH model under normal distribution, student-t distribution and skewed student-t distribution using Standard & Poor 500 stock market daily closing price index and MSCI EUROPE INDEX and found that the skewed student-t distribution is the most efficient.

Miron and Tudor [5] investigated the presence of leverage effects in empirical time series on United States and Romanian daily stock return data corresponding to the 2002-2010 time intervals using different asymmetric GARCH-family models such as EGACH, PGARCH and TGARCH in the presence of Normal, Student's t and GED error distributions. They found that GARCH models with normal errors were not capable of capturing fully the leptokurtosis in empirical time series data, while GED and Student's t errors provide a better description for the conditional volatility.

Ahmed and Suliman [6] used symmetric and asymmetric heteroskedastic models to estimate volatility in the daily returns of Khartoum Stock Exchange (KSE) in Sudan over the period from January 2006 to November 2010. The empirical results show that the conditional variance process was highly persistent, explosive process and provided evidence on the existence of risk premium for the KSE index return series which supported the

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positive correlation hypothesis between volatility and the expected stock returns. Their findings also show that the asymmetric models provide better fit than the symmetric models, which confirms the presence of leverage effect. Their results in general explained that high volatility of index return series was present in Sudanese stock market over the sample period.

Floros [7] investigated the volatility using daily data from two Middle East stock indices viz., the Egyptian CMA index and the Israeli TASE-100 index and used GARCH, EGARCH, TGARCH, Component GARCH (CGARCH), Asymmetric Component GARCH (AGARCH) and Power GARCH (PGARCH). The study found that the coefficient of EGARCH model showed a negative and significant value for both the indices, indicating the existence of the leverage effect. AGARCH model showed weak transitory leverage effects in the conditional variances and the study showed that increased risk would not necessarily lead to an increase in returns.

Ahmed and Aal [8] examined Egyptian stock market return volatility from1998 to 2009 and their study showed that EGARCH is the best fit model among the other models for measuring volatility. The study showed that there is no significant asymmetry in the conditional volatility of returns captured by GARCH (1,1) and GARCH (1,1) and it was found to be the appropriate model for volatility forecasting in Nepalese stock market.

In Nigeria, several studies have been conducted on volatility modelling which provide more insights on the subject matter. For instance see [9-17] for surveys.

In this paper, we extend the existing literature by modelling the conditional variance of eight banking returns in Nigerian stock market using both symmetric and asymmetric GARCH type models with varying innovation densities.

II. Materials And Methods

A. *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 ECO Bank 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.

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

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 $(t-1)$.

B. *The Basic GARCH Model*

We first try to estimate persistency in variance using the basic GARCH model. The basic Generalized Autoregressive Conditional Heteroskedasticity or GARCH model was first introduced by [2]. The basic GARCH specification is given by:

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

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. The requirements for stationarity in basic GARCH model are that $\alpha_i + \beta_j < 1$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\omega > 0$.

C. *EGARCH Model*

The EGARCH model is an asymmetric GARCH model first proposed by [18] 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 model can be expressed as:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left\{\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right\} + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{k=1}^{r} \gamma_k \left[\frac{\varepsilon_{t-k}}{\sigma_{t-k}}\right] \quad (3)$$

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

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the stationarity of the EGARCH model is that $|\beta| < 1$. The model equation (3) 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.

D. TGARCH Model

We apply yet another asymmetric model called threshold GARCH or TGARCH introduced independently by [19] and [20]. The generalized specification of TGARCH model is given by:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i \sigma_{t-i}^2 + \sum_{k=1}^{v} \gamma_k \varepsilon_{t-k}^2 S_{t-k}^- \quad (4)$$

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.

E. Innovation Density

In assessing the essential parameters of GARCH-type models, error distribution has significant role to play. Engle [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 [18] in the basic GARCH model and student-t distribution in the asymmetric GARCH models to overcome this problem as anticipated by [2].

The Generalized Error Distribution introduced by [18], where the parameter is degree of freedom models the heavy tails of returns is given as:

$$f(\eta_t) = \frac{v e^{-\frac{1}{2}|x/\lambda|^v}}{\lambda 2^{\left(v+\frac{1}{2}\right)} \Gamma\left(\frac{1}{v}\right)} \quad (5)$$

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

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:

$$f(\eta_t) = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{\pi(v-2)}\left(1 + \frac{\eta_t^2}{v-2}\right)^{v+\frac{1}{2}}} \quad (6)$$

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.

F. 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:

$$\boldsymbol{L}_{half} = 1 - \left\{\frac{\log(2)}{\log(\alpha_1 + \beta_1)}\right\} \quad (7)$$

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.

III. Results And Discussion

A. 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

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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

B. *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. To test for ARCH effect in the return series, the Lagrange Multiplier (LM) test procedure introduced by [1] was employed. The result is also reported in Table 2. The p-values of the F-statistics 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 modelled 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	F-statistic	P-value
ACCESS	-41.97	-41.97	0.0000	-3.41	9.985869	0.0009
ECO	-33.31	-33.34	0.0000	-3.41	11.125789	0.0029
DIAMOND	-41.44	-41.26	0.0000	-3.41	347.6080	0.0000
FBANK	-48.25	-47.99	0.0000	-3.41	7.032574	0.0080
GTB	-47.34	-46.88	0.0000	-3.41	15.81881	0.0001
UBA	-28.84	-55.21	0.0000	-3.41	901.3974	0.0000
UNION	-50.97	-50.94	0.0000	-3.41	8.193377	0.0002
ZENITH	-42.05	-41.56	0.0000	-3.41	9.497262	0.0021

C. *Symmetric and Asymmetric GARCH models*

We first applied symmetric GARCH (1,1), asymmetric EGARCH (1,1) and TGARCH (1,1) to the eight bank returns. The results are presented in Table 4 and Table 5. In the symmetric GARCH (1,1) model all the parameters in the conditional variance equations are highly statistically significant. The 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 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

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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.

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 3: Symmetric GARCH (1,1) Result with GED Innovations

Bank	μ	ω	α_1	β_1	$\alpha_1 + \beta_1$	v	ARCH LM	P-value
ACCESS	0.0002	1.0592*	0.3882*	0.5648*	0.9680	1.0244*	0.0054	0.9416
ECO	-0.0912*	0.0436*	0.3528*	0.6471*	0.9999	1.0524*	0.0025	0.9604
DIAMOND	0.0004	0.1327*	0.2933*	0.6802*	0.9735	0.9424*	0.0006	0.9807
FBANK	0.0003	0.0360*	0.2746*	0.6928*	0.9674	0.9641*	0.0041	0.9491
GTB	-0.0001	0.9655*	0.2993*	0.6910*	0.9903	0.7783*	0.0048	0.9446
UBA	-0.0002	3.4855*	0.1520*	0.8465*	0.9985	0.8881*	0.0039	0.9501
UNION	0.0001	3.1113*	0.0260*	0.9253*	0.9513	1.1235*	0.5434	0.4611
ZENITH	-0.0000	0.2120*	0.2808*	0.7073*	0.9881	0.8843*	0.0050	0.9439

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

Table 4: Asymmetric GARCH Results without Structural Breaks with t Innovations

EGARCH Models Results									
Bank	μ	ω	α_1	β_1	$\alpha_1 + \beta_1$	γ	v	ARCH LM	P-value
ACCESS	-0.000	-0.088*	0.351*	0.634*	0.985	-0.144*	3.170*	0.0017	0.9670
ECO	-0.000	0.442*	0.429*	0.563*	0.992	-0.038	3.728*	0.0314	0.8593
DIAMOND	-0.002	-0.192*	0.385*	0.559*	0.944	0.014	3.668*	0.0144	0.9044
FBANK	0.001	-0.154*	0.336*	0.641*	0.977	-0.228*	2.094*	0.0028	0.9580
GTB	0.000	-0.197*	0.267*	0.726*	0.993	-0.137*	2.811*	0.0847	0.7711
UBA	-0.009	-0.196*	0.245*	0.752*	0.997	0.019	3.305*	0.0658	0.7976
UNION	0.000	0.020*	0.047*	0.846*	0.993	-0.121*	4.540*	0.0006	0.9800
ZENITH	0.001*	-0.203*	0.461*	0.538*	0.999	-0.450*	2.184*	0.1364	0.7120
TGARCH Models Results									
ACCESS	0.000	0.000*	0.310*	0.685*	0.995	-0.304*	2.816*	0.8963	0.8963
ECO	0.000	0.586*	0.373*	0.625*	0.998	0.032	2.718*	0.9723	0.9723
DIAMOND	0.000	0.001*	0.491*	0.505*	0.996	0.341	2.269*	0.9699	0.9699
FBANK	-0.000	0.000*	0.292*	0.664*	0.956	-0.177*	2.306*	0.9808	0.9808
GTB	0.000	0.000*	0.375*	0.589*	0.964	-0.376*	2.318*	0.9852	0.9852
UBA	-0.000	0.000*	0.420*	0.564*	0.984	-0.183	2.717*	0.8317	0.8317
UNION	0.000	0.000*	0.178*	0.801*	0.979	-0.856*	2.083*	0.9728	0.9728
ZENITH	0.000	0.000	0.425*	0.574*	0.999	-2.923*	2.044*	0.9618	0.9618

D. *Half-Life Shocks to Volatility*

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 5. The half life measures the average number of days it takes a shock to volatility to decrease by 0.5 to its size. For some models, the volatility half-lives are small while for GARCH models the volatility half-lives are quite high. However, all the models are mean reverting indicating that no matter how low or high the stock prices shall move, they will eventually come back to the long-run average level.

V. Conclusion

This study have attempted to model the conditional volatility and mean reversion of daily banking stock returns in Nigeria using both symmetric and asymmetric volatility GARCH models in the presence of varying innovation densities for the period 17th February, 2003 to 31st September, 2016. The study employed standard GARCH, EGARCH and TGARCH models to evaluate variance persistence, mean reversion rates and leverage effects while estimating conditional volatility. The results

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showed volatility clustering and high persistence in conditional volatility for the banking stocks.

Table 5: Half-Life Shocks to Volatility in Days.

Model	ACCESS	ECO	DIAMOND	FBANK	GTB	UBA	UNION	ZENITH
GARCH (1,1)	22	7	27	22	72	463	15	59
EGARCH (1,1)	47	87	13	31	100	232	100	694
TGARCH (1,1)	139	347	174	16	20	44	34	694

The asymmetric GARCH models found asymmetry and leverage effects in ACCESS, FBANK, GTB, UNION and ZENITH while in ECO, DIAMOND and UBA banks the impacts of positive and negative shocks are the same. All the estimated models are found to be stable, stationary and mean reverting. TGARCH was found to be the best fitting model among the standard GARCH and EGARCH models. All the estimated models retain the fat tails behaviour typical of financial time series data. This study recommends estimation of volatility

using asymmetric GARCH models which captures the asymmetry and leverages 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.

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