# Comparing Predictive Accuracy of Nonlinear Asymmetric Volatility Models: Evidence from the Nigerian Bank Share Prices

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**Abstract**

*This present work is motivated by the articles titled "Answering the skeptics: yes, standard volatility models do provide accurate forecasts" (Andersen and Bollerslev, 1998) and "A forecast comparison of volatility models: Does anything beat a GARCH(1, 1)?" (Hansen and Lunde, 2005). In the latter paper, the authors could not obtain a single winner amongst different volatility models considered, as it was different models that emerged as best in forecasting the volatility of the asset prices, this implying that the best models did not perform better than GARCH(1,1) model on forecasts. We were motivated by this assertion. We presented four types of nonlinear asymmetric volatility models, and applied these in predicting the volatility of 12 bank share prices in Nigeria. The pairwise forecasts comparison was investigated using the Diebold and Mariano (DM) test. The initial estimation disproved linear GARCH model since it failed to satisfy stationarity and regularity conditions for the model and we proceeded to estimating the asymmetric types. The Asymmetric Power ARCH (APARCH) model emerged the best model in terms of fitness in 9 out of the 12 cases, and other models that could not fit the data well were suggested as the best models in making volatility forecasting.*

**Key words**: Asymmetry, Banks share prices, Regime Switching model, Volatility

## 1 Introduction

Recent market consolidation[1] in banking industries as ordered by the Central Bank of Nigeria (CBN) has kindled the interest of financial time series analyst towards monitoring bank share prices and buying/selling of these shares. Recent global financial crisis has gingered financial time series analyst into studying volatility in stock prices and its after match effect on the economy. The financial crisis was as a result of credit crunch, the sub-prime crisis and the housing bubble issues in America and in Europe (Avgouleas, 2008; Chang, 2012). Adamu (2009) remarked that the crisis was as a result of the current policy on the global financial regulation at that time, housing price market which experienced boom and bust, new financial architecture and the risks on loans and government policies as quoted in Sanusi (2011). The effect of the crisis began to show effects on the world economy in the third quarter of 2007 and continued to 2008. The attack on Lehman Brothers building on September 14, 2008 also triggered a new phase in the crisis, and many financial institutions in the world faced serious liquidation (Chang, 2012). The term financial crisis refers to a situation where some financial institutions (banking industries, mortgage houses, insurance companies and other related firms) suddenly lose a large part of their values due to incoming shocks (Sanusi 2010; 2011). Then, when the financial crisis affects the entire world, we refer to it as the global financial crisis. Between 19th and 20th centuries, quite a lot of financial crises occurred and these were linked to panics about future of banking industries, and many global recessions coincided with these panics (see Kindleberger and Aliber, 2005, Laeven and Valencia, 2008).

The commercial banks in Nigeria are responsible for channelling funds, like credits and loans to various economic agents and individuals. Other financial institutions performing similar activities of directing

[1]As at the end of 2004, a high degree of fragmentation and low levels of financial intermediation was observed in the Nigerian banking sector and that made the CBN to make a reform that drastically increased the capital base of Banks from 2 billion Nigerian naira to 25 billion Nigerian naira. The reform also led to the merging of banks from 89 to 25, where some weaker banks were acquired by some financially stabled banks, and some merged together to form new banks in the country. (see Hesse, 2007). Missmanagement of funds and over re-presentation of share prices were experienced in some of the remaining 25 Banks after the CBN reform in 2006, and with merging and acquisition, the number of Banks was further reduced to 21.

funds from saver to users in the economy are the mortgage houses, saving and loans associations and other non-bank institutions such as credit unions, insurance companies and other financial service providers (Adam, 1998; Khan and Senhadji, 2003; Duruji and Osabuohien, 2005). The CBN acts as the bank to these commercial banks and the target is to ensure that the banks have enough financial capital to carry out their operations. Adamu (2009) predicted a fall in commodity prices, decline in export, lowering of portfolio and foreign direct investment, fall in equity market and decline in remittance in Nigeria and abroad as a result of the global financial crisis. The effect of the financial crisis was also felt in the Nigerian capital market and the amount/quality of credit released for trading in the capital market reduced drastically as well and exchange rate risk and greater loan-loss provisioning were triggered (Ashamu and Abiola, 2012).

In financial time series modelling, risk in an asset is measured in terms of volatility, of which is not observable but could be modelled. The appropriate volatility model is then used to predict future volatility. This prediction of volatility is crucial for option pricing and value-at-risk management. The history of volatility modelling is dated back to seminal article in Engle (1982) when Autoregressive Conditionally Heteroscedastic (ARCH) model was proposed. Later, a generalized version of the model named as Generalized ARCH (GARCH) was proposed in Bollerslev (1986). Both models are linear and symmetric in their specifications.

Asymmetric in the sense that volatile periods, are often preceded by large negative shocks, suggesting that positive and negative shocks have an asymmetric impact on the conditional volatility of subsequent observations[2]. Literature has shown that a negative shock increases the conditional variance more than a positive shock of the same magnitude, in particular negative shocks are meant to increase future conditional volatility more than positive shocks only if the shock is larger in absolute value. The GARCH model cannot capture these asymmetric properties of positive and negative shocks, therefore different asymmetric volatility specifications have been proposed in this regards, and these model are nonlinear by econometric specifications.

The first nonlinear asymmetric GARCH type model is the Exponential GARCH (EGARCH) model of Nelson (1991). Other propositions are the Asymmetric Power ARCH (APARCH) model of Ding et al, (1993), Glosten, Jaganathan and Runkle (1993) GARCH (GJR-GARCH) model and Quadratic GARCH (QGARCH) model of Sentana (1995).

We apply the forms of asymmetric volatility models in this paper to bank share prices in Nigeria and compared the results with those obtained from linear GARCH model. Model forecast performances are also investigated using Diebold and Mariano (1995) test. The rest of the paper is structured as follows: Section 2 and 3 discuss the GARCH and other asymmetric GARCH models as well as the estimation procedure, and forecasts evaluation method. Section 4 presents the data analysis and discussion, while Section 5 gives the concluding remarks.

## 2 The Linear Volatility Model

The definition of GARCH model starts from the log-returns series, $r_t$ of an asset price $P_t$ at time t given as,

$$r_t = \log(P_t) - \log(P_{t-1}) \tag{1}$$

where $P_{t-1}$ is the price at previous time, $t-1$. Let the conditional mean and conditional variance of $r_t$ given $C_{t-1}$ be $E(r_t|C_{t-1}) = \mu_t$ and $Var(r_t|C_{t-1}) = E\big[(r_t - \mu_t)^2|C_{t-1}\big] = \sigma_t^2$ where $C_{t-1}$ is the information set available at time $t-1$. The time series $r_t$ is represented as the sum of a predictable and unpredictable part as

$$r_t = E(r_t|C_{t-1}) + \epsilon_t \tag{2}$$

[2]The property of asymmetry was first given in Black (1976).

and $\epsilon_t$ is conditionally heteroscedastic once $\epsilon_t = z_t\sigma_t$, where $z_t$ follows a particular distribution, either Gaussian, Student $t$ and Generalized Error distributions or skewed versions of these distributions[3] and $\sigma_t$ is root of the conditional volatility series.

The first volatility series, ARCH model is proposed in Engle (1982) and Bollerslev (1986) and Taylor (1986) independently proposed a generalization of the ARCH model to allow for past conditional variances in the current conditional variance equation. This is the GARCH model. In this paper, all the volatility models will be specified to the lowest order, that is, 1. Then, the GARCH(1,1) model is specified as,

$$\sigma_t^2 = \omega + \alpha_i\epsilon_{t-1}^2 + \beta_i\sigma_{t-1}^2 \tag{3}$$

where $\omega$, $\alpha_i$, and $\beta_i$ are the parameters defined with the conditions $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$ and $\alpha_i + \beta_i < 1$ to ensure stationarity.

# 3 The Nonlinear Asymmetric Volatility Models

The first nonlinear asymmetric volatility model is the EGARCH (1,1) model

$$\log\sigma_t^2 = \omega + \alpha_i\epsilon_{t-1}^2 \left|\frac{\epsilon_{t-1}}{\sigma_{t-1}} - E\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right)\right| + \gamma_i\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_i\log\sigma_{t-1}^2 \tag{4}$$

with the parameters as defined in the GARCH model in (4) except $\gamma_i \neq 0$ in order to allow for the asymmetric effect. The initial motivation of Nelson (1991) was to propose a model that could capture asymmetric relationship between stock returns and volatility changes. It is noted that $\log\sigma_t^2$ is linear in $z_t = \epsilon_t/\sigma_t$ with slope $\alpha_i + \gamma_i$ whenever $z_t$ is over the range $0 < z_t < \infty$ and $\log\sigma_t^2$ is also linear on $-\infty < z_t \leq 0$ with the slope $\alpha_i - \gamma_i$. The $\alpha_i$ gives the magnitude effect while the second term, $\gamma_k$ measures the asymmetric effect as in the ARCH model. The asymmetric representations of the models allows for both positivity (good news) and negativity (bad news) of the innovations to determine the variance.

Ding *et al.* (1993) introduced the asymmetric power ARCH (APARCH (1, 1)) model. This is given as,

$$\sigma_t^\delta = \omega + \alpha_i\left(|\epsilon_{t-1}| - \gamma_i\epsilon_{t-1}\right)^\delta + \beta_i\log\sigma_{t-1}^\delta \tag{5}$$

where $\delta > 0$ and $-1 < \gamma_i < 1$. The model imposed a Box and Cox (1964) power transformation, $\delta$ of the conditional standard deviation process and asymmetric absolute innovations. This power parameter $\delta$ is estimated along with other parameters in the model. The APARCH model converges to GARCH(1, 1) when the power parameter is squared ($d = 2$) and the asymmetric parameter nullified ($\gamma_i = 0$).

Glosten *et al.* (1993) also proposed the Glosten Jagannathan and Runkle (GJR-GARCH(p, q)) model,

$$\sigma_t^2 = \omega + \alpha_i\epsilon_{t-1}^2 + \gamma_i d(\epsilon_{t-1} < 0)\epsilon_{t-1}^2 + \beta_i\sigma_{t-1}^2 \tag{6}$$

where $\gamma_i$ are the additional parameters to be estimated and $d(.)$ is the indicator function defined such that $d(\epsilon_{t-1} < 0) = 1$ if $\epsilon_{t-1} < 0$ and $d(\epsilon_{t-1} > 0) = 0$ otherwise. Therefore, the model is said to allow good news ($\epsilon_{t-1} > 0$) and bad news ($\epsilon_{t-1} < 0$) to have differential effects on the conditional variance. Sentana (1995) proposed the Quadratic GARCH (QGARCH) model. The QGARCH (1,1) specification is,

$$\sigma_t^2 = \omega + \alpha_i\epsilon_{t-1}^2 + \beta_i\sigma_{t-1}^2 + \gamma\epsilon_{t-1} \tag{7}$$

where the term $\gamma\epsilon_{t-1}$ makes it possible for positive and negative shocks to have different effects on conditional volatility.

[3]Review of different GARCH probability distributions is found in Xekalaki and Degiannakis (2010).

## 3.1 Quasi Maximum Likelihood Estimation

The conditional normality of $\epsilon_t$ is not often realistic in high frequency financial time series due to the fact that the resulting model fails to capture the tail distribution of the innovations. Instead, $z_t$ follows Student $t$, Generalized Error or the skewed versions of these distributions. The choice of the appropriate GARCH probability is determined as the model estimation is carried out, with information criteria and possibility of algorithm convergence as criteria. Due to the departure from normality, Quasi Maximum Likelihood Estimation (QMLE) approach is used.

The parameters in the GARCH models are estimated by maximizing the likelihood function, $L(\theta)$ where $\theta$ is the parameter set. The resulting log-likelihood function does not have a closed form solution, and in that case, iterative procedures are often applied to simplify the likelihood function. The commonest iterative procedures are the Marquadt, Berndt, Hall, Hall and Hausman (1974) (BHHH) and Maxsa algorithms of Goffe, Ferrier and Rogers (1994) implemented in OxGARCH software of Laurent (2007) and Laurent and Peters (2006). The Marquadt computes slowly since its uses second derivatives, while the BHHH uses first derivative and computes faster than Marquadt. Both algorithms are implemented in EViews software[4], and these often fail to converge when dealing with structurally complex model. The Ox software is computationally more effective, computes very fast and gives similar results to Eviews when dealing with complex models. This software is used to estimate the volatility models.

## 3.2 Forecasts Evaluation

Test of forecast accuracy between a pair of competing models is given in Diebold and Mariano (1995) (DM test). The DM test has been applied in Sarma et al. (2003) and Angelidis *et al.* (2004) for evaluating Value at Risk (VaR) forecasting accuracy. Ferreira and Lopez (2005) applied the DM test in a Multivariate VaR framework for an international interest rate portfolio and noted that volatility forecast from multivariate models appear to perform as well as those from computationally simpler GARCH models. Other similar application of the DM test are found in Taylor (2004), Patton (2005), Kapetanios *et al.* (2006), Moser *et al.* (2007), Angelidis and Degiannakis (2008) and Bhattacharya and Thomakos (2008). The test checks the significance of Mean Square Prediction Errors (MSPEs) of the two volatility models denoted by $A$ and $B$. The daily log-returns is equivalent to the squared residuals of the estimated model which is an unbiased estimator of the daily variance given by $\sigma_t^2$. Denote the in-sample forecasts of $\sigma_t^2$ by $\sigma_{t+h|t}^{2A}$ and $\sigma_{t+h|t}^{2B}$ , respectively. Then, the forecast errors are,

$$\xi_{t+h|t}^{A} = \sigma_{t+h}^{2} - \sigma_{t+h|t}^{2A},\ \xi_{t+h|t}^{B} = \sigma_{t+h}^{2} - \sigma_{t+h|t}^{2B} \tag{8}$$

where the $h$-step forecasts are computed for $t = t_0, t_1, \cdots, N_0$ forecasts. The squared error loss function is given as,

$$L(\xi_{t+h|h}^{i}) = (\xi_{t+h|h}^{i})^2 \tag{9}$$

where $i = \{A, B\}$ are the two competing models. The DM test sets the null hypothesis as $H_0 : E\left[L(\xi_{t+h|h}^{A})\right] = E\left[L(\xi_{t+h|h}^{B})\right]$ against the alternative $H_1 : E\left[L(\xi_{t+h|h}^{A})\right] \neq E\left[L(\xi_{t+h|h}^{B})\right]$ using the loss differential $L(\xi_{t+h|h}^{A}) - L(\xi_{t+h|h}^{B})$.

The $DM$ test statistic is,

$$DM = \frac{\bar{d}}{\left[asy \cdot Var(\bar{d})\right]^{1/2}} = \frac{\bar{d}}{\left(\frac{1}{N_0} L\hat{R}V_{\mathfrak{a}}\right)^{1/2}} \tag{10}$$

where $\bar{d} = \frac{1}{N_0}\sum_{t=t_0}^{N_0} d_t$ and $L\hat{R}V_{\mathfrak{a}} = \gamma_0 + 2\sum_{j=1}^{\infty} = \gamma_0 + 2\sum_{j=1}^{\infty} Cov(d_t, d_{t-j})$ . The $L\hat{R}V_{\mathfrak{a}}$ is a constant estimate of the asymptotic (long-run) variance of $\sqrt{ND}$ . Negative DM test statistic implies that the first model (A) has smaller forecast error, in that case model A forecasts better than model B. Positive DM statistic test then implies that model A has larger forecast error than model B, implying that model B forecasts better than model A. The DM test statistic is asymptotically distributed with mean zero

[4]EViews software version 8 was distributed by IHT Global Inc. Details about the derivatives are found in the Users Guide for the software.

and unity variance. Then, under hypothesis of equal predictive accuracy, we reject the null at $\alpha$-level of significance when $|DM| > Z_{\alpha/2}$.

# 4 The Data and Empirical Results

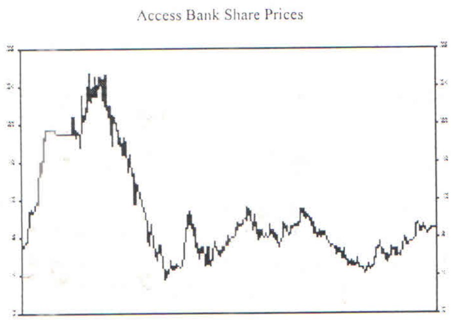
The data used in this study are the daily share prices of 12 highly capitalized commercial banks in Nigeria listed on the platform of Nigerian Stock Exchange (NSE). They are the Access Bank, Diamond Bank, First City Monument Bank (FCMB), FirstBank, Guaranty Trust Bank (GTB), Sterling Bank, United Bank for Africa (UBA), Unity Bank, Union Bank, Wema Bank and Zenith Bank. Different episodes of banks re-capitalization have taken place and some banks were stopped from operating by the CBN, while others merged with those with stronger financial backings. Based on these reasons, and for consistency in the sample data points, we resolved at using the banks that have been listed on the platform of NSE, far back as 2001. The share prices for each bank therefore span from 2nd January 2001 to 28th December 2012 and no adjustment was made for non-trading days (weekends and holidays).

The time plots representing the share prices of these banks over the time periods are presented in figures below. We notice a general increase in the share prices of these banks from 2001, and this peaked at the end of year 2002. The prices started reducing drastically at the beginning of 2003 and reached the trough in 2004.
Between 2003 and 2004, these banks did not have enough capital-base, and the pressure of CBN to meet the financial target further pushed the bank shares prices down. Some of these banks that absorbed other banks also reduced their bank share prices in order to have a balance with the share prices of banks absorbed. In 2009, there was another sharp dropped in prices which affect some banks till now. The CBN reform of 2011 also contributed to inability of these banks to recover financially on time.

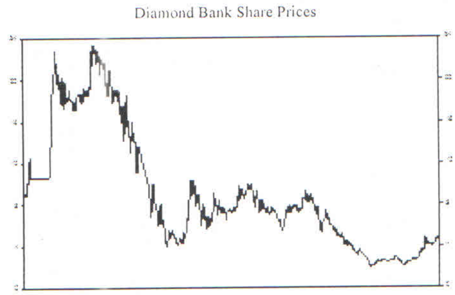
Model estimation results are presented as QML estimates using the MaxSa algorithm. The convergence time was very slow while estimating EGARCH model. In all cases, the mean parameters, except for the intercept are significant at 5% level. The lag order has been selected via the AIC criterion, and this criterion lead to the choice $p = q = 1$.

The initial estimation of GARCH models was carried out on all the series, and the condition for unconditional volatility was not satisfied by the parameters of the model. This may be as a result of untreated asymmetry in the returns series and in that case, GARCH models were not presented as competing models for predicting volatility in bank share prices. We proceed to estimating the asymmetric models.

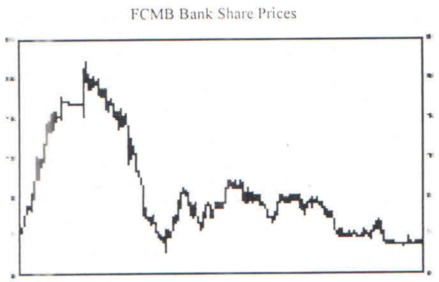
For Access bank returns (Table 1), the best volatility models based on minimum Akaike Information Criterion (AIC) is APARCH with AIC value of $-7.671$, followed by GJR model, and EGARCH as the least representative model with AIC of $-6.156$. Actually, the AICs for GJR and QGARCH models are very close. Comparing EGARCH model to APARCH, GJR and QGARCH models in terms of forecasts, we obtained DM statistic values 5.0908, 5.0890 and 5.0997 respectively, which are positive significant values at 5% level. These mean that the forecast errors generated by EGARCH model were larger in magnitudes than any of the competing forecasting model, and actually, there were very serious large values of in-sample conditional forecasts estimates which made the estimates of conditional volatility series of EGARCH model to dominate, in the computations and hence very close DM statistic values were estimated when comparing a model with EGARCH model. These results for EGARCH model are in agreement with the conclusion from the information criterion. Dropping EGARCH model in the group, we compared APARCH model with GJR and QGARCH models and obtained DM values of 0.1494 and 2.9283 respectively and these were both significant at 5% level. The APARCH and QGARCH models indicated significant pairwise forecasts performance with QGARCH model performing better than APARCH model. Between GJR and QGARCH model, positive significant DM value was obtained implying that QGARCH model performed better than GJR model on the time series. the QGARCH model is then rated as the best volatility forecasting model for Access bank share prices. Table 2 presents the results of forecasts performances for volatility models of Diamond bank share prices. The minimum AIC was recorded in APARCH model suggesting the model as the best in terms of fitness. The EGARCH model realized very



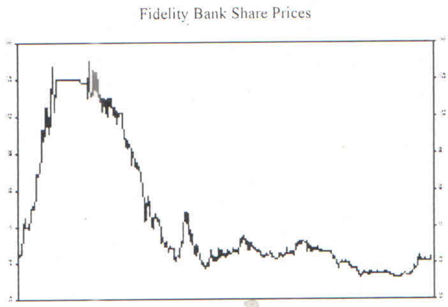

(a) ACCESS BANK



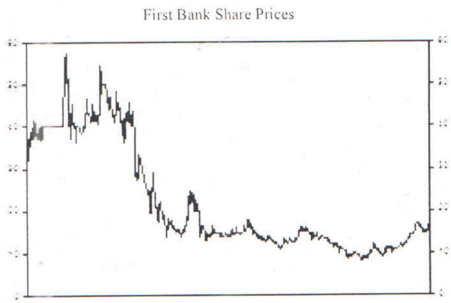

(b) DIAMOND BANK



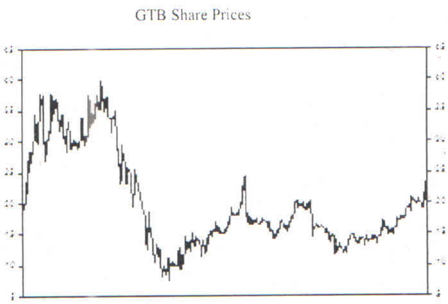

(c) FCMB




(d) FIDELITY BANK



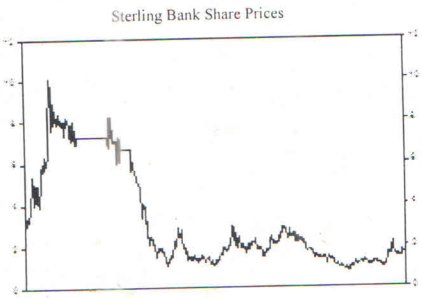

(e) FIRST BANK



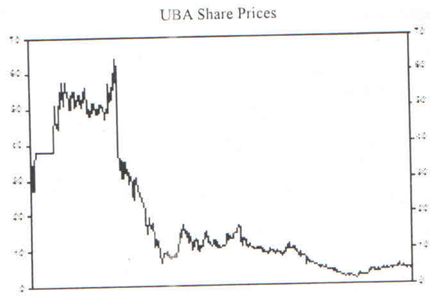

(f) GTB

high conditional volatility series and this made the model to perform worst in terms of forecasts, as we can see in the significant positive DM values, though this model has been the worst in terms of fitness. Actually, the AICs of APARCH, GJR and QGARCH models are very close, with that of APARCH model marginally smaller than that of GJR and QGARCH models. We found here, APARCH model with the smallest AIC performing better than GJR model in terms of forecasts, though the DM statistic was not significant at 5% level (-0.2630). The QGARCH model performed better than GJR model in terms of forecast, and this makes QGARCH model as the best volatility forecasting model for Diamond bank share prices.

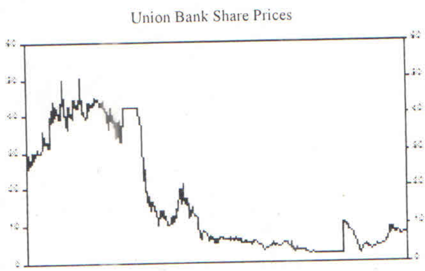
Table 3 presents the pairwise forecasts comparison results for FCMB share prices. Here, APARCH model emerged as the best estimated based on the minimum AIC (-7.064), and the worst model was EGARCH model. Between EGARCH and APARCH models, there was no significant forecast performance, and this applied to EGARCH and QGARCH models as well. Between EGARCH and GJR models, there was a negative significant forecast performance (-2.5266), implying that GJR model would perform better



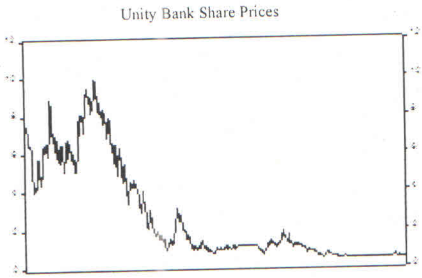

(g) STERLING BANK



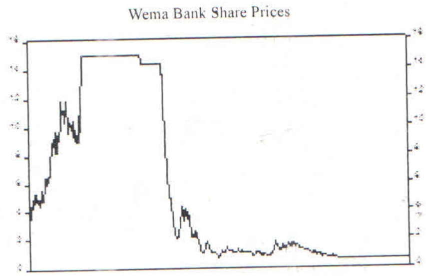

(h) UBA



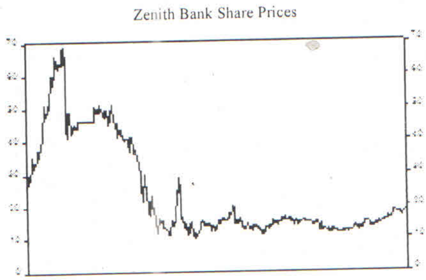

(i) UNION BANK




(j) UNITY BANK




(k) WEMA BANK




(l) ZENITH BANK

than EGARCH model in the real sense. Between APARCH and GJR models, there was also a negative significant relationship, implying the GJR model is better than APARCH models. We noted the equality of the DM statistics (-2.5266) in the two forecasts pairs, which was as a result of insignificant difference in the performances between EGARCH and APARCH models. Between GJR and QGARCH models, there was a positive significant forecast performance implying that GJR model would perform better than QGARCH models. Finally, GJR model emerged as the best volatility forecasting model for FCMB share prices, though it was the second best model in terms of model fitness.

Table 4 presents the results for volatility forecasting models of Fidelity bank share prices. Here, QGARCH model was picked by AIC as the best volatility model that fits the data well. The EGARCH model, as compared with APARCH, GJR and QGARCH models showed significant positive DM statistics implying that the models would perform better than EGARCH model in forecasting the volatility series. The EGARCH model realized explosive in-sample conditional volatility forecasts which made it the worst forecasting model. Between APARCH and GJR models, we found positive significant forecast performance implying that GJR model would perform better on forecasts than the APARCH model. Between GJR and QGARCH models, negative significant forecast performance was obtained implying that GJR model would perform better than QGARCH model. Finally, GJR model emerged as the best volatility

Table 1: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Access Bank Returns

| Model (AIC)[5] | EGARCH (-6.156) | APARCH (-7.671) | GJR (-6.174) | QGARCH (-6.171) |
|---|---|---|---|---|
| EGARCH (-6.156) | NA | 5.0908*** | 5.0890*** | 5.0997*** |
| APARCH (-7.671) | NA | NA | 0.1494 | 2.9283*** |
| GJR (-6.174) | NA | NA | NA | 2.7755*** |
| QGARCH (-6.171) | NA | NA | NA | NA |

*** significance of DM test at 5% level

Table 2: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Diamond Bank Returns

| Model (AIC) | EGARCH (-5.940) | APARCH (-5.976) | GJR (-5.974) | QGARCH (-5.975) |
|---|---|---|---|---|
| EGARCH (-5.940) | NA | 5.1704*** | 5.1703*** | 5.1815*** |
| APARCH (-5.976) | NA | NA | -0.2630 | 4.0168*** |
| GJR (-5.974) | NA | NA | NA | 3.6164*** |
| QGARCH (-5.975) | NA | NA | NA | NA |

*** significance of DM test at 5% level

forecasting model for Fidelity bank share prices, and QGARCH model which was the best model in terms of fitness is on the 3rd rank in terms of forecasts.

In Table 5, APARCH model is the best model in terms of fitness, with AIC of -7.534. The results of pairwise forecasts comparison of EGARCH model with APARCH, GJR and QGARCH models gave negative significant DM statistics implying that EGARCH model emerged the best forecasting model, though this model is the worst model in terms of fitness. The APARCH model with GJR model gave significant DM values of -5.0486 meaning that APARCH model forecasts better than GJR model. The APARCH model gave negative significant DM values with QGARCH model meaning that APARCH model would perform better than QGARCH model in forecasting. The GJR model also gave negative significant DM statistic with QGARCH model implying that GJR model would perform better than QGARCH model. Here, EGARCH model emerged the best forecasting model for FirstBank share prices, though this model has been the worst model in terms of fitness. The APARCH model is the 2nd best forecasting model, followed by GJR, then QGARCH model as the least in the rank.

Table 6 presents the results for GTB bank share prices. The three models, APARCH, GJR and QGARCH have similar AIC value of -6.273 (by approximation). The forecasts from EGARCH and APARCH models

Table 3: :Results of Pairwise Forecasts Comparison Test of Volatility Models for FCMB Bank Returns

| Model (AIC) | EGARCH (-6.202) | APARCH (-7.064) | GJR (-6.347) | QGARCH (-6.317) |
|---|---|---|---|---|
| EGARCH (-6.202) | NA | 0.3794 | -2.5266*** | 0.9797 |
| APARCH (-7.064) | NA | NA | -2.5266*** | 1.4403 |
| GJR (-6.347) | NA | NA | NA | 2.6510*** |
| QGARCH (-6.317) | NA | NA | NA | NA |

*** significance of DM test at 5% level

Table 4: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Fidelity Bank Returns

| Model (AIC) | EGARCH (-6.342) | APARCH (-6.195) | GJR (-6.178) | QGARCH (-6.363) |
|---|---|---|---|---|
| EGARCH (-6.342) | NA | 10.3957*** | 10.3957*** | 10.3957*** |
| APARCH (-6.195) | NA | NA | 1.9858*** | -14.3932*** |
| GJR (-6.178) | NA | NA | NA | -14.3935*** |
| QGARCH (-6.363) | NA | NA | NA | NA |

*** significance of DM test at 5% level

gave negative significant DM value meaning that EGARCH model would forecast better than APARCH model. Also, EGARCH model would perform better than QGARCH model in terms of forecasts. Between EGARCH and GJR models, there was no significant forecast performance. There was positive significant forecast performance between APARCH and GJR models implying that GJR model forecasts better than APARCH model. The QGARCH model also forecasts better than APARCH model since the DM statistic is positive and significant. Between GJR and QGARCH models, there is also a positive significant forecast performance meaning that QGARCH model forecasts better than GJR model. Therefore, QGARCH model is the best forecasting model followed by either EGARCH or GJR model.
Table 7 presents the results for Sterling bank share prices. The best model given by minimum AIC is APARCH model. The EGARCH model, as compared with APARCH, GJR and QGARCH models gave negative significant forecasts comparison test statistics implying that EGARCH model forecasts better than the other three models in forecasting the returns series. Between APARCH and GJR models, there is a negative DM values, implying that APARCH model forecasts better than GJR model. Between APARCH and QGARCH models, the forecasts comparison test is also negative implying that APARCH model still forecasts better than QGARCH model. The GJR model in comparison with QGARCH model gave positive DM test statistic, implying that QGARCH model would forecast better than GJR model.

Table 7: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Sterling Bank Returns

| Model (AIC) | EGARCH (-6.141) | APARCH (-8.785) | GJR (-6.468) | QGARCH (-6.511) |
|---|---|---|---|---|
| EGARCH (-6.141) | NA | -6.5681*** | -8.8636*** | -6.0103*** |
| APARCH (-8.785) | NA | NA | -8.8636*** | -2.9298*** |
| GJR (-6.468) | NA | NA | NA | 8.8636*** |
| QGARCH (-6.511) | NA | NA | NA | NA |

*** significance of DM test at 5% level

Table 8: :Results of Pairwise Forecasts Comparison Test of Volatility Models for UBA Bank Returns

| Model (AIC) | EGARCH (-6.055) | APARCH (-6.045) | GJR (-6.154) | QGARCH (-6.258) |
|---|---|---|---|---|
| EGARCH (-6.055) | NA | -7.1108*** | -6.7521*** | -6.7147*** |
| APARCH (-6.045) | NA | NA | 7.1285*** | -6.7024*** |
| GJR (-6.154) | NA | NA | NA | -6.7147*** |
| QGARCH (-6.258) | NA | NA | NA | NA |

*** significance of DM test at 5% level

In Table 9, APARCH model is the best model in terms of minimum AIC. None of the forecasts tests is significant at 5% level, though these were negative except in the pairwise forecasts comparison between GJR and QGARCH models. Looking at the signs of the DM test, it is much likely for EGARCH model to forecasts better than the other three models, though EGARCH model was the least model in terms of model fitness.

Table 10 presents the volatility modelling for unity bank share prices. The EGARCH model gave negative significant pairwise forecasts comparison test with APARCH, GJR and QGARCH models implying that EGARCH model forecasts better than the three models. Comparing APARCH and GJR models, there is negative significant DM statistics, meaning that APARCH model forecasts better than GJR model. There is positive significant DM test statistic between APARCH and QGARCH models implying that QGARCH model forecasts better than APARCH models. The QGARCH model is then found to forecast better than GJR model. Therefore, EGARCH model, which was ranked lowest by AIC emerged the best forecasting model, while APARCH model which was ranked best by minimum AIC emerged 3rd in forecasts ability.

Table 11 presents the case of Wema bank share prices. The APARCH model has the minimum AIC which makes it the best model in terms of parameter estimates and fitness. Between EGARCH and APARCH

Table 9: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Union Bank Returns

| Model (AIC) | EGARCH (-6.008) | APARCH (-6.854) | GJR (-6.540) | QGARCH (-6.540) |
|---|---|---|---|---|
| EGARCH (-6.008) | NA | -1.4753 | -1.2344 | -1.4367 |
| APARCH (-6.854) | NA | NA | -1.2343 | -0.2768 |
| GJR (-6.540) | NA | NA | NA | 1.2340 |
| QGARCH (-6.540) | NA | NA | NA | NA |

*** significance of DM test at 5% level

Table 10: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Unity Bank Returns

| Model (AIC) | EGARCH (-6.116) | APARCH (-11.142) | GJR (-6.965) | QGARCH (-7.115) |
|---|---|---|---|---|
| EGARCH (-6.1164) | NA | -4.7500*** | -3.0075*** | -4.1270*** |
| APARCH (-11.1419) | NA | NA | -3.0075*** | 3.2656*** |
| GJR (-6.9652) | NA | NA | NA | -3.0075*** |
| QGARCH (-7.1152) | NA | NA | NA | NA |

*** significance of DM test at 5% level

models, there is no significant pairwise forecasts comparison and similar result is also obtained between EGARCH and QGARCH models. Between EGARCH and GJR models, there is negative significant forecast comparison, implying that EGARCH model forecasts better than GJR models. Between APARCH and GJR models, there is negative significant forecasts comparison test implying that APARCH model forecasts better than GJR model. Between APARCH and QGARCH models, we found QGARCH model to forecast better since the pairwise forecasts comparison test computed positive DM statistic value. Between GJR and QGARCH models, we found QGARCH model also to forecast better. We can then rate EGARCH model first in terms of forecasts, followed by QGARCH model. The APARCH model is rated third in terms of forecasts. Table 12 presents the results for Zenith bank share prices. The optimal model based on minimum AIC is also the APARCH model. The EGARCH model as compared with APARCH and GJR models gave negative significant DM statistic value implying that EGARCH model forecasts better than the other two competing models. Between EGARCH and QGARCH models, we obtained positive significant forecasts comparison test meaning that QGARCH model forecasts better than EGARCH model. Between APARCH and GJR models, there is negative significant forecasts comparison, implying that APARCH model forecasts better than GJR model. Between APARCH and QGARCH models, there is positive significant forecasts comparison implying that QGARCH model forecasts better

Table 11: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Wema Bank Returns

| Model (AIC) | EGARCH (-7.364) | APARCH (-13.531) | GJR (-9.524) | QGARCH (-8.538) |
|---|---|---|---|---|
| EGARCH (-7.364) | NA | 1.0039 | -5.5718*** | 1.0039 |
| APARCH (-13.531) | NA | NA | -5.5718*** | 4.5813*** |
| GJR (-9.524) | NA | NA | NA | 5.5718*** |
| QGARCH (-8.538) | NA | NA | NA | NA |

*** significance of DM test at 5% level

than APARCH model. Between GJR and QGARCH models, there is positive significant forecasts comparison, implying that QGARCH forecasts better than GJR model. Finally, QGARCH model is the best volatility forecasting model for Zenith bank share prices.

Table 12: :Results of Pairwise Forecasts Comparison Test of Volatility Models for Zenith Bank Returns

| Model (AIC) | EGARCH (-6.494) | APARCH (-7.116) | GJR (-6.654) | QGARCH (-6.590) |
|---|---|---|---|---|
| EGARCH (-6.494) | NA | -6.1679*** | -9.5623*** | 3.2048*** |
| APARCH (-7.116) | NA | NA | -9.5623*** | 6.1421*** |
| GJR (-6.654) | NA | NA | NA | 9.5623*** |
| QGARCH (-6.590) | NA | NA | NA | NA |

*** significance of DM test at 5% level

We then summarize the results obtained in Tables 1-12 below in Table 13. The APARCH model was picked by minimum AIC in 9 out of 12 returns series for the volatility models. This implies that, the distribution of bank share prices in Nigeria is likely to follow power distribution in the specification of APARCH model. Therefore, when the interest is on the volatility, APARCH model would have been the best asymmetric model to consider. In terms of forecasts, this model is the worst. It was never selected as a better model in the 12 returns series. We can then say that the power specification of APARCH model greatly affects the model during forecasting.

Table 13: Table 13: Summary of Results

| Volatility Series (Share prices) | Best model by AIC | Best model by Forecasts |
|---|---|---|
| Access bank | APARCH | QGARCH |
| Diamond bank | APARCH | QGARCH |
| FCMB bank | APARCH | GJR |
| Fidelity bank | QGARCH | GJR |
| FirstBank | APARCH | EGARCH |
| GTB | Undecided | QGARCH |
| Sterling bank | APARCH | EGARCH |
| UBA | QGARCH | EGARCH |
| Union bank | APARCH | Undecided |
| Unity bank | APARCH | EGARCH |
| Wema bank | APARCH | EGARCH |
| Zenith | APARCH | QGARCH |

## 5 Concluding Remarks

In this paper, we have examined the pairwise volatility forecasts performances of variants of GARCH models that are nonlinear and asymmetric. We considered the daily bank share prices of 12 highly capitalized banks in Nigeria between 2001 and 2012. This period was intentionally chosen since it covers different periods of market contractions (bear periods) particularly, the time of great stock market crash, between 2008 and 2009. The banks are: Access Bank, Diamond Bank, First City Monument Bank (FCMB), FirstBank, Guaranty Trust Bank (GTB), Sterling Bank, United Bank for Africa (UBA), Unity Bank, Union Bank, Wema Bank and Zenith Bank. Initial GARCH models estimated for the returns of the share prices were discarded since they failed to satisfy stationarity and regularity conditions of GARCH modelling, therefore only nonlinear models were then considered.

The idea in this paper came up as a result of a seminal article of Hansen and Lunde (2005). These authors applied a battery of GARCH(1,1) variants and examined the forecasts ability of the models and found GARCH(1,1) model of Bollerslev (1986) being beaten by other asymmetric GARCH models considered in the paper. Other volatility models were then ranked according to their performances. Our emphasis here is to judge the asymmetric volatility models and check if the best fit model also performs better in terms of forecasts.

Due to the fact that stock returns data incorporate leverage effects, and by taking into consideration the asymmetric behaviour of volatility, it is possible to obtain more accurate predictions, using the asymmetric volatility models. The asymmetric nonlinear volatility models considered are the EGARCH, GJR and QGARCH models. The APARCH model emerged the best fitting model in 9 out of 12 stocks returns series considered and this model was never ranked first in volatility forecasting. It was the other models that ranked first in forecasting better the volatility in the share prices. The results therefore reconfirmed what was obtained in Hansen and Lunde (2005). Andersen and Bollerslev (1998) in their paper showed that an optimal volatility model should also provide better forecasts but this was disproved in Hansen and Lunde (2005). Awartani and Corradi (2005) also established the findings of Hansen and Lunde (2005), as obtained in this paper.

This work can be extended by identifying the expansion period (bull) and contraction period (bear) in the banks share prices and split the time series into these market phases, then, resulting into different subsamples. These subsamples are then estimated using the four volatility models considered and forecasts are examined. We can then verify Andersen and Bollerslev (1998) and Hansen and Lunde (2005) assertions, accordingly.

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